Université de Montréal

# Le modèle bayésien de l’intégration identitaire : vers une approche dynamique des processus internes du soi

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*Ce mémoire intitulé*

**Le modèle bayésien de l’intégration identitaire : vers une approche dynamique des processus internes du soi**

*Présenté par*

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## Résumé

Nos sociétés évoluent et se transforment constamment. Il devient de plus en plus difficile pour chacun de nous d'éviter le changement social. Lorsqu'un changement survient, nous devons modifier qui nous sommes afin de s'adapter à notre nouvel environnement et ressentir du bien-être. Plusieurs études ont proposé des étapes menant à l'intégration identitaire, mais ces processus demeurent limités sur une perspective statique. Les processus statiques ne parviennent pas à expliquer le processus itératif utilisé chaque jour pour intégrer une nouvelle identité. Le but de notre étude est de fusionner deux champs de la littérature : la psychologie sociale et les neurosciences afin de créer le Modèle bayésien d'intégration identitaire (MBII). Lors d'une première étude, nous discutons du fondement théorique du MBII ainsi que deux exemples fictifs de l'intégration d'une identité personnelle et sociale. Dans la seconde étude, nous testons certaines parties du MBII dans le contexte de la légalisation du cannabis au Canada. Ce contexte peut avoir changé l'intégration du cannabis des Canadiens dans leur identité de groupe. Nous avons mesuré l'intégration du cannabis de 1682 Canadiens sur trois temps de mesure à l'aide d'un questionnaire. Nous avons utilisé le MBII sur les trois temps de mesure afin de prédire l'intégration du cannabis au temps 3. Des analyses de régression montrent que les scores prédits par le MBII prédisent positivement les scores rapportés par les participants au temps 3. Les implications théoriques, méthodologiques et pratiques sont discutées.

*Mots-clés :* Intégration identitaire, opérations bayésiennes, processus dynamique

# Abstract

Societies grow and modify themselves continually. It becomes more and more difficult for people to avoid social change. When social change does show up, people need to modify who they are as to adapt themselves to their new environment and experience well-being. Several studies propose stages that lead to identity integration, but these processes remain limited to a static perspective. Static processes cannot explain how people actualize their identities on an iterative basis every day. The goal of the present study is to develop a new dynamic conceptualization of identity integration. To do so, we merge two fields of research: social psychology and fields of computed neuroscience and machine learning as to create our model: The Bayesian Model of Identity Integration (BMII). We discuss and test the BMII in two studies. In the first study, we describe the theoretical basis of our model along with two examples of how the BMII could explain a personal and a social identity integration. In the second study, we test several parts of the BMII in the context of cannabis legalization in Canada. Such context may have changed people's integration of cannabis into their identity of Canadians. We measure cannabis integration of 1682 Canadians over three measurement time questionnaires. The BMII is used on all three questionnaires and produce scores that aim to predict cannabis integration at time 3. Regression tests between predicted scores and actual scores of cannabis integration at time 3 shows positive predictions. Theoretical, methodological and practical implications are discussed.

*Keywords:* Identity integration, Bayesian operations, dynamic process

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# Liste des sigles et des abréviations

| | |
|---|---|
| β | Standardize regression coefficient |
| BMII | Bayesian Model of Identity Integration |
| Covid-19 | Coronavirus disease 2019 |
| H1 | Hypothesis 1 |
| H2 | Hypothesis 2 |
| H3 | Hypothesis 3 |
| H4 | Hypothesis 4 |
| H5 | Hypothesis 5 |
| SD | Standard deviation |
| $M$ | Mean |
| $M_{Age}$ | Mean of age |
| MBII | Modèle bayésien de l'intégration identitaire |
| MCDII | Modèle cognitif-développemental de l'intégration des identités |
| MULTIIS | The Multicultural Identity Integration Scale |
| N | Total number of participants in our sample |
| $p$ | Probability to commit an error of type 1 |
| $r$ | Correlation coefficient |
| α | Cronbach's alpha; internal consistency coefficient |
| 95% CI | 95% Confidence interval |

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# Introduction générale

## Problématique

Notre monde est le centre de plusieurs changements sociaux. Récemment, nous avons dû nous adapter à la propagation de la Covid-19. Un tel phénomène social a modifié notre manière d'agir et d'entrer en contact avec les autres. Ces changements ont le potentiel de modifier la manière dont nous nous définissons. Sommes-nous toujours aussi chaleureux qu'auparavant maintenant que nous ne pouvons plus serrer la main d'inconnu et embrasser nos enfants ou petits-enfants? Sommes-nous toujours un concessionnaire automobile si notre commerce a fermé ses portes ou que notre gestionnaire nous a mis à la porte pour faute de coupe budgétaire? Ces changements identitaires ne sont pas toujours faciles à surmonter. Le processus derrière l'acquisition d'une nouvelle identité peut parfois être long et ardu. Pourtant, notre monde continue de changer et nous force à nous acclimater à ses changements. Afin de pouvoir surfer sur les vagues de changements, nous devons résoudre l'une des questions actuelles les plus fondamentales: comment les personnes intègrent-elles une nouvelle identité?

## Modèles d'intégration identitaire en psychologie sociale

La psychologie sociale offre un grand volet de théories sur les processus identitaires et le soi. Nous conceptualisons le soi comme le processus cognitif central de tout être humain. Notre soi nous permet de réfléchir, de nous remémorer et d'agir (Markus et W1urf, 1987). Les identités sont des petites parties du soi (Markus, 1977). Nous avons généralement plusieurs identités; certaines sont personnelles (p. ex., nos goûts, notre orientation sexuelle) et d'autres sont sociales (p. ex., notre culture, notre travail). Ces identités sont susceptibles d'être changées. Les immigrants doivent généralement composer avec un changement au niveau de leur identité culturelle. Ils devront intégrer l'identité de leur nouvelle culture afin de pouvoir présenter des niveaux d'adaptation (Berry, 1997, 2005) et de bien-être (Amiot et al., 2007) plus élevés. Par ailleurs, la récente propagation de la Covid-19 a menacé beaucoup d'emplois. Certaines personnes ont perdu définitivement leur poste dans leur entreprise. Ces personnes devront aussi composer avec le changement d'identité de travailleur à celui de personne sans-emploi.

Comme nos sociétés sont de plus en plus multiculturelles, plusieurs travaux se sont intéressés à la manière dont les personnes pouvaient concilier leurs multiples identités culturelles. Berry (1997) a été l'un des pionniers à proposer un modèle qui permet de comprendre les différents états d'intégration identitaire. Sa théorie tourne autour du processus d'acculturation; c'est-à-dire le processus par lequel les personnes vont s'adapter à une nouvelle culture (Berry, 2003). Berry propose qu'il existe quatre états dans lesquelles les personnes immigrantes peuvent se retrouver: assimilation, séparation, marginalisation et intégration. L'état d'assimilation décrit une personne qui entretient beaucoup de contacts avec sa nouvelle société et garde très peu de contacts avec sa société d'origine. L'état de séparation décrit une personne qui entretient très peu de contacts avec sa nouvelle société, mais conserve ses contacts avec sa société d'origine. La marginalisation est l'absence de contacts avec les deux sociétés et l'intégration est l'entretien des contacts avec les deux sociétés. Selon Berry, les personnes intégrées auraient de meilleurs niveaux d'adaptation et plus de bien-être.

La théorie de l'acculturation nous a permis de mieux comprendre l'expérience de personnes faisant face à un changement identitaire. Par contre, la théorie ne nous informe pas du processus par lequel une personne en vient à atteindre l'état d'intégration. Plusieurs chercheurs se sont intéressés aux processus derrière le changement identitaire. Ces processus ont été étudiés tant au niveau des identités personnelles que sociales. Pour l'identité personnelle, plusieurs modèles ont tenté de comprendre comment une personne viendrait à intégrer une nouvelle identité sexuelle (gai et lesbienne). Le modèle de Cass (1979, 1984) a été l'un des pionniers à proposer un processus à l'intégration d'une nouvelle identité sexuelle. Le modèle proposé est construit sur six étapes. Chaque étape décrit le passage d'un état de questionnement « suis-je gai? » jusqu'à l'intégration d'une identité de gai ou lesbienne et à l'engagement dans un mode de vie en conséquence.

Amiot et collègues (2007) propose un processus cognitif néo-piagétien à l'intégration d'une identité sociale: Le modèle cognitif-développemental de l'intégration des identités (MCDII). Ce modèle présente trois avantages. Premièrement, il décrit le processus cognitif par lequel une nouvelle identité vient à s'intégrer à une autre. Deuxièmement, l'élaboration du modèle s'est inspirée d'un point de vue développemental; c'est-à-dire que notre concept de soi se développe d'un état fractionné vers un état intégré. Donc, avec notre développement, nos identités en viennent à se fusionner dans notre soi plutôt que de demeurer dissociées les unes des autres. Troisièmement, le MCDII décrit la manière dont les personnes peuvent cheminer vers l'intégration. Selon la théorie d'Amiot et collègues, les personnes viennent à percevoir de plus en plus de similitudes entre la nouvelle identité et leurs identités actuelles. Ces similarités vont créer des liens cognitifs entre la nouvelle identité et les identités présentent dans le soi. Plus il y aura de liens cognitifs, plus l'identité sera intégrée. Le processus est construit sur quatre étapes: l'anticipation, la catégorisation, la compartimentation et l'intégration.

L'anticipation est une étape avant même que le changement survienne. À ce moment, les personnes anticipent ce que pourrait être leur « nouveau soi » et commence à créer des liens cognitifs entre leur nouvelle identité et leur soi actuel. Par exemple, un immigrant souhaitant venir s'établir au Canada pourrait s'imaginer ce qu'est un Canadien et commencer à créer des liens cognitifs entre l'identité de Canadien et qui il est.

La catégorisation est la deuxième étape du processus d'Amiot et collègues. À cette étape, les personnes entrent en contact avec leur nouveau groupe et perçoivent une incohérence entre le nouveau groupe et qui ils sont. Les personnes vont donc adopter une identité et en rejeter une autre. L'identité sélectionnée pourrait être celle de leur nouveau groupe ou celle de leur groupe d'origine. Avec le temps, les personnes catégorisées devraient déceler des similitudes entre leurs deux identités conflictuelles. Ces similitudes devraient les faire avancer vers une étape subséquente de leur processus d'intégration.

La compartimentation est l'une des étapes où les personnes peuvent expérimenter leurs deux identités, mais pas au même moment. Les deux identités pourront être vécues seulement dans leur contexte social respectif. Donc, l'immigrant pourra s'identifier à son identité d'origine lorsqu'il est en famille; avec des personnes qui partagent et valorisent l'identité d'origine. Par contre, lorsqu'il sera dans un contexte canadien, l'immigrant pourra se définir en tant que Canadien.

Finalement, l'intégration se produit lorsque plusieurs similitudes sont faites entre les deux identités conflictuelles. À ce moment, les identités ne sont plus perçues comme contradictoires, mais plutôt compatibles et complémentaires. Le processus d'intégration identitaire peut aussi avoir lieu à l'aide d'un autre processus. Si les identités sont trop conflictuelles, la personne pourrait créer une nouvelle identité (supra ordinale) qui inclurait les deux identités en elle. Par exemple, l'immigrant pourrait s'identifier en tant que citoyen du monde; ce qui comprend à la fois son identité d'origine et son identité de Canadien.

Les processus actuels de l'intégration identitaire décrivent le cheminement des individus d'un point de vue statique. Plus précisément, chaque étape menant à l'intégration identitaire est décrite, mais le mécanisme dynamique interne qui permet d'expliquer pourquoi les personnes cheminent d'une étape à une autre (ou demeure à l'étape où ils sont) demeure une énigme trop longtemps ignorée.

**Modèles dynamiques en psychologie sociale**

Depuis plusieurs années, la psychologie sociale s'est tournée vers une définition dynamique du soi (Markus & Wurf, 1987). Le soi est de plus en plus conceptualisé en tant que *processus* cognitif régissant qui nous sommes. Malgré tout, les méthodes portant sur l'intégration de nouvelles identités sont demeurées statiques. Nous décrivons l'intégration identitaire en termes d'*états* ou d'*étapes* identitaire plutôt qu'en termes de processus. À travers nos recherches, nous avons déniché deux théories dynamiques pouvant expliquer le changement d'états internes dont l'identité.

La première théorie est celle de la boucle de rétroaction négative développée par Carver et Scheier en 1982 (voir Figure 1A). Selon cette théorie, les personnes régulent leurs comportements en fonction d'un processus itératif. Dans un premier temps, les personnes perçoivent leur environnement et comparent leur perception à un comparateur; c'est-à-dire une représentation interne. Le résultat de cette comparaison vient guider le comportement de la personne. En retour, le comportement vient modifier l'environnement, ce qui génère une nouvelle perception de la personne. La personne procède alors à une nouvelle comparaison et ainsi de suite. Dans leur article, les auteurs donnent l'exemple d'un conducteur sur une autoroute. Le conducteur perçoit une route droite devant lui (perception) et compare cette perception avec un comparateur interne. Selon les auteurs, les personnes sont portées à conceptualiser les routes comme des chemins droits (comparateur). Bien entendu, les routes doivent tourner de temps en temps, mais dans l'idéal, les routes demeurent droites. Puisque la perception correspond bien au comparateur, le conducteur continue de garder le volant droit (comportement); ce qui aura pour impact de conserver la voiture sur la route (environnement). Par contre, si le conducteur perçoit une courbe sur la route devant lui, sa perception et son comparateur seront différents. Le conducteur adaptera donc son comportement en tournant le volant afin de conserver la voiture sur la route.

La seconde théorie est celle du cycle d'apprentissage de Kolb's (1984). Tout comme le modèle de Carver et Scheier le processus derrière le changement de nos états internes est itératif (voir Figure 1B). Selon la théorie de Kolb, les personnes font face à une nouvelle expérience (expérience concrète) qui les amènent à réfléchir; c'est-à-dire trouvé s'il y a des inconsistances entre la nouvelle expérience et leur compréhension de cette expérience (observation réflective). Suite à cette réflexion, les personnes acquièrent une nouvelle idée de leur expérience ou à une modification des connaissances qu'ils avaient déjà sur l'expérience en question (conceptualisation abstraite). Finalement, les personnes peuvent appliquer leur nouvelle connaissance sur leur environnement et récolter de la rétroaction sur leur comportement. La rétroaction viendrait déclencher un second cycle au modèle d'apprentissage de Kolb.

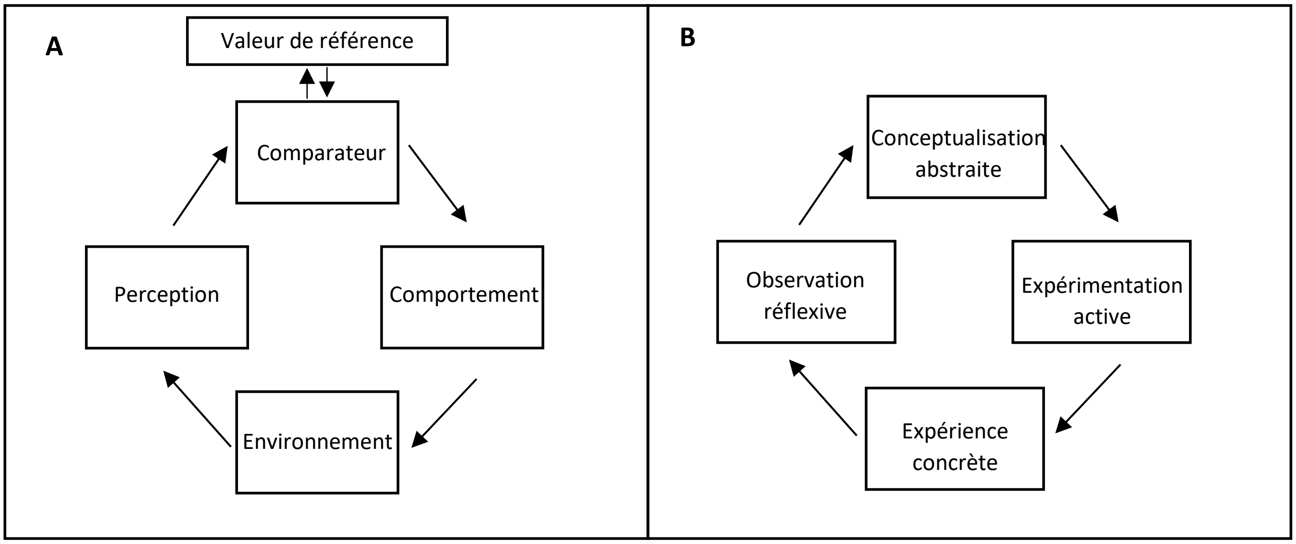


Figure 1. Théories dynamiques en psychologie sociale. *(A) La boucle de rétroaction négative de Carver et Scheier (1982) est présenté sur la gauche et (B) le cycle d'apprentissage de Kolb (1984) est présenté sur la droite*

Bien que les modèles de Carver et Scheier (1982) et Kolb (1984) abordent deux théories dynamiques sur le processus itératif au changement d'états internes, aucune méthode n'a été proposée afin de tester leur modèle de manière dynamique. Sur ce point, la psychologie fait face à un mur qu'elle peut difficilement contourner. Nos méthodes de modélisation des processus dynamiques sont déficitaires. Afin de pouvoir comprendre le processus derrière l'intégration identitaire, nous devons nous tourner vers des champs de recherche experte en modélisation de processus dynamique: la neuroscience et les l'intelligence artificielle.

**Modèles d'optimisation en neuroscience**

Un grand intérêt s'est installé sur les processus dynamiques de l'être humain dans les champs de neuroscience et d'intelligence artificielle. Les chercheurs en neuroscience computationnelle ont tenté de concevoir la manière dont les états internes venaient à se modifier de manière dynamique (Clark, 2016; Friston, 2009). Le but de ses recherches est de comprendre comment l'être humain arrive à se représenter son environnement et à le comprendre (Frison, 2009).

Les modélisations actuelles en neuroscience s'apparentent au modèle de dynamique de Friston (2009). Friston et ses collaborateurs (2009, 2013) ont proposé un modèle d'inférence dans lequel les personnes tentent de comprendre leur environnement (voir Figure 1). Les inférences sont des hypothèses que nous faisons sur notre environnement. Comme notre environnement ne nous apparait pas toujours clairement, nous formons des hypothèses sur ce dernier. Le modèle de Friston nous fournit une explication sur la manière dont nous allons valider nos hypothèses sur notre monde ou les invalider.

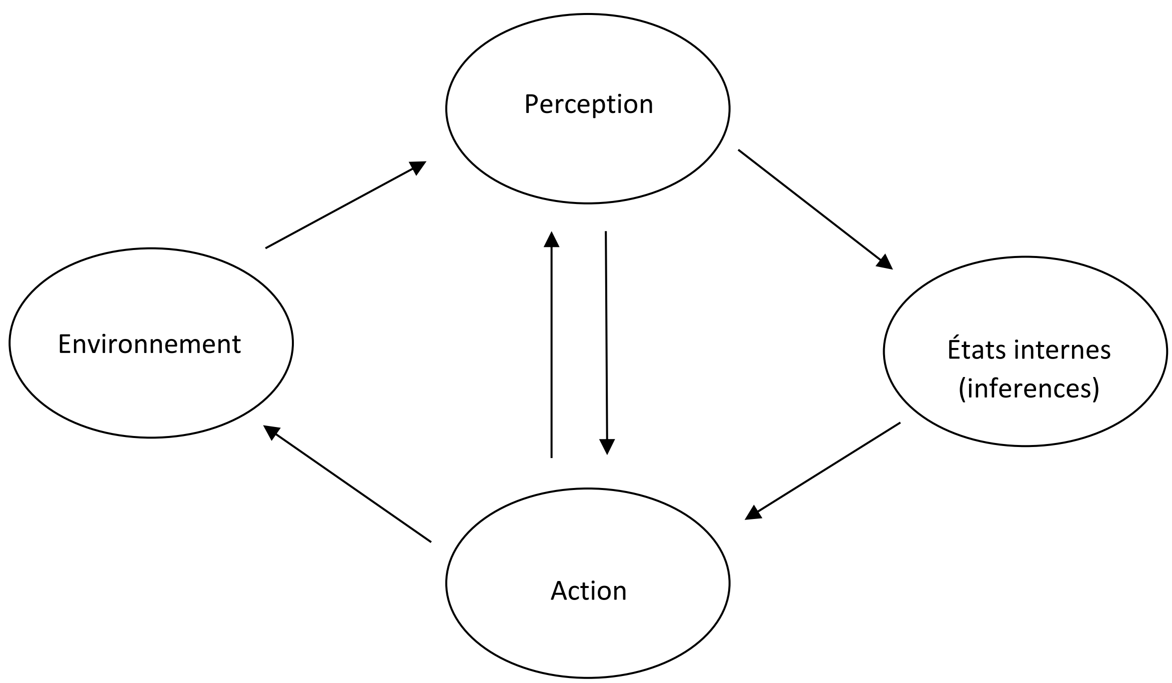


Figure 2: *Modèle dynamique de Friston*

Le modèle de Friston est construit sur trois raisonnements fondamentaux: (1) les états internes sont probabilistes, (2) le modèle cherche à réduire l'écart entre nos inférences et les perceptions de notre environnement; c'est-à-dire notre entropie et (3) le modèle est basé sur des opérations bayésiennes. Chacun de ses points sera abordé et discuté.

En premier lieu, les inférences que nous posons sur notre monde sont probabilités. Nos croyances sur notre environnement sont accompagnées d'un certain degré d'incertitude.

Deuxièmement, l'objectif du modèle de Friston est de réduire l'entropie. L'entropie est définie comme une mesure de chaos cognitif (Friston, 2009). Plus précisément, l'entropie est une mesure d'écart entre nos états internes et la perception que nous avons de notre environnement. Le but est de réduire cet écart afin que nos inférences correspondent avec notre environnement.

Troisièmement, le modèle de Friston est basé sur des opérations bayésiennes. Selon les travaux de Friston, les personnes construisent leurs inférences d'un processus computationnel interne. Dans ce processus, les personnes considèrent leur inférence a priori et tente de la modifier au regard de nouvelles informations appelé évidences. Le processus est inspiré des méthodes Bayésiennes où nous considérons un état probable a priori et nous calculons sa transformation en état a posteriori (Jackman, 2009).

Le modèle proposé par Frison (2009) est itératif; c'est-à-dire que les mêmes mécanismes sont en œuvre et se répètent dans le temps. Les états internes sont les inférences que nous posons sur notre monde. Les actions sont les comportements que nous faisons. Généralement, nos actions vont de pair avec nos inférences. L'environnement est le contexte dans lequel nous nous trouvons (p. ex., salle de classe, lieu de travail) et nos perceptions sont les éléments de notre environnement qui informe nos états internes. Donc, si je me trouve dans une salle de classe, je devrais voir un tableau, des pupitres, peut-être un projecteur. Ces perceptions renseignent ma croyance d'être dans une classe.

Le modèle propose aussi deux chemins alternatifs à la boucle complète. Premièrement, nos perceptions peuvent mener directement à une action. Dans un tel cas, nos états internes ne seraient pas responsables de nos actions, seulement notre perception. Nous retrouvons cette situation lorsque nous avons un réflexe; notre corps produit un mouvement involontaire à la suite d'une perception. Par exemple, nous allons cligner des yeux lorsque nous percevons que nos globes oculaires s’assèchent par une rafale de vent. Nous allons aussi involontairement lever notre jambe si le médecin teste le réflexe du genou et nous donne un léger coup sur le ligament patellaire. Deuxièmement, nos actions peuvent mener directement à une perception, sans avoir eu d’incidence sur notre environnement. À titre d’exemple, nous pouvons saluer de la main l’un de nos amis dans la rue sans que ce dernier ne nous voient. Dans cette situation, nous percevrons que notre action n’a pas d’incidence sur notre environnement et nous arrêterions notre action de saluer notre ami.

Plusieurs recherches ont investigué les processus dynamiques derrière la manière dont les personnes percevaient leur environnement et se représentaient leurs perceptions. Ces recherches ont étudié plusieurs types de perceptions (p. ex., visuel et auditif, Battaglia et al., 2003; et proprioceptive, Ostwald et al., 2012). Par ailleurs, une méthode a été mise de l’avant pour étudier la manière dont les personnes pouvaient se représenter leurs interactions avec une autre personne (voir, Moutoussis et al., 2014). Toutefois, aucune n’études ne s’est penchée sur des états internes plus complexes tels que l’intégration identitaire.

**Modèle bayésien de l’intégration identitaire**

Le modèle bayésien de l’intégration identitaire (MBII) a vu le jour grâce à la fusion de la théorie de l’intégration identitaire d’Amiot et collègues (2007) et les processus dynamiques de Friston (2009). Plus précisément, nous postulons que les personnes peuvent modifier qui ils sont et transiger dans les étapes de l’intégration identitaire (anticipation, catégorisation, compartimentation et intégration) en fonction de leurs actions et de leurs perceptions de leur environnement. La figure 2 présente le MBII. Nous avons ajouté le rôle des besoins comme modérateur de la relation entre nos perceptions et nos états internes (identités).

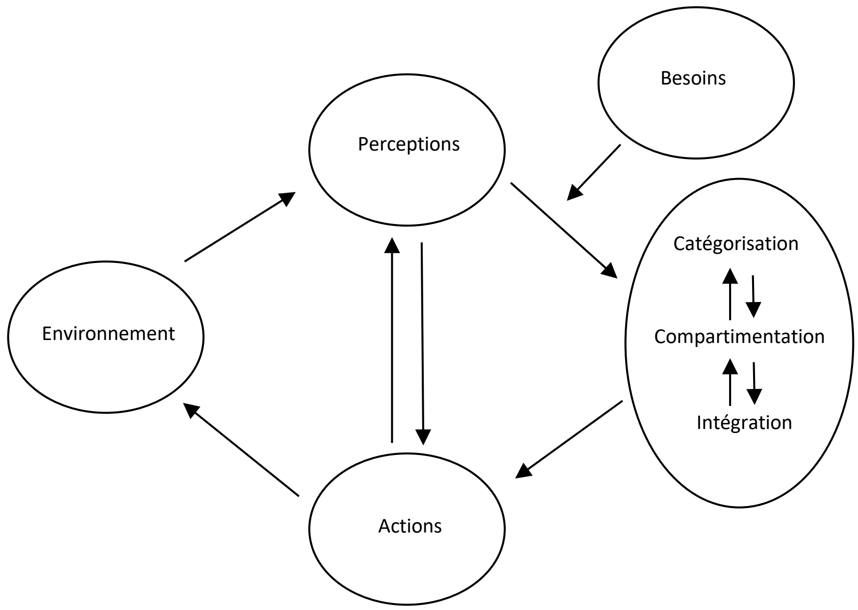


Figure 3: *Modèle bayésien de l'intégration identitaire*

*Note*. Les flèches au centre du modèle ont été reproduites à des fins théoriques, mais ne seront pas considérées dans les explications subséquentes du modèle.

Les besoins sont définis comme les nécessités qui nous permettent de fonctionner optimalement et de ressentir du bien-être (Deci & Ryan, 2000; Maslow, 1954, 1970). Plusieurs besoins peuvent venir influencer l'impact de notre perception sur nos identités. Nous argumentons toutefois que deux types de besoins résident au cœur du processus d'intégration identitaire: le besoin de sécurité et le besoin d'appartenance. Le besoin de sécurité se définit par la nécessité d'être à l'abri de menaces ou de situations chaotiques (Maslow, 1970). Les personnes ayant un faible besoin de sécurité pourraient avoir la confiance de s'investir au sein d'une nouvelle identité. À l'opposé, les personnes avec un fort besoin de sécurité pourraient se retrancher vers leur identité d'origine. Cette identité garantirait une stabilité de leur concept de soi et agirait comme base sécurisante. Le besoin d'appartenance se définit comme le désir de s'engager dans des relations avec les autres et appartenir à un groupe (Maslow, 1970). Nous postulons que le besoin d'appartenir à un nouveau groupe pourrait motiver les personnes à intégrer une nouvelle identité, alors qu'un faible besoin d'appartenir à un nouveau groupe pourrait les en dissuader.

Pour démontrer le MBII à l'aide d'un exemple, nous allons nous baser sur le contexte de la légalisation du cannabis; le contexte de notre deuxième étude. Suite à la légalisation du cannabis, les personnes pourraient être sujettes à plusieurs types de perceptions. Nous argumentons que les personnes seront surtout sensibles à la perception de normes sociales. Donc, ce que les autres valorisent et font viendrait influencer le niveau d'intégration du cannabis des personnes (Cialdini & Trost, 1998). Ces perceptions seront filtrées par les besoins de sécurité et d'appartenance. Si le besoin de sécurité est élevé, les personnes pourraient se méfier du cannabis et être plus attentives aux perceptions négatives sur le cannabis. Notre état d'intégration du cannabis va venir dicter le type de comportement que nous devrions adopter. Si nous sommes dans un état de catégorisation, nous devrions éviter la consommation du cannabis. L'état de compartimentation pourrait favoriser la consommation de cannabis dans certains contextes. Finalement, l'état d'intégration pourrait faire en sorte que l'on a intégré le cannabis en nous et, donc, nous n'avons pas nécessairement besoin d'un contexte social précis pour consommer. Une fois que nous aurons fait nos comportements, nous allons percevoir s'ils étaient adaptés au sein de notre environnement. Cette deuxième perception va venir informer notre état d'intégration du cannabis. À titre d'exemple, si nous nous faisons reprocher de consommer du cannabis sur notre balcon avant, nous pourrions reconsidérer le niveau d'intégration du cannabis dans notre identité de groupe. Le MBII est un processus itératif. Nous allons constamment adapter notre état identitaire en fonction de ce que nous faisons et de ce que nous percevons par la suite.

**Méthodes bayésiennes utilisées pour le MBII**

Nous basons les fondements du MBII sur des opérations bayésiennes inspirées des statistiques bayésiennes. Les statistiques bayésiennes sont une méthode pour tester des hypothèses de manières probabilistes. Pour se faire, les statisticiens élaborent un état a priori sur leurs hypothèses. Par exemple, des chercheurs intéressés au lien entre l'argent et le bonheur pourraient s’entendre sur une valeur hypothétique pour représenter la force d’association entre les deux variables. En statistique, la régression est souvent utilisée pour trouver la force de relation entre deux variables. La valeur « Beta standardisé » s’étale de -1.0 (relation parfaitement négative) à 1.0 (relation parfaitement positive) en passant par la valeur 0.0 (relation nulle). Dans notre exemple, les chercheurs pourraient s’entendre sur une valeur $\beta = .50$. Ils vont donc accorder une plus grande probabilité à la valeur 0.5 et attribuer moins de probabilités aux valeurs qui s’en éloignent. Ensuite, les chercheurs collectent des données sur leur phénomène d’intérêt. Les résultats sont considérés en terme probabiliste. Nous allons utiliser le terme « évidence » pour référer aux données collectées. Dans notre exemple, les chercheurs pourraient avoir trouvé un lien de $\beta = .40$. Pour terminer, les chercheurs multiplient leur état a priori avec l'évidence qu’ils ont trouvé grâce à leur étude. Le résultat est une nouvelle distribution de probabilités. Cette distribution subira une correction afin que la somme des probabilités soit égale à 1. Le résultat finalement sera une distribution a posteriori. La valeur la plus probable sera probablement plus faible que $\beta = .50$, puisque nous avons trouvé une évidence qui tire le coefficient de corrélation vers une valeur plus faible de $\beta = .40$.

Nous utilisons une méthode semblable pour notre modélisation du processus d’intégration identitaire. Le MBII considère la probabilité d’intégrer une identité comme état a priori et considère nos perceptions de l’environnement comme évidences. Selon cette optique, notre croyance quant à l’intégration d’une identité est modifiée grâce aux informations (évidences) que nous allons chercher dans notre environnement.

**Méthodologie**

Nos méthodes pour tester notre modèle se divisent en deux étapes. Premièrement, nous devons modéliser le changement identitaire. Cette étape est au cœur du présent projet de recherche. Nous avons modélisé les processus internes d’intégration identitaire à l’aide de méthodes bayésiennes. Les méthodes bayésiennes nous permettent de construire un état probabiliste a priori (une identité a priori) et de le modifier avec de nouvelles évidences (de nouvelles données que nous recueillons grâce à nos perceptions).

À travers le processus bayésien, les probabilités que nous avions accordées a priori viennent à se modifier avec l'exposition à de nouvelles évidences. Le résultat du MBII est un ensemble de scores (un score pour chaque participant) sur la valeur que devrait prendre leur état identitaire futur. Notre deuxième étape vise à comparer si les scores produits par le MBII sont adéquats. Les scores produits par le MBII seront comparés à des scores d'intégration identitaire future avec des tests de régressions. La valeur des coefficients de régressions pourra nous informer de la justesse du MBII.

Pour la présente étude, nous avons considéré les perceptions, les besoins et les actions au même titre comme évidence. Par cette approche, nous voulons tester une seule et même méthode de modéliser les états internes d'identité et comparer les différents résultats des différentes simulations. Ainsi, à titre d'exemple, le besoin de sécurité ne sera pas considéré comme un modérateur de la relation entre l'évidence et l'a priori, mais plutôt comme une évidence au même rang que les perceptions.

**Participants et procédure**

Nous avons distribué trois questionnaires à 1682 Canadiens de la province de Québec suite à la légalisation du cannabis au Canada (45,84% femmes, Mage = 50,91). Nous avons fait appel à la firme de sondage AskingCanadians pour la distribution de notre questionnaire. La firme s'est assuré que l'échantillon était représentatif de la population du Québec. Pour se faire, AskingCanadians compare fréquemment les caractéristiques de leur panel aux résultats de Statistiques Canada. Le premier questionnaire a été distribué la journée même de la légalisation du cannabis; le 17 octobre 2018. Le second questionnaire a été distribué une semaine plus tard (43,57% femmes) et le troisième questionnaire un an plus tard (42,33% femme). Les questionnaires ont été envoyés de manière électronique par la firme. Les participants bénéficiaient d'une description de l'étude et devaient consentir avant de pouvoir répondre aux items. Comme le questionnaire était envoyé de manière électronique, les participants pouvaient choisir leur lieu de convenance pour répondre aux questions.

**Mesures**

**Données sociodémographiques.** Nous avons inclus plusieurs questions sociodémographiques à notre questionnaire tel que l'âge de nos participants, le genre auquel ils s'identifient, le plus haut diplôme atteint, ce qu'ils font dans la vie (p. ex., travailleur, étudiant) et leur statut socioéconomique. Le statut socioéconomique a été mesuré sur une échelle de 0 (bas de l'échelle, faible revenu et condition de vie) à 4 (haut de l'échelle, bons revenus et conditions de vie).

**Perception des normes sociales.** Nous avons mesuré la perception des normes sociales à l'aide de deux types de normes : les normes descriptives et injonctives. Les normes descriptives représentent les comportements faits par les membres de notre groupe et les normes injonctives représentent ce que le groupe valorise. Nous avons mesuré la norme descriptive avec l'item « Selon moi, quand le cannabis sera légal, la fréquence de la consommation de cannabis par les (group) va…» sur une échelle de 0 (diminuer) à 4 (augmenter). Nous avons mesuré la norme injonctive avec l'item « Croyez-vous que les changements portant sur la légalisation du cannabis soient négatifs ou positifs? » sur une échelle de 0 (très négative) à 4 (très positive). Nous sommes conscients que l'item ne mesure pas exactement la norme injonctive du groupe, mais plutôt l'évaluation personnelle de chaque participant de la légalisation du cannabis. Néanmoins, l'évaluation personnelle pourrait approximer la norme injonctive perçue. Ces items ont été utilisés au sein d'études antérieures (de la Sablonnière & Tougas, 2008; de la Sablonnière, Tougas, & Lortie-Lussier, 2009) et ont le potentiel de bien capter la perception du changement social. Nous demeurons toutefois conscients de ne pas capter parfaitement l'effet de la norme injonctive. Les recherches futures pourront répondre à cette limite.

**Besoin de sécurité.** Nous avons mesuré le besoin de sécurité à l'aide de trois items de l'échelle de Strong et Fiebert (1987) inspiré de la théorie des besoins de Maslow (1954, 1968). Un exemple d'item est « Je vis dans une société ordonnée et pourvue de lois ». Chacun est mesuré sur une échelle de 0 (Fortement en désaccord) à 4 (Fortement en accord). La consistance interne est adéquate sur les trois temps de mesure ($\alpha_{T1}$ = .77, $\alpha_{T2}$ = .79, $\alpha_{T3}$ = .81).

**Action.** Nous avons mesuré l'action de s'informer sur la légalisation du cannabis de nos participants. Nous avons utilisé l'item « J'ai suivi le débat politique (p. ex. dans les médias) portant sur la légalisation du cannabis » mesuré sur une échelle de 0 (Fortement en désaccord) à 4 (Fortement en accord).

**Intégration du cannabis dans l'identité de groupe.** Chaque étape du processus d'intégration a été mesurée avec l'échelle de Yampolsky et collègues (2016). Afin d'adapter les items au groupe des participants, nous avons demandé s'ils s'identifiaient plus au Québécois et/ou aux Canadiens. Leur réponse est venue construire les présents items d'intégration identitaire. Un item a été utilisé pour mesurer la catégorisation « je m'identifie exclusivement à mon identité (group) », deux items pour la compartimentation « mon identité (group) et mon identité liée au cannabis représentent des parties séparées de qui je suis » et « mon identité (group) et mon identité liée au cannabis ne peuvent pas être réconciliées » et trois items pour l'intégration « mon identité (group) et mon identité liée au cannabis sont liées», « mon identité de (group) inclut mon identité liée au cannabis» et « je perçois des similarités entre mon identité (group) et mon identité liée au cannabis ». Chaque item a été mesuré sur une échelle de 0 (Fortement en désaccord) à 4 (Fortement en accord). La consistance interne de la compartimentation et de l'intégration est adéquate à travers les trois temps de mesure $r_{T1} = .75$, $r_{T2} = .71$, $r_{T3} = .75$ pour la compartimentation et $\alpha_{T1} = .94$, $\alpha_{T2} = .94$, $\alpha_{T3} = .94$ pour l'intégration).

**Identification aux consommateurs de cannabis.** Nous avons mesuré le niveau d'identification de nos participants aux consommateurs de cannabis avec trois items de l'échelle de Cameron (2004). Les items utilisés sont « je m'identifie aux consommateurs de cannabis », « j'ai beaucoup en commun avec les consommateurs de cannabis » et « être un consommateur de cannabis est une partie importante de qui je suis ». Chaque item a été mesuré sur une échelle de 0 (Fortement en désaccord) à 4 (Fortement en accord). La consistance interne de l'échelle est adéquate sur les trois temps de mesure ($\alpha$T1 = .88, $\alpha$T2 = .88, $\alpha$T3 = .89).

**Articles**

Nous discutons du MBII au travers de deux articles. Le premier article a pour objectif de décrire le fondement théorique du MBII. Le second article a pour objectif de tester certaines parties du MBII.

# Article 1: The Bayesian Model of Identity Integration: A Theoretical Proposal for a Probabilistic View of Identity Integration Processes

**Abstract**

Our world is more complex and multicultural than ever. The lives of millions of people are redefined every day. To understand how people integrate new identities into their self-concept has become more salient than ever. Research has highlighted several facilitators and inhibitors to identity integration; but has yet to discover the internal process leading someone to integrate a new identity. The present theoretical proposal discusses the Bayesian Model of Identity Integration which uses our actions, our needs and our perceptions of the environment to shape our self. Our model is iterative, which means the internal process repeats itself perpetually. Our model is based on Bayesian operations, which allows us to quantify change in time and could be a useful tool to understand how people change who they are. The present Bayesian model of identity integration has the potential to explain the mechanism associated with one of the most profound and unanswered questions: How do we become who we are?

*Keywords:* Identity Integration, Bayesian operations, Self-concept, dynamic processes

## The Bayesian Model of Identity Integration: A Theoretical Proposal for a Probabilistic View of Identity Integration Processes

Change is an undeniable part of life. While some changes are simple to overcome, others can challenge ourselves beyond what we can bear. When civil wars burst, natural disasters strike or virus spread, the lives of millions are brought to a turning point. In these times of change, many of us could lose track of *who we are* and be forced to redefine ourselves (Amiot et al., 2007). As long as our self differs from our current environment, we could feel confused, be less adapted (Berry, 1997, 2005; Nguyen & Benet-Marítnez, 2013) and feel less well-being (Benet-Martinez et al., 2002; Berry et al., 2006; de la Sablonnière et al., 2010; Yampolsky et al., 2013). Since our lives are in perpetual motion, changes will always remain an issue. In our world of massive migration, climate changes and exponential technological advancements, understanding how people change who they are become one of our biggest challenges.

Current understandings of people's self-definition reside into theories of the self and identities. Everyone holds an internal representation or "self-concept" of who they are. Our self-concept is conceived of many identities (e.g., being a student, a waiter, a gym instructor). When people change who they are, they reorganize their self-concept as to include new identities into existing ones (Benet-Martínez et al., 2002; Berry, 1990). Such internal negotiation can hardly be done overnight. Many must process the new identity before they could accept it as a part of who they are. Numerous researchers have studied processes of identity integration (e.g., sexual identity integration, Cass, 1979, 1984; personal identity integration, Harter, 2003; and social identity integration, Amiot et al., 2007). Many of these processes are developed into a series of stages where each stage ahead of us brings us closer to the integration of a new identity. The process of identity integration is not always a straight line. People are not obligated to follow each stage to reach integration (Coulombe et al., in progress). For instance, people can skip a stage or return to a previous one. In this sense, models of identity integration are considered dynamic instead of linear. However, present theories on identity integration hardly put forward a methodology to assess the evolution of identity stages through time. Only a dynamic conceptualization and methods of analysis can inform us on the way identities become more or less integrated through time.

Our goal is to propose a *dynamic* model of identity integration, namely The Bayesian Model of Identity Integration (BMII). To do this, we merge two fields of research: social psychology and fields of computational neuroscience and machine learning. Only with the understanding of identity processes of social psychology and the mathematical conceptualization of dynamic internal processes from computational neuroscience and machine learning can we create a dynamic model of identity integration. The BMII has both theoretical and methodological implications in current research on identity processes. As a theoretical implication, the BMII offers unique insights on the way people change their states of identity integration through time. Such understanding could open our eyes on deep and fundamental mechanisms that make us who we are. On a methodological perspective, the BMII has the potential to estimate changes of identity integration. The BMII is conceived on Bayesian formulas that can measure and assess the states of identity integration through time. In the present proposal, we will discuss the theoretical foundation of our dynamic model.

**Who I Am**

Understanding how people change who they are starts with a closer look into their self. The self is the inner entity that holds every aspect of us and, as a whole, makes us who we are. Every answer to the question, “Who am I?” is a piece of ourselves (Gordon, 1968; Kuhn & McPartland, 1954). We usually conceive ourselves along what we do, what we like, what we value, and to which group we belong (Cárdenas & de la Sablonnière, 2018; Gergen, 1971). For instance, studying makes us students, hunting makes us hunters and living in Canada makes us Canadians.

The self plays a fundamental role in our daily lives. Everything we experience is somehow proceeded by ourselves (Leary & Tangney, 2014). In this line, the self stands as the most central cognitive process of every human being. Our self orients our thoughts, manage our experiences, and regulates our behaviours (Baumeister, 1998; Brewer, 1991;

Brown, 1998; Oyserman, 2007) in order to meet our goals and needs. When we feel lonely, our self knows to whom we can turn to find a sense of belonging. Plus, our self knows what to do and what to say to maintain our social relations. With some people, we might avoid certain subjects of conversation and, with others, certain activities. We fit who we are according to our surroundings (Festinger et al., 1950; Tafarodi et al., 2002) and, in return, we tend to choose our surroundings according to whom we are (Kandel, 1978). As such, our self allows us to fit within our environment and creates an environment that reflects who we are.

Our self did not come from air, but rather from the experience of several social influences such as friends, parents and teachers (Harter, 2014). What people think of us is of great matter in how we define ourselves (Cooley, 1902; Felson, 1993). Others, be them real or imaginary, form a social standard to which we can compare and evaluate aspects of ourselves (see, Alicke et al., 2014; Okuno-Fujiwara & Postlewaite, 1995). Several researchers support that people align who they are according to their social contexts (Gurin & Markus, 1988; Oyserman & Markus, 1993; Turner et al., 1987). Different social contexts will surely drive different kinds of selves.

The main function of the self, if not the most pivotal one, is to organize itself into a structure that enables the encoding of information relevant to different contexts (Oyserman et al., 2014). In our lives, we are usually exposed to several contexts, each of them requires different responses from us. For instance, being both a student and a hockey player requires two distinct patterns of thoughts and behaviours. In the academic context, people are expected to have reflective thoughts and produce behaviours such as reading and listening to a class. On ice, strategic thoughts and teamwork behaviours are mandatory. The self must thus operate into a coherent organization as to facilitate the encoding and recovery of certain patterns of thoughts and behaviours adapted to each of the context it might find itself in. To do so, we have stored the different patterns of thoughts, behaviours and values into identities, which are small part of the self based on the experience we have in several contexts (Hogg, 2003; Markus & Wurf, 1987; Oyserman et al., 2014; Stryker & Burke, 2000).

Several kinds of identity may define ourselves. In the present paper, we will discuss the integration process of two: personal identity and social identity. Personal identities refer to the attributes that describe us as a person independently to the groups we belong (e.g., qualities, tastes, abilities; Gergen, 1971; Owens et al., 2010). Social identity, as define by Tajfel (1981, p. 255), is the "part of the individual's self-concept which derives from his or her knowledge of membership to a social group (or groups) together with the value and the emotional significance to it" (e.g., cultural identity, work-related identity).

Each kind of identity will be discussed into fictive cases to illustrate the different ways people can define themselves and, later on, how they manage to change one of their identities through the BMII. To assert the personal identity integration, we will discuss the case of a young man who is about to clarify his sexual orientation toward other boys. Social identity will be discussed through the experience of a Brazilian immigrant in Canada.

**How I Become Who I Am**

Changing who we are mean integrating a new identity to ourselves. Many people remain reluctant to modify something as fundamental as their identities. In fact, people may pass through a whole process where they negotiate who they are and who they aspire to become. Several researchers postulated theories on the complex process of identity integration (Amiot et al., 2007; Cass, 1979, 1984; Marcia, 1993). All of them discuss a series of stages leading people toward identity integration. However, only one theory describes the cognitive process of identity integration: The Cognitive Model of Social Identity Integration (Amiot et al., 2007). Such internal look into people's head helps us conceptualize how new identities join the ones who constitute the self.

The Cognitive Model of Social Identity Integration (Amiot et al., 2007) describes the integration of an identity as a process where more and more cognitive links come to be created between the new identity and the current ones. If cognitive links cannot be made, the self could create a higher order identity in which the two conflicted identities can coexist. Higher order identities are "bigger" identities that includes sub-identities

(Amiot et al., 2007). For instance, people could identify themselves as "citizen of the world" to encompass two incompatible cultural identities. Authors of the Cognitive Model of Social Identity Integration have proposed a process in four stages leading to integration; which is the fourth and final stage. The first stage – anticipatory categorization- can only be applied when the integration of a new identity is expected. During this stage, people tend to identify with their new identity without having been in contact with this very identity (Amiot et al., 2007). For instance, people moving from one country to another could experience a feeling of belonging to their new country even if they have not set foot in it yet. At this stage, some cognitive links between new and current identities are developed. The second stage – categorization – occurs when people identify with only one identity and reject another one (Amiot et al., 2007). Categorized people see the new identity as distinct from whom they are and resist its integration. For instance, people who have moved into a new country could define themselves with their former cultural identity and reject the cultural identity. In the third stage – compartmentation – people can identify themselves to new and former identities, but not at the same time (Amiot et al., 2007). Identities are activated alternatively depending on the social context people are in. For instance, immigrants could identify themselves to their new cultural identity when being with foreign friends and identify as their former cultural identity in the context of home, with their family. Each social context will activate the proper identity and turn down the other one. Finally, integration is reached when people can identify to former and new identities at the same time (Amiot et al., 2007). Through integration, people perceive their identities as consistent and complementary.

Stages of the Cognitive Model of Social Identity Integration reside into a dynamic process. Dynamic processes, instead of linear ones, consider that people will not always follow a linear path of stages to achieve a goal. For instance, people in their quest for identity integration could experience the same stage more than once or skip stages (see, Coulombe et al., in progress). However, the methods to analyze the dynamic process of the Cognitive Model of Social Identity Integration is nonexistent. To do so, we need to conceptualize the *iterative* mechanism that can assess the changes of identity integration across time.

**Learning Who I Can Be**

Being who we are means *knowing* who we are. All the patterns of thoughts and behaviours that reside into our different identities are information that we have collected through the experience of being in touch with these very identities (Markus & Wurf, 1987). In other words, to pass time in certain social contexts will make us learn the identity of that very social context. Being a surgeon means knowing the human body and how to practise medical operations on it. Being a student (or at least a good student) usually means knowing what it is to do homework and study for tests. Since identities are mostly made of knowledge, they can be *learned*.

Learning is a process leading to a permanent change of our *capacities* that is not the result of biological maturation (Illeris, 2007, p. 3). So, learning allows us to modify the way we see our world and do things in it, which could ultimately change who we are. Research in the field of learning has already taken interest in the way people learn *who they are*. One particular field known as "transformative learning" discuss transformation in one's identity. More precisely, transformative learning has been defined as the process of restructuring ourselves after an important disruption into our life (Illeris, 2018). People moving from one country to another or experiencing natural disasters may experience the kind of rupture in the flow of their lives that forces them to modify who they are. Research addressing transformative learning argues in favour of a cognitive restructuration of the self, but do not provide the internal mechanism leading to those internal modifications.

Fields of computational neuroscience and machine learning are one step ahead in the study of dynamic models of learning. Their work focus on understanding how people seize their world and make sense of it (e.g., Clark, 2016; Friston, 2009). With such question in mind, neuroscience and machine learning researchers may bring fundamental outcomes to the way people adapt themselves to new environments. Most of their models and theories are conceived according to the principle of *optimization* (e.g., Agakov et al., 2006; Bogacz, 2007; Friston, 2009; Snoek et al., 2012; Sra et al., 2012; Tanaka et al., 2018). Optimization is the process through which people will reach optimal decision considering noisy data (Bowers & Davis, 2012). Our world is uncertain and the perceptions we have of it are uncertain too (Clark, 2016). However, people are usually able to make sense of what they see and hear. They do so by optimizing their thoughts and behaviours.

Optimization is an ongoing process. Everything that we come across in our daily lives is uncertain and we may have to understand our environment to behave in it properly. If we see something odd, we might renegotiate what we know about our world to avoid being surprised again. If we see something usual, we will reinforce what we already know.

Current research on optimization has given great importance to the role of perception in the process of learning our environment (e.g., Clark, 2016; Friston, 2009). We consider perceptions as every sensory stimulation we can catch from our environment. Our many receptors are open doors to upcoming information regarding our world. So, everything we see, hear, smell, taste and feel inform us about what kind of environment we are in. Without our perceptions, optimization would be a useless process. However, we argue, along with Friston (2009), that perception is not the only key to optimization. People are active agent; they don't assimilate the information of their world passively. Every one of us can act upon our environment and get some control over what we perceive. In this sense, we can change our environment if we feel unhappy in it. For instance, people can quit their job, leave their romantic partner or emigrate into a new country. We should thus consider the role of perception and action into a single iterative process of optimization.

Friston and colleagues have developed a model of optimization that unites the role of perception and action into a single iterative model of learning (Friston, 2009, 2010; Friston et al., 2013). This optimization model was created to explain how people will change their internal states in order to minimize free energy (Friston, 2009). Minimizing free energy means reducing the gap between what you expect in your environment and what you perceive in your environment (Friston, 2009). When what you expect and what you perceive are highly different, you might be surprised and enter in an internal state of entropy. Entropy is a chaotic state of mind. When entropy governs our internal states, we do not understand our environment.

Free energy has been the centre of Friston's theories (2009). His model of optimization attempts to explain how people will reduce free energy and find adaptative internal states and behaviours. As shown in Figure 1, Friston's model of optimization takes the form of a loop in four consecutive stages.

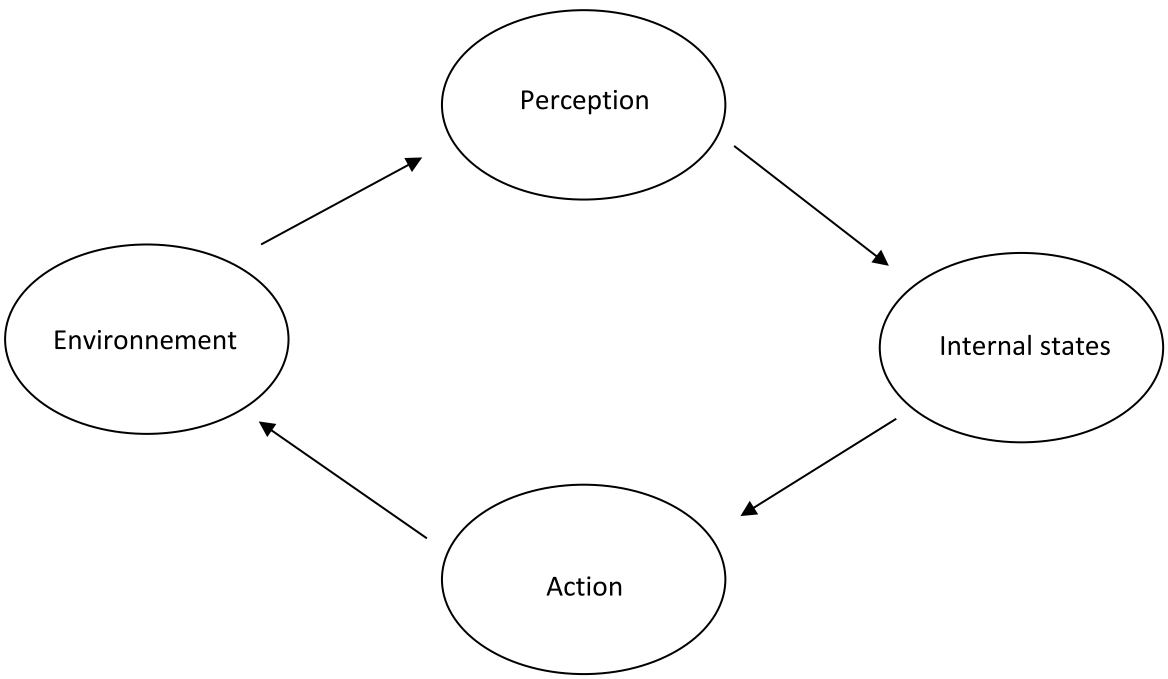


Figure 1. *Friston's Model of Active Inference*

Perceptions are every information coming from our senses that inform our internal states. Internal states are active inferences people holds about their world (Friston, 2009). Active inferences are propositions or hypotheses that we have about what our world is like. For instance, we usually hold the inference that dogs have four legs. This inference helps us understand what dogs are. If we come across a five legs dog, we might be surprised and misunderstand what kind of animal is standing in front of us. Our internal states generally influence the way we behave in our world. In return, our behaviours will produce some outcomes in our environment; be them expected or not. Then, the wheel turns again. We will likely perceive the impact of our behaviour in our world. This perception will inform our internal states as a *feedback* to validate or modify our internal states and thereafter our behaviours. The cycle goes on and on again in our everyday life.

To illustrate optimization with a concrete example, suppose you are coming home at night and there is an animal on your front door (not a five-legged dog). The animal is the size of a cat, black and white, but since it is dark outside you remain uncertain as if it is really a cat or a skunk. At this moment, you don't understand completely your world, since the identity of the animal remain uncertain. What you think the animal is will influence your behaviours. You could move closer to the animal and gather more information. On the other hand, you could stay away from the animal and don't risk being spread by its powerful secretion. Hopefully, if you keep a distance from the animal, it will leave your front door and you would be able to enter safely into your home. In this situation, you try to make sense of the identity of the animal with noisy perceptions of it. Such understanding of the animal could be critical for your next move and probably for the way you are going to smell the next few days.

Optimization has been well studied in perception (Clark & Yuille, 1990; Knill & Richards, 1996; Ernst & Banks, 2002; Battaglia et al., 2003) and attention (Dayan et al., 2000; Dayan & Yu, 2003; Yu & Dayan, 2002; Yu, 2014). We argue that optimization could be applied to identity integration processes. So, in the context of identity integration, we could define optimization as the selection of thoughts and behaviours that are probably the best (more adapted) ways to respond in a given social context. Such selection of thoughts and behaviours will likely avoid us of being surprised by unexpected events (Friston, 2009). In a new social context, people's inferences regarding their environment will likely be uncertain and, at times, wrong. To remedy erroneous beliefs, people must learn what is expected from their environment.

So far, we have come to understand that our perceptions of the environment shape our internal states and that we can apply some control to our perceptions through our actions (Friston, 2009). Several studies have supported the effect of perception on our internal states (see, Battaglia et al., 2003 for visual and auditory perceptions and Ostwald et al., 2012 for proprioceptive perception). Now that we understand *what* shapes our internal states according to Friston's perspective, we can focus on *how* our internal states change. The heart of Friston's model rest on Bayesian operations. People will try to reduce their predictive error and refined their inferences using an internal process using internal computations that approximate Bayesian operations.

**Bayesian Operations: The Fuel Behind Dynamic Models**

If humans are in fact optimal, they should think and behave in ways that they believe are the best for a particular social context. Active inferences play an important role in our understanding of our various social contexts and the kinds of thoughts and behaviours that seems more adaptative to them. Unfortunately, active inferences are just assumptions. Sometimes we can be right, sometimes we can be wrong. Good inferences will likely generate adaptative thoughts and behaviours, while poor inferences will probably not.

Since our inferences can be right or wrong, we should consider them through a probabilistic perspective. *What is the probability that I am right? What is the probability that I am wrong?* Each answer would receive some probabilities. These probabilities might not be the same for everyone; they are certainly subjective to who we are, what we know and what we have previously experienced. Optimistic hockey players in a team that is down to two points might allocate more probabilities to winning, while other players might strongly believe in defeat and others might be uncertain about the outcome of the game. To illustrate this example with numbers and make it more concrete, the optimistic players could believe that his team will win the game and be 90% sure of it (leaving 10% chances to the possibility of losing). The pessimistic players could believe his team is going to lose and be 90% sure of it (leaving 10% chances to the possibility of winning). Finally, uncertain players could think winning is equally likely than losing, giving 50% chances of winning and 50% chances of losing. In this example, the environment remained the same, but the beliefs about winning can be quite different from player to player. To explain such difference of opinion, we need to dig into each player's experience, knowledge, personality traits and other influences of their beliefs; which is not the purpose of the present study.

Probabilities allocated to our inferences are not fixed; they can change. For instance, optimistic hockey players might despair as the time goes by and no points have been made. According to several researchers (Norris, 2006, 2009; Norris et al., 2010; Weiss et al., 2002), internal processes in the allocation of probabilities could be approximated by a Bayesian conceptualization of the human mind.

Bayesian conceptualization of the mind is inspired by Bayesian statistics, which are a set of analyses to test the credibility of a hypothesis. Mathematically, Bayesian statistics are the multiplication of a *prior* by an *evidence* to obtain a *posterior* (Jackman, 2009). The prior is a set of probabilities that represent our initial state of belief about a hypothesis (Kruschke, 2011). Evidence is a set of probabilities originated from data gathering (Kruschke, 2011). Once the prior distribution of probabilities has been multiplied by the evidence distribution of probabilities, we can obtain the posterior distribution. The posterior is the new distribution of probabilities about the credibility of our hypothesis (Kruschke, 2011).

Bayesian conceptualization of the human mind gives us a unique advantage to understand internal processes. Indeed, through a Bayesian vision of identity integration, we take into consideration a prior probabilistic state of identity integration and quantify its change into a posterior distribution with the use of evidence gathering (Kruschke, 2011). In short terms, Bayesian conceptualization allows us to understand how a starting state of identity integration (prior) change into a future state (posterior) with the use of a specific perception acting as evidence. For now, some theories have supported the use of a Bayesian process for human cognitions and perceptions. For instance, Weiss and colleagues (2002) proposed a Bayesian conceptualization of our belief about an object motion considering the perception of its speed. Also, Norris and colleagues (Norris, 2006, 2009; Norris & Kinoshita, 2008; Norris et al., 2010) developed a Bayesian model to explain how people recognize words and manage to read. Even if several studies have supported Bayesian processes for human cognitions, none were applied to higher and more complex cognitive processes such as identity integration. In order to understand how people learn their environment and become who they are, we need to take a leap into more abstract processes of learning.

**The Bayesian Model of Identity Integration**

Building on previous conceptualization of the self (Markus & Wurf, 1987), process of identity integration (Amiot et al., 2007) and models of active inferences (Friston, 2009), we propose a Bayesian Model of Identity Integration (BMII) that could capture the dynamic process behind the integration of a new identity. The BMII combines Friston's loop of learning and stages of identity integration proposed by Amiot and colleagues (2007). Such model will allow us to understand each stage leading to identity integration and how people transition from one to another. More specifically, we argue that people will use their actions and perceptions to reduce their prediction errors. By doing so, people come to realize that some aspects of their new and former identities are similar; which allows them to build cognitive links between their identities. So, when people are in a new group and they make good predictions (no prediction error) based on their former identities, they perceive similarities between their identities and form cognitive links.

In order to unify Friston and Amiot's models, one additional consideration needs to be made. Friston's model was conceived for simple schema integration and not for complex identity processes. As such, the perceptions related to our identities might be more complex than simple visual or auditory stimuli. There are multiple ways people could perceive information that inform their identities. We argue that some of this information comes to people's attention and others do not. To understand what increase and decrease the probability that a perception will be perceived, we turned ourselves toward a fundamental aspect of every human being: needs.

Needs are every necessity that human beings require to be healthy, grow and experience well-being (Deci & Ryan, 2000; Maslow, 1970). Some needs are physiologic (e.g., eat, sleep), others are psychological (e.g., belong). Several researchers tempted to conceptualize psychological needs (e.g., Maslow, 1968, 1970; Ryan & Deci, 2000). In the present proposal, we have isolated two psychological needs that, as we argue, are related to identity integration: security and belonging. Security is the need to feel safe, away from any threat or chaos (Maslow, 1970). People who do not feel secure in a new social context might be reluctant to destabilize their self and integrate a new identity. On the contrary, unsecured people might seek comfort into what is familiar to them; which are their current identities. We acknowledge that need for security could also work backward. People with high need for security might seek the integration of a new identity to be part of a group and feel safe. So, people in need of safety could seek two purposes: the stability of their self and the protection of another group. Pursuing stability of the self should disfavour identity integration, while searching for another group protection should favour this group identity integration.

Belonging is the need to be part of a group or engage relations with others (Maslow, 1970). In a new social context, high need to belong might generate a motivation to be accepted by our peers and integrate their identity. So, high levels of need to belong could reduce negative perceptions of a new social identity and increase its positive features. These positive perceptions of our new identity will likely favour identity integration. From another optic, needs to belong could also discourage identity integration. For instance, people could turn down a fundamental personal identity to match the identity of their peers. The impact of our need to belong on our perception might depend upon the nature of the identity (social or personal). Need to belong might encourage social identity integration and discourage personal identity integration.

In sum, we argue that needs of safety and belonging will filter the perception we have of our environment. So, the fact that we perceive some information and not others should mostly be explained by our focus; which is driven by our needs. To conceptualize the role of needs in a statistical perspective, we consider that needs will moderate the relation between perception and stages of identity integration. The influence of some perceptions on our internal states will be decrease or increase, depending on our needs. The direction of the moderation for both needs can differ according to the kind of safety seek (stability of the self or protection of another group) and the nature of the identity (social or personal). Figure 2 shows the BMII.

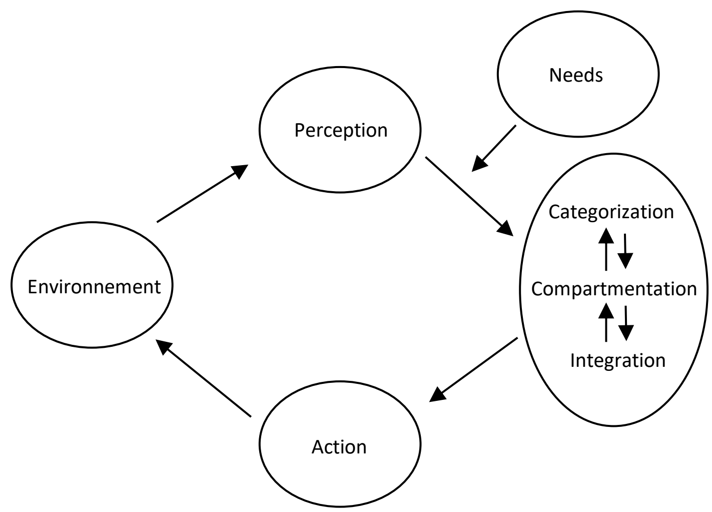


Figure 2. *Bayesian Model of Identity Integration*

To fully understand the BMII, we will describe the process of each stage of identity integration; starting at the moment where people are faced with a new identity. Our environment is the source of our perceptions. In their new environment, people could perceive the new identity as incongruent with who they are and enter a stage of categorization (Amiot et al., 2007). The influence of their perceptions on their stage of integration should be filtered by their needs. So, from the vast quantity of perceptions regarding the new identity, only some have an influence on people's identity integration. People who are categorized should perceive more incongruence between themselves and the new identity. Likewise, perceptions of similarities between the new identity and the current self should receive less importance. As a result, people will identify themselves according to who they are and behave accordingly. Such behaviours ought to shape people's environment as to favour perceptions that are consistent with their categorized stage. Unfortunately, our behaviours cannot always remove perceptions related to our new identity. At these times, behaviours incongruent with our social context will return a perception of being inadequate. We argue, along with Friston's models (2009) that frequent perception of being inadequate will modify our behaviours as to create upcoming perceptions of adequateness. We will thus adapt our behaviour to our social context even if we do not necessarily identify with this kind of behaviour. Behavioural change can be the first step on the road of changing ourselves and could lead to a further stage of identity integration (see, Cárdenas & de la Sablonnière, 2018 for the impact of behaviour on the level of identification to groups).

People in compartmentation's stage hold a fragmented sense of their self (Amiot et al., 2007). In some social contexts, compartmentalized people think and behave in a certain manner that cannot be transposed to another social context. We argue that needs for security and belonging will play an important role into which context the new identity can be experienced and in which context it cannot. In some social contexts, needs for safety and belonging could favour positive perception of the new identity. The new identity has more chances to be experienced at these instants. In other social contexts, needs for safety and belonging could decrease positive perceptions of the new identity. Perceptions of the kinds of social contexts people find themselves in activate one identification over another and allows people to use appropriate behaviours for the current social context.

Finally, people who are integrated can display behaviours that define who they are in various social contexts. As such, people know how to think and behave in their different social contexts without casting apart a piece of who they are. Every stage of identity integration will be illustrated with the examples of a personal and a social identity integration process.

## Personal and Social Identity Integration

In this section, we will display two fictive examples of identity integration using the BMII as our framework. We will discuss the integration of a personal identity integration and a social identity integration. Even if we present our example in a certain manner; we do not argue that the model works in a single way that is discussed. Our focus is to show two ways the model could work on two different persons and identities. We are aware that other people undergoing similar challenges could have different ways of integrating their new identity. Still, we remain confident that the BMII could catch their experience as they navigate toward identity integration.

Personal identity integration requires learning our own attributes. Since the focus is on ourselves, our perceptions and actions should be directed into discovering who we are personally. Each stage of personal identity integration will be discussed according to the BMII using the example of Julien, a young man who is in the process of integrating his sexual orientation toward same-sex peer.

*Categorization stage*

At first, Julien could realize that he has an attraction toward other boys instead of girls. Such preference can inform Julien about his sexual orientation; which is a personal identity that Julien will have to manage into his self-concept. To discover a preference for boys could lead Julien to a stage of categorization; where he will reject his new sexual orientation (**internal states**). We propose that Julien will likely identify as heterosexual since we live in heteronormative societies and we tend to assign a heterosexual orientation to people until proven otherwise. In categorization stage, Julian will display **actions** that go against his sexual orientation (e.g., seduce women, avoid gay people). Such actions will shape his **environment** into a more “none-gay lifestyle”. In return, this environment will surely produce **perceptions** related to a heterosexual lifestyle. The perceptions that inform the internal states will be moderated by the needs of Julien. So, some perceptions will receive more credit than others. Since Julien has categorized himself into a heterosexual orientation, we could hypothesis that he feels insecure about expressing a homosexual orientation (strong **need for security**) and wants to fit into his group of heterosexual friends (strong **need for belonging**).

*Transition from categorization stage to compartmentation stage*

One's sexual orientation is something that cannot be easily set aside. Even if Julien identifies to a heterosexual orientation, he will still feel attracted to other men (**internal states**). So, while Julien identifies with a heterosexual orientation and produces **actions** that shape an **environment** where he is defined as heterosexual, some of his **perceptions** will produce predictive errors. Every time Julien engage in a relationship with a girl, he will experience a discrepancy between his perceptions of the girl and his sexual orientation (**internal states**). Perceptions that create predictive errors can be moderated by needs. Strong needs for security and strong need to belong into a heterosexual group might alter Julien's perceptions as to reduce the predictive errors. This said, we still argue that Julien perceives to some extent a feeling of being inadequate in a heterosexual lifestyle. With time, these predictive errors will keep repeating themselves and could take more and more weight on Julien internal states. When such predictive errors become salient, Julien could decide to modify his sexual orientation as to reduce the constant flow of predictive errors. To do so, Julien could enter a compartmentation phase

*Compartmentation stage*

In compartmentation stage, Julien can allow himself to be attracted to other men (**internal state**), but on some occasions only. For instance, in the intimacy of his room, Julien might feel free to let himself be attracted to other men, which would not be possible with friends. Inside his room, Julien could write (**action**) to other men on a dating application for gay people. Such actions can change Julien's **environment**. Now, Julien has gay contacts with which he can relate to and develop affinities. Such online discussions will produce **perceptions** of being in line with his homosexual orientation. **Needs** for security and belonging will not discourage the perception of being adequate while experiencing homosexual actions because, in that particular context, Julien feels more secure about his sexual orientation and is alone (no friends to belong to).

With friends and family, Julien still resist sharing and act upon his sexual orientation. So, in social context such as family and friends, Julien **perceive** more positive feedback from being heterosexual. Such perceptions will still be moderated by **needs** for safety and belonging to friends and family. As a result, these perceptions motivate Julien to keep his sexual orientation (**internal state**) to himself and act as someone who is attracted to girls instead of boys (**actions**).

*Transition from compartmentation to categorization*

In compartmentation, Julien has found a way to reduce some of his predictive errors. When Julien is in his bedroom, chatting with gay men, he perceives that his actions are consistent with his sexual orientation. However, Julien is far from being completely safe from predictive errors. Consider these two situations:

Julien is in his room, chatting with a gay man (**actions**). The man proposes to meet Julien for a coffee. Julien read the invitation via text message (**perception**) and cannot possibly think of identifying as a man attracted to other men outside of his room (**internal state**). As a result, Julien might turn down the invitation (**action**) and while doing so perceive that his action is inconsistent with his sexual orientation; leading to predictive errors.

Outside his room, Julien still perceives himself as a man attracted to women; which is not consistent with his homosexual orientation. In order to resolve both kinds of predictive errors, Julien could disclose his sexual orientation to both his parent and his friends. By doing so, Julien would allow himself to act as a man attracted to other men outside his room and his surroundings will give him consistent feedback with his homosexual orientation.

*Categorization*

Julien may experience a second time the stage of categorization; this time categorizing himself as a man attracted to other men. Such return to a categorization stage seems common in people integrating a same-sex sexual orientation or a gay identity. We have noticed it in one of our experiences (Coulombe et al., in preparation) and similar idea was discussed in a previous model of sexual identity integration (see stage of identity pride in Cass's model, 1979, 1984). In this categorization stage, Julien identify mostly as a man attracted to other man (**internal state**) and reduce the importance of his other identities (e.g., being a student, a partial worker). As such, Julien could dedicate most of his **actions** to searching soul mate or sexual partner and reduce his time of studying and working. Such strong actions of being a man attracted to other men will shape an **environment** where Julien would certainly be perceived as someone who is attracted to other men. So, the **perceptions** he will get from his environment would most likely be in line with his homosexual orientation. In short, to categorize into a homosexual orientation will prevent Julien from receiving more predictive errors regarding his sexual orientation.

*Categorization to integration*

Julien's identification, actions and perceptions are congruent with a homosexual orientation are likely to produce again predictive errors. Since Julien turned down his other identities to let his homosexual orientation shine (**internal states**), most of his **actions** are made as to meet his homosexual orientation goals. By doing so, goals regarding other identities are not met and can be **perceive** as predictive errors. For instance, Julien could perceive that actions such as going to bars till late and give much time to meet new men made him fail a class. Again, we support that needs should mediate Julien's perceptions.

*Integration*

To remove most predictive errors, Julien will have to reach the stage of integration. At this stage, all identities represent equally and coherently the self of Julien. So, Julien will identify with all his identities equally which will reduce most of the predictive errors.

Social identity integration requires endorsing thoughts and behaviours that are shared by a group (Ashmore et al., 2004). To illustrate social identity integration more concretely, we will rely on the example of Ramón an immigrant from Brazil coming to Canada with his close family.

*Categorization*

During his first moments in Canada, Ramón could **perceive** that the culture of his host country is not congruent with who he is. Such perceptions might be emphasized by **needs** for stability and to belong to his family. As a result, Ramón could continue to identify himself to his former cultural identity (**internal state**), **act** according to his Brazilian identity and shape an **environment** accordingly. For instance, since Ramón speaks only Spanish, he could perceive that Canadians people who usually speak English or French may not understand him. Even if Ramón speaks slowly and mime at it best, chances are that Canadian people will still struggle to understand what he is trying to say. So, Ramón's expectations to be understood using "Brazilian" actions such as speaking Spanish do not match what he perceives; which can generate predictive errors. To reduce the predictive errors, Ramón could pass most of his time home or create relationships with other Brazilian people who have moved to Canada. Those actions will likely reduce Ramón's predictive errors and support the categorization stage of its identity integration.

*Categorization to compartmentation*

Even if Ramón identify mostly to Brazilian (**internal state**) and can shape an environment mostly "Brazilian", he cannot escape all "Canadian" contexts. When Ramón display "Brazilian" **actions** in such "Canadian" **environment,** he will surely **perceive** predictive errors. At some point, Ramón would most likely want to reduce such predictive errors by acting in more Canadian ways. This is a first step toward the stage of compartmentation.

*Compartmentation*

To reduce the predictive errors when being in a Canadian context, Ramón could learn gradually what being a Canadian is like and display consistent actions when he is in a Canadian context. By doing so, Ramón will allow himself to identify a bit at a time to Canadians people. However, identifying as Canadian and Brazilian cannot be done at the same time; each of the two identities will be activated in their own context.

Specifically, Ramón could still identify himself as Brazilian (**internal state**), **act** like it at home or with other Brazilian people (**environment**) and **perceive** congruent feedback with who he is. Such perceptions would be moderate by **needs**. The need for stability in his house and belonging to his family might increase positive perceptions associate with a Brazilian identity and increase negative perceptions associated with a Canadian identity. And, Ramón could also identify himself as Canadian (**internal state**) when he **acts** like it with Canadians (**environment**) and **perceive** less or no prediction errors. Again, **needs** would moderate the impact of our perceptions on our internal states. For instance, Ramón could speak Spanish at home and avoid English or French which are Canadian's languages that are incongruent with his Brazilian identity. Similarly, Ramón could speak only French or English in Canadian contexts.

*Compartmentation to integration*

Identifying to both Canadian and Brazilian each in his specific context does not solve Ramón's problem of predictive errors. In compartmentation, every time Ramón identify to Canadians, he shuts down his Brazilian identity. Similarly, every time Ramón identify to his Brazilian identity, he turns off his Canadian identity. Making himself fit with only one identity at a time can also generate predictive errors. So, Ramón could identify to Canadians (**internal state**), **act** consistently in a Canadian context (**environment**) and **perceive** that even if his behaviour was right, a Brazilian response could have been even better. For instance, Ramón might be tired of going to the same Canadian type restaurants at lunch time with his Canadian coworkers. At some point, Ramón could prefer to eat more typical Brazilian foods, but feels constraint act in a Canadian way. So, Ramón's wishes to eat more Brazilian food and perceiving that he is yet again in a Canadian restaurant might generate predictive errors. To solve it, Ramón might try to reconciliate his Canadian identity with his Brazilian identity. For instance, Ramón could propose to his coworkers to go eat at a restaurant who serves Brazilian food.

*Integration*

Ramón's predictive errors will surely decrease in the integration stage. At this stage, Ramón identify to both Brazilian and Canadian at the same time. By doing so, Ramón will behave more faithfully with who he really is regardless of the social context he finds itself in.

**Theoretical and Practical Implications**

Research on identity integration has come to face one of its biggest challenges: understanding which dynamic laws our self follows to undergo profound changes such as identity integration. So far, we have built our knowledge of identity integration on several processes made with different stages. Such processes depict a static view of how identities come to be integrated into people's self. The present theoretical proposal discusses a model founded on a Bayesian conceptualization of the mind that could lead the way of future research to a more dynamic understanding of identity integration. The BMII can quantify an initial state of identity integration and its change through the exposure to new evidence. Such conceptualization of identity integration can help us understand all the steps of changes: the starting point of identity integration (prior), the new information that comes to change the prior (evidence) and the new state of identity integration (posterior). In addition to these theoretical implications, the BMII can inform social practitioners in the process behind identity integration and how identity interventions should be oriented.

We presented the BMII in the context of specific kinds of identity integration (sexual orientation and cultural identity). However, we argue that the BMII could be extended to other kinds of integration such as a new lifestyle. To illustrate this point, we rely on the worldwide crisis that changed the life of millions of people: the Covid-19. Such threat toward human health forced governments to adopt drastic measures as to prevent virus spread. People were strongly encouraged to keep a social distance with others, stay home as much as possible and avoid gathering in large groups. During this crisis, millions of workers lost their job temporarily and, in several cases, definitely. Life as we knew it changed and pressured us to adapt ourselves to the new constrains quickly. The BMII could be a valuable tool to understand the internal process through which people adapted themselves to the Covid-19 spread.

**Conclusion**

The BMII is a very simplistic conceptualization of the way the human mind operates. At its core, the BMII proposes that each and every one of us stand in a certain state of identity integration, and this state will change according to some evidence we have perceived in our environment. Identity integration is a very complex set of processes and we do not argue that the BMII perfectly matches those internal processes. What we do argue is that the BMII process could approximate internal processes of identity integration. The current conceptualization of the BMII is still embryonic. Some factors may complexify the process of identity integration. For instance, evidence we find in our environment may not have the same signification for everybody and will have different impacts on our process of identity integration. The BMII should thus be adapted to the way people perceive their environment and hold importance to certain perceptions over others.

To conclude, the present proposal for a Bayesian Model of Identity Integration could offer insight regarding the iterative internal process of identity change, but rests on a theoretical basis. Empirical evidence should be provided to support the idea of a Bayesian process behind identity integration. We are currently working on mathematical formulas to simulate the BMII into a context of identity integration.

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# Article 2: The Bayesian Model of Identity Integration: A Longitudinal Study of Cannabis Integration into Canadians Identity following Cannabis Legalization

**Abstract**

Societies are constantly evolving. New social changes could push people to redefine who they are and integrate new identities into themselves. As long as people do not integrate the novelty of their environment, they tend to feel maladaptive and experience lesser level of well-being. Current theories addressing identity issues remain static; they do not propose a method to quantify identity change through time. The goal of the present study is to test a dynamic perspective of identity integration. We developed the Bayesian Model of Identity Integration to understand and measure identity change. Three online questionnaires were answered by 1 682 Canadians following cannabis legalization in Canada, a month later and a year later. We used the Bayesian Model of Identity Integration to understand the process behind identity change and predict further scores of identity integration. Results support the prediction of our model. The Bayesian Model of Identity Integration could answer several remaining lacks into our knowledge on identity integration processes.

*Keywords:* Identity integration, Bayesian model, dynamic internal processes

**The Bayesian Model of Identity Integration: A Longitudinal Study of Cannabis Integration into Canadians Identity following Cannabis Legalization**

We live in a world of constant transformation. Societies become more culturally diverse, the economy of the whole country can crash overnight, and diseases spread regardless of territorial barriers. Such changes can shake the structure of an entire collectivity and force its residents to renegotiate the identity of their group. Group identities are significant aspects deeply rooted in ourselves. Changing one of our group identities could represent a considerable challenge to achieve. When people modify such fundamental parts of who they are, they could experience a lack of identity landmarks leading to a blur toward one's self-definition and a decrease in their levels of well-being (see, Usborne & Taylor, 2010). The need to understand the internal process behind group redefinition is growing and can benefit millions of individuals worldwide experiencing social change.

Social psychology is the *number one* scientific field interested in identity crisis in times of change and redefinition. Identities are profound parts of ourselves. Together, identities forge our self; the pivotal internal process of who we are (Leary & Tangney, 2014). Many years of theories have supported the importance of the group to the formation and maintenance of the self (e.g., Amiot et al., 2007; Markus & Conner, 2014; Usborne & Taylor, 2010). In response to group novelty, many researchers have discussed the experience of redefining oneself with the *integration* of new aspects of the environment (e.g., acculturation theory; Berry, 1997, 2005; bicultural identity, Benet-Martínez et al., 2002; cognitive model of social identity integration; Amiot, et al., 2007). Identity integration is a complex process that change who we are in time. In order to capture the internal mechanisms responsible for the integration of a new identity, we need to turn ourselves toward a dynamic process. Unfortunately, current theories on identity integration hardly test their process with a dynamic methodology, leaving present knowledge incomplete.

Our objective is to conceptualize identity integration through a dynamic process. Dynamic processes, in contrast to static ones, can explain the internal mechanism for every update of identity integration. To test such a dynamic process, we rely on a new theoretical model of identity integration: The Bayesian Model of Identity Integration (BMII; Mérineau et al., in progress). The BMII was designed to explain the dynamic process of identity change and as not receive any empirical support yet. The present study aims to test only parts of the BMII – not the entire model. We wish to understand the BMII on a gradual basis before considering the whole model. The BMII will be applied in the context of cannabis legalization in Canada. Cannabis legalization is a new policy that took place on October 17, 2018 and allows Canadians to buy cannabis from government stores and used it recreationally. Since the legalization of cannabis, Canadians may have witnessed some changes in their group, such as new opinions regarding cannabis use, an increase of people using cannabis, new knowledge and recommendations for a responsible use of cannabis and a rise of cannabis's discussions in the media. These changes can initiate a process of group identity change where cannabis could now be part of what it is to be a Canadian.

**Identity Integration**

Thinking about who we are is one of the main attributes that make us human. Through introspective reflection, we can forge a representation of ourselves: a self-concept (Rosenberg, 1979). Our self-concept provides a meaning to who we are. We think, remember, set goals and behave according to the way our self-concept is conceived (Baumeister, 1998; Brewer, 1991; Brown, 1998; Oyserman, 2007). Everything we encounter in our daily lives is at some level of consciousness proceeded by our self.

In order to function optimally, our self needs to work through a well-organized structure (Markus, 1977). All the patterns of thoughts and behaviours that we hold are categorized into specific identities. Identities are small generalization of our self build with experience (Markus & Wurf, 1987). So, time spent in a social context taught us how to think and behave in that specific context. We usually possess many identities (e.g., being a mom, a lawyer, a Canadian); each of them comprises several schemas. In the present paper, we will consider schemas as small aspects of our self that defines our identities (Markus & Wurf, 1987).

Identities and schemas are not fixed. On the contrary, people can change who they are by incorporating a new identity into their self-concept or a new schema inside one of their identities. When cannabis was legalized in Canada, several Canadians could have experience schemas change. In some cases, the schema of cannabis could have joined the many schemas that constitute the identity of Canadians. Adding a new schema to an identity should follow the same process as identity integration. Identity integration is the internal mechanisms through which people connect new identities (or schemas) to existing ones as to create a coherent self-concept (or identity; Amiot et al., 2007).

Works on identity integration is abundant (e.g., Amiot et al., 2007; Cass, 1979, 1984), but the understanding of its internal process is scarce. To our knowledge, the Cognitive Model of Social Identity Integration (CMSII, Amiot et al., 2007) is the only one to explain *how* people will integrate a new identity into their self-concept. The CMSII is made through the creation of cognitive ties between new and current identities (Amiot et al., 2007). If these cognitive ties are impossible, the new identity can still be integrated with the formation of a bigger and level-up identity (supra-ordinal categorization) that could include conflicted sub-identities. For instance, to identify as being "human" could encompass conflicted cultural identities into a common category.

According to the CMSII, people confronted to environmental change could visit four stages of identity integration: anticipatory categorization, categorization, compartmentation and integration. Each stage describes the internal dynamics between new and current identities of the self. Anticipatory categorization stage occurs before people get in touch with the new identity. For instance, immigrants planning to move into a new country could experience anticipatory categorization. During this stage, people begin to create cognitive links between who they are and the new identity. More precisely, people tend to project their own characteristics in the new identity and thus find similarities between the new identity and themselves (see self-anchoring process;

Otten & Wentura, 2001). In the context of cannabis legalization, Canadians could find similarities between themselves and new laws making cannabis legal.

In the second stage - categorization, people perceive a great incoherence between two or more of their identities (Amiot et al., 2007). In this sense, categorized people will identify themselves exclusively to one identity and reject the other; be it the new one or the current one. The unwanted identity will be rejected of the self-concept. In the context of cannabis legalization, people may feel that the new “cannabis schema” is incompatible with being a Canadian. These people will likely identify themselves as Canadians and oppose the association of cannabis with their group identity.

In compartmentation, new and current identities can be used to describe the self. However, neither identity can be activated at the same time. The social context in which we find ourselves will play a fundamental role to our identification. In some context, we will identify ourselves to one identity and reject the other. In other social context, we will do the opposite. In the context of cannabis legalization, people could define their group only with the use of their cannabis schema (e.g., Canada is only a provider of cannabis, Canadians are mostly cannabis users, cannabis legalization is the only great thing about Canada) with certain people. In other social context, people could define the identity of Canadian with all its current schemas except cannabis.

Finally, integration is met when all identities are recognized as simultaneously important to describe one’s self (Amiot et al., 2007). Through identity integration, people resolve the conflict between their identities and can see their self as a coherent whole. In the context of cannabis legalization, people could integrate the schema of cannabis into the identity of being Canadian. So, the schema of cannabis will hold an equivalent place in the identity of Canadians as the other schemas do.

The CMSII informs us on the different cognitive stages and the role of cognitive links and supra-ordinal categorization for identity integration. However, the CMSII does not inform us on the dynamic mechanism that will create cognitive ties or supra-ordinal categorization. The capacity of people to form their identities day by day can only be faithfully understood with the use of a *dynamic* internal process. Unfortunately, dynamic processes go beyond the current research and understanding in the field of social psychology.

**Neuroscience Models of Internal Changes**

To fill our limitations on dynamic identity integration processes, we have turned our attention toward fields of research who have already addressed the issue of dynamic internal processes of the human mind. Fields of neuroscience and machine learning have given many thoughts on dynamic internal processes. Their theories and studies are mostly centred in the process of optimization. Such process is comparable to deep learning in the field of artificial intelligence and free-energy theory in the field of computational neuroscience. Optimization, as defined by Bowers & Davis (2012) in their review of Bayesian processes, is the process through which people will make sense of their world despite noisy inputs. Such topic extended in multiple fields such as philosophy (Clark, 2016) and occasioned recent debates in psychology (Bowers & Davis, 2012a, 2012b; Griffiths et al., 2012). In sum, optimization is basically a process of learning. Through optimization mechanisms, people can learn their environment and, as we argue, learn a new identity.

Learning is a continual process. People learn their environment by collecting information from it and then, they continue to gather more information to validate what they already know. This ongoing process is iterative (see, Friston, 2009); the same mechanisms are activated over and over in time. Iterative processes could inform us on the way people change the representation of their world every time they learn something new in it. We will now focus on the mechanisms essential to the process of learning.

In order to lean our environment, we need to perceive it. Perceptions are every sensory stimulation (e.g., seeing, touching, earing) that vehicle the information of our environment to our attention (Goldstein, 2016). Without our perceptions, we would be helpless to understand our environment. Several researchers have supported the role of perception on the way we represent our world. For instance, Weiss and colleagues (2002) developed a model to assess how fast we represent an object in motion based on our perception of its speed. In this example, our perception of the object's speed can inform our understanding of its motion. Norris (2006, 2009) used a Bayesian approach to understand how people read. In this context, understanding what we read, begins with the perception of the words. Perceptions are vital to seize the information in our environment, but they are not the only essentials in the process of learning.

A claim raised in favour of actions in the process of learning (Friston, 2009). Actions are everything we do in our environment. Thanks to their actions, people can have some control over what they perceive. Everybody can turn away from undesirable perceptions and focus their attention on desirable ones. With such control, we can select to some extent the kinds of perceptions that will form our understanding of our world. In the vast literature of machine learning, neuroscience and deep learning, one model emerges with all the consideration of learning: Friston's model of active inference (2009).

Friston's (2009) has united fundamental aspects of learning (perceiving and acting) into an iterative model of optimization. With optimization, we can remove the uncertainty of our world by learning it. With less uncertainty, people should have a better understanding of their environment. Figure 1 shows Friston's model of optimization. Friston conceptualize the environment as every object, situation or phenomenon that is outside of us. If you take a look around you, you may see different things (e.g., chairs, computer, coffee). All these things are part of your environment. The only way you are able to appreciate your environment is through your perceptions. What you perceive will shape how you will understand your world. According to Friston, we understand our world by making inferences. Inferences are hypotheses we hold about our world (e.g., "My coffee is still hot"). Those inferences help us predict the nature of our environment and understand it. Inferences can be changed along with the perceptions we have of our environment. For instance, if we take a sip of coffee, we could attest that it is still hot. The feeling of heat on our lips can only be perceived along the action of taking our cup of coffee and taken a sip. So, actions can expose us to perceptions that will inform ourselves on our environment.

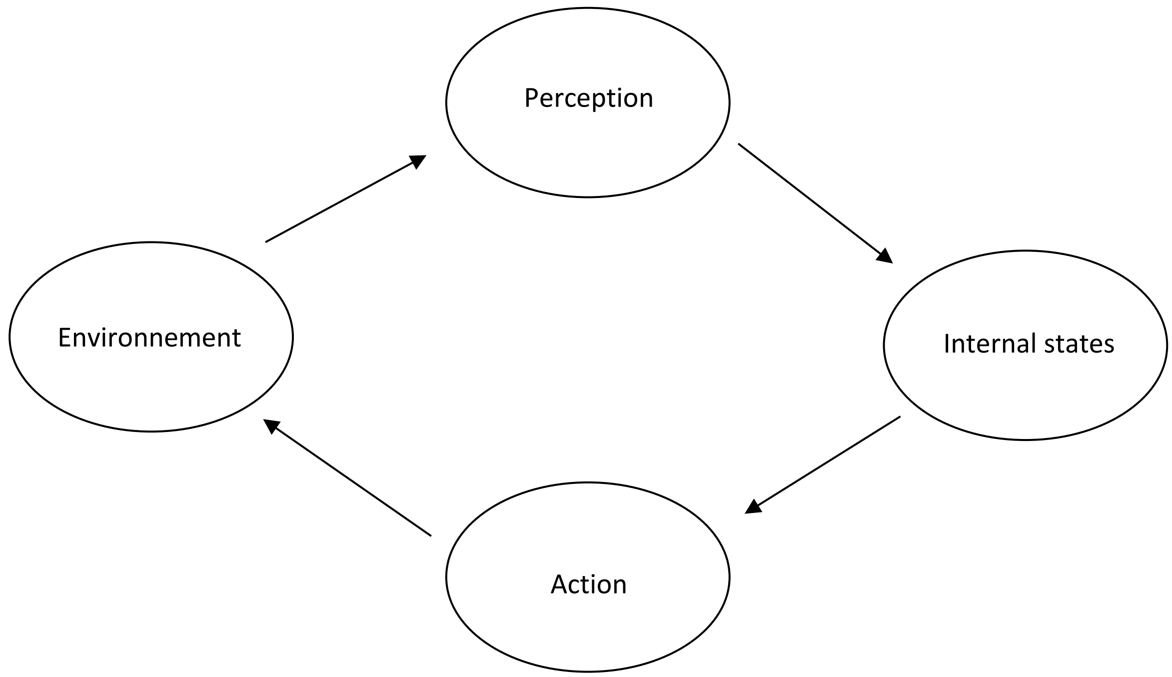


*Figure 3: Friston's model*

Consider Friston model with the example of a young child learning what a chair is. Nobody came into this world with a “chair schema” in mind; we had to learn it through the experience of seeing a least one chair. Young children pointing at a chair and asking, *“What is that?”* have no idea what they have in front of them. To create a schema of what a chair is, children need to *perceive* the chair, misunderstand what it is and make the *action* of pointing and asking. Moms and dads usually come into play at this moment and provide feedback to their children. Parents can give the word “chair” and create an association between the visual perception of the chair and its name. The infant can thereafter upgrade his new schema of a chair by using more actions that trigger more feedback. For instance, the infant could point the second chair next to the first one and say “chair”. Parents will probably give positive feedback to their infant such as “good job!”. If the infant points a table and says “chair”, parents are (hopefully) going to give a corrective feedback, explaining the difference between a chair and a table. In this example, the chair, the table and the parents are parts of the environment of the child. The child used visual and auditory perceptions to form his schema of a chair. Finally, behaviours such as pointing to the chair and asking what it is are actions used to gather informative perceptions.

Neuroscience models received empirical support for a large range of perceptual stimulation (e.g., viewing and earing, Battaglia et al., 2003; touching, Ostwald et al., 2012). Some researchers have even applied neuroscience models to more complex human attributes such as interpersonal relations (see, Moutoussis et al., 2014). However, all previous studies investigating neuroscience models have been interested in simple schemas and have never deepened their research up to identity schemas.

**The Bayesian Model of Identity Integration: How do we integrate cannabis into our group identity?**

Everybody can learn what their group identity is, just like a child can learn what a chair is. We argue that the iterative process of our perceptions and actions in learning simple schemas can be applied to more complex schemas such as group identity. However, perceiving and behaving in our group can be more complex than perceiving a chair and asking what it is. So, the dynamic model of identity integration we present should consider the complexity of identity schemas.

The Bayesian Model of Identity Integration (BMII) unites Friston's loop model (2009) and Amiot and colleagues' stages of identity integration (2007) into a single process (see Figure 2). We added the role of needs, which are necessities required to survive, function optimally, grow and experience well-being (Deci & Ryan, 2000; Maslow, 1954, 1970), as a filter of our perceptions. Perceiving an identity is more complex than seeing a chair. There are numerous ways people could draw information from their environment that update their group identity. Actually, there is too much perception informing our group identity that nobody can perceive them all. We argue that needs will moderate how strongly people will perceive aspects of their group. Some needs will favour certain perceptions and decrease others.

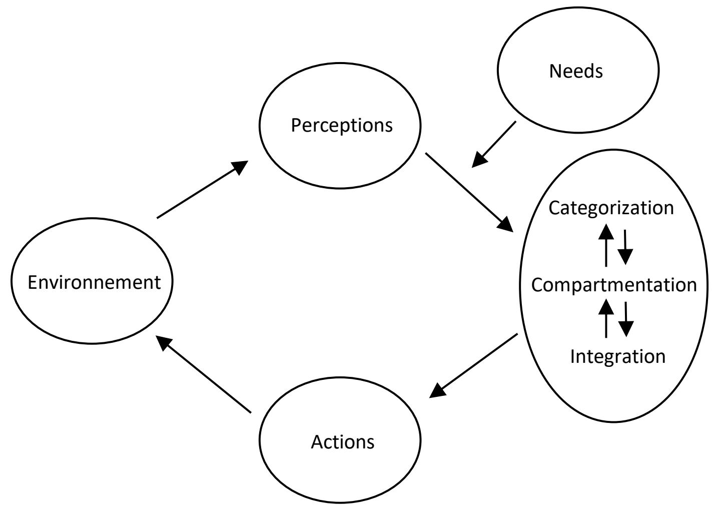


*Figure 4:* Bayesian Model of Identity Integration

If we apply the BMII to the context of cannabis legalization, we argue that people define their group according to their perception of it. Every time we interact with members of our group is a possibility to learn something new that changes our group definition. People tend to align their group identity with what their group does and values (Cialdini & Trost, 1998). In fact, when many people in our group share thoughts or do the same behaviour, they create a norm that others can perceive and follow (Cialdini et al., 1990). Norms are rules prescribed by our societies about what is accepted and disapproved (Grusec & Lytton, 1986). We argue that people in quest of redefining their group identity should be sensitive to the perception of norms. Since the legalization of cannabis in Canada, Quebeckers could be exposed to new opinions regarding cannabis use and see the emergence of new behaviours from members of their group. These perceptions of what their group thinks and does might alter the way Quebeckers previously defined their group. For instance, Quebeckers might see their group as more attuned to cannabis if they perceive that more Quebeckers use cannabis.

Our perceptions are limited. Quebeckers, just like everyone else, are incapable of seeing or hearing everything that is related to cannabis. As such, a lot of information in their environment will remain outside of their consciousness. We believe that needs will play a fundamental role in which kind of perception will be perceived and which one will not. For instance, Quebeckers in needs for security and stability might be more aware of the negative opinions related to cannabis. As such, these people will be less open to integrate the schemas of cannabis into their group identity. As a second example, people in need to belong in a group might be more open to cannabis as it is now accepted by Canadian governments.

The combined role of perceptions and needs are not quite enough to fully learn something. Information rarely comes to us without any action on our side. Infinite actions could be done to collect information from our environment. In the present context of cannabis legalization, Canadians could discuss with friends and gather their opinions on cannabis. Friends' opinion has a powerful impact on people's own opinion and was frequently associate to cannabis use among teenagers (Agrawal et al., 2007; Haug et al., 2014). Canadians could also walk down the street and see the prevalence of cannabis users. Prevalence of people using cannabis might inform Canadians on the degree to which cannabis is accepted into their society.

**Bayesian Approach to Understand the Dynamic of Identity Integration**

The foundation of the BMII rests on a Bayesian conceptualization of the internal processes behind identity integration. To understand what a Bayesian conceptualization is and how it is applied to our model, we need to discuss what Bayesian statistics are.

Bayesian statistics are probabilistic methods of hypothesis testing. The goal is to see how probable our hypothesis is after some analyses (Kruschke, 2011). In its simplest form, Bayesian statistic is the product of a *prior* and an *evidence*. Priors are distribution of probabilities on our hypothesis before we run any tests. Bayesian researchers interested to know the value of some parameter (e.g., mean, regression coefficient, standard deviation) would make a hypothesis about its value and attribute some probabilities to their hypothesis. Evidence is a distribution of probabilities made around the result of an empirical test. The multiplication of the prior with the evidence provides a third distribution of probabilities called the posterior (Jackman, 2009). The posterior informs

Bayesian researchers on both the value of the parameter studied and the probability attached to this value.

The main quality of Bayesian statistics is its consideration for uncertainty. Human knowledge is uncertain. Even the most evident belief such as sunrise is probabilistic. Bayesian statistics allow researchers to catch this uncertainty and quantify it in terms of probabilities. So, prior beliefs about a hypothesis and evidence found in the data are both uncertain information and should be considered probabilistically. The same apply to the posterior distribution. If our phenomenon of interest is highly uncertain, all the values it could take should share the same amount of probability; any value is as likely to happen as the others. On the other hand, if we believe our phenomenon should take a certain value, we could place more probability around our believed value and less to others. One use of Bayesian testing is to remove uncertainty from our belief. This can be done when prior and evidence are coherent with one another. In such analysis, the posterior distribution of probabilities will support the prior with less uncertainty.

Bayesian statistics rest on the transformation of a prior belief into a posterior belief using evidence. Such process could approximate the way people change their schemas and identities. More precisely, people may hold a prior belief about the extend to which cannabis is integrated into their group identity. Such belief will remain uncertain. So, people will allocate probability to the degree to which cannabis is being part of their identity of Canadians. Prior states of cannabis integration will be modified through the information collected in one's environment. This information plays the same role as the evidence in Bayesian statistics. The information perceived about cannabis integration can either favour its integration into Canadians or not. The product of the prior and the evidence will generate a posterior belief surrounding cannabis integration. We argue that this posterior distribution should approximate the belief of cannabis integration for every person. The BMII has the potential to quantify the internal process of identity integration. With such models, social workers helping confuse people and governments working on new laws could ease the process of identity integration.

## Models and Hypotheses

The integration of a new aspect such as cannabis into one's identity is an internal process specific to each and every one of us. Canadians should thus hold different levels of cannabis integration before its legalization. Some Canadians might have already integrated cannabis into the identity of their group, while others remained reluctant to do so. Similarly, Canadians have probably perceived different social norms, experienced different kinds of needs and produce different kinds of actions. For instance, some might perceive a decrease of cannabis use by their group, while others may have perceived an increase. These considerations for idiosyncratic process of identity integration justify the application of the BMII on each participant individually.

Simulations of the BMII were made through three periods of time. We used cannabis integration at time 1 as our prior. Perceptions, need and action were used at times 2 and 3 as evidences. We argue that prior of participants at the beginning of the study will change according to further evidences in times 2 and 3. The BMII provides "predicted" scores of cannabis integration for each of our participants. Those predictions will be compared to the "actual" cannabis integration scores reported by each participant at time 3.

We performed 106 simulations of the BMII with the use of *levels of cannabis integration into people's group* as our prior. With cannabis integration, we aim to measure the extent to which cannabis is linked to the other schemas of people's group identity. This conceptualization will allow us to understand how the level of cannabis integration change along people's perception, need and action. Perceptions that inform our internal states are various. In the present study, we will consider two kinds of perception. First, the frequency of cannabis used by other members of our group. What people do form a social norm that we could perceive and use to modify our level of cannabis integration. If many Canadians adhere to cannabis use, people will probably perceive that cannabis is something well integrated into their group identity. For our second perception, we analyze the valence of cannabis legalization. People who perceive cannabis legalization as a positive change might be more attuned to the integration of cannabis into their group identity. We consider the need for safety as a possible evidence that comes to inform our level of cannabis integration. For action, we took interest in the extend to which people inform themselves about cannabis legalization through media.

Two considerations have to be made with the BMII. First, evidence may not hold the same strength in the modification of priors. For instance, one kind of perception may be more effective to change people's internal state than the other. Canadians may base their level of cannabis integration more strongly into what other Canadians do than about the valence of cannabis legalization. As such, we need to consider the strength to which evidences modify the level of cannabis integration. To assess these strengths for our perceptions, we will rely on a theoretical basis. We, authors, argue that perceptions are the pivotal influence of identities. We learn who we are by getting information through our perceptions. As such, we judge imperative to determine the strength between both perceptions and cannabis integration theoretically. In this sense, our analyses will verify a theory instead of a process govern by our own data. For evidence of need and action, we rely on a data-driven basis. More precisely, we correlate variables of need and action with cannabis integration and use the two resulting correlation coefficients as indicators of strength between prior and evidences.

Another consideration for the BMII is the uncertainty of prior and evidences. People may give more credibility to one or the other. For instance, people may be more confident about their prior and be less certain about their perceptions. In this optic, priors should receive more strength and be less influenced by evidence. On the other hand, since cannabis legalization is a new change, people may not be so sure about their prior and be more subjected to change their level of cannabis integration according to their perceptions. To answer this issue, we will investigate five degrees of uncertainty for both prior and evidence; for a total of 25 simulations per evidence (100 simulations for both perceptions, need and action).

For the last four simulations, we used a sociodemographic variable (age of participant) as a control variable. We argue that age should not explain people's cannabis integration change at the same extend as simulations made with variables of perceptions, need and action. So, results of simulations with age as the evidence should produce more misleading scores of cannabis integration. Since they are 4 main simulations of the BMII (both perceptions, need and action), we need to perform four simulations of the BMII with age. The variable of age will substitute the four main evidence of the BMII without modifying the original strength of relation between prior and evidence. For instance, we will preserve the same strength between frequency of cannabis use by others and cannabis integration but replace the former by the variable of age. In this way, age will act as a control variable inside BMII built for our four evidence of interest, instead of being another evidence inside its own BMII.

For our analyses we performed several simulations; those are computations that run the BMII. In all and for all, a total of 104 simulations of the BMII were performed with the variable *level of cannabis integration into people's group* as the internal states (50 simulations with various degrees of uncertainty for frequency of cannabis use by other members of people's group as evidence, 50 simulations for valence of cannabis legalization, 50 simulations for need for safety, 50 simulations with the variable of action and 4 simulations with the control variable of age). Table 1 shows all simulations of the BMII made with the internal state of cannabis integration into people's group.

**Table 1**
*Simulations of the BMII for cannabis integration into people's group*

| Evidences | Number of degrees of uncertainty for prior | Number of degrees of uncertainty for prior | Total simulations |
|---|---|---|---|
| Frequency of cannabis used by others | 5 | 5 | 25 |
| Valence of cannabis legalization | 5 | 5 | 25 |
| Need for safety | 5 | 5 | 25 |
| Action | 5 | 5 | 25 |
| Age of participants (variable control) | 1 | 1 | 4 |

We argue that the BMII can explain, and thus predict, scores on cannabis integration into people's group. To verify so, we perform three different kinds of statistical tests as to triangulate our results. The use of different tests will only ensure the validity of the BMII. For our first statistical test, we compared predicted scores of cannabis integration with actual scores of cannabis integration at time 3. So, the scores on cannabis integration resulting from BMII simulations were compared with the scores reported by participants at the end of the study.

**H1:** Scores resulting from the BMII with levels of cannabis integration as the internal state and frequency of cannabis use by members of participants' group as perception will positively predict the actual scores of cannabis integration reported by participants at time 3.

**H2:** Scores resulting from the BMII with levels of cannabis integration as the internal state and valence of cannabis legalization as perception will positively predict the actual scores of cannabis integration reported by participants at time 3.

**H3**: Scores resulting from the BMII with levels of cannabis integration as the internal state and the need for safety will positively predict the actual scores of cannabis integration reported by participants at time 3.

**H4**: Scores resulting from the BMII with levels of cannabis integration as the internal state and the action of staying inform about cannabis legalization through media will positively predict the actual scores of cannabis integration reported by participants at time 3.

For our second statistical test, we compare the extend to which simulations made with perceptions, need and action are better predictor of cannabis integration at time 3 than simulations made with the control variable (age). To verify so, we switch evidence variable of perceptions, need and action with age without modifying the original strength between prior and evidence for each model. Every simulation is made with a medium degree of uncertainty for prior and a medium-high degree of uncertainty for age.

**H5:** Predicted scores coming from simulations of the BMII made with the four main variables of evidence will better predict cannabis integration at time 3 than scores coming from BMII simulations made with age as the evidence.

For our third and final statistical test, we will analyze to which extent the level of cannabis integration at the beginning of our study (time 1) predict cannabis integration at the end of the study (time 3). We hypothesis that predicted scores of cannabis integration from the BMII using perceptions, need and action will be better predictors of cannabis integration at time 3 than scores of cannabis integration at time 1. With this statistical test, we wish to measure if the BMII is better (or as good) to predict cannabis integration than scores of cannabis integration at the beginning of our study.

We produce additional simulations with the BMII on two other conceptualizations of cannabis integration. Those simulations aim to see if results from other priors will support the ones previously discussed. First, we replicated the previous analyses (the 104 previous simulations) with the variable of identification to cannabis users. With such variable, we can conceptualize "cannabis" as an identity rather than a schema that comes to be integrated into a group identity. We thus rely on the identity of being a cannabis user. Cannabis users are a group of people that share some attributes. For instance, they all use cannabis, they usually know different tricks to use it and are familiar with cannabis cost, dose and variety. So, cannabis users form a distinct group of people that share a common identity. Following cannabis legalization, people could relate more strongly to cannabis users.

Secondly, we will use cannabis integration into people's group along with two other stages of integration (categorization and compartmentation). Our previous consideration for only one stage of the Cognitive Model of Social Identity Integration (Amiot et al., 2007) may oversimplify people's identity integration process. After all, people could experience more than one stage of identity integration at a time. In this optic, we should be able to consider and quantify the differences between someone who is high on cannabis integration (and low on categorization and compartmentation) with someone who is also high on cannabis integration (and high on categorization and compartmentation as well). Considering categorization and compartmentation in the BMII will be relevant to catch faithfully people's internal changes. To this end, we consider the *probabilities* of every stage of identity integration for every participant. So, chances that people experience each stage of identity integration will be quantified probabilistically. Probabilities will be allocated to the extend to which participants report feeling every stage of identity integration. Stages with high rates will receive higher probabilities. However, if people report feeling high on all three stages, probabilities will be allocated fairly across all stages (1.0 / 3 = .33 probabilities for each stage). Such consideration for the global process of identity integration will give us a better understanding of every process of identity integration. With this final conceptualization of internal states, we are interested to understand how probabilities regarding the three stages of cannabis integration will change. For this latter set of simulations, we only compared predicted scores of BMII with actual scores at time 3.

## Method

### Participants

All participants reside in Québec, a province of Canada. A total of 1 682 Quebeckers accepted to answer all the questions of the first measured questionnaire, 1 251 to the second questionnaire and 1 004 in the third and final questionnaire. People were invited to fill up the questionnaire across all times; even if they missed a previous questionnaire. Participants were given a week to answer each questionnaire. We lost 25.62% of people (N = 431) from the first questionnaire to the second and 19.74% (N = 247) from the second questionnaire to the third one. To participate, people needed to be age 18 or more and reside in Québec. We made sure the selection of our participants was representative of Québec's population. To verify so, we compare sociodemographic variables of our sample with census from Statistics Canada; Canada national statistical agency. Statistic Canada reports 50.4% of women in 2010 (Urquijo & Milan, 2011). Such statistic matches with our sample across all times of measure (45.84% women respondents at time 1, 43.57% women at times 2 and 42.33% women at time 3). Also, the average age of Quebec's population in 2016 is 41.1 (Statistic Canada, 2017), which is fairly similar to the mean of age at our first questionnaire ($M_{Age}$ = 50.91).

**Procedure**

Participants were invited through the firm of surveys *AskingCanadians*. The firm is an agency of *Delvinia* and holds a panel of more than a million Canadian participants. Samples from *AskingCanadians* and constantly compared to Statistic Canada data for statistical representativeness. *AskingCanadians* keeps profile of their participants in more than 500 criteria and renew their participants' profile annually. The firm sent an invitation to participate in the present study of members of their panel along with a brief description of the present research project. On our demand, the firm selected participants as to be representative to the Québec population. Participants were informed of the three measure time of the questionnaire. Questions were answered on an electronic device at the place of convenience of every participant. The first questionnaire took place on October 17, 2018, which is the very first day of cannabis legalization in Canada. Second questionnaire was assessed on November 19, 2018, and final questionnaire was given on November 5, 2019.

**Measures**

**Sociodemographic.** Several sociodemographic items are added to the questionnaire such as age, gender (woman, man or other), the higher diploma achieved, what people do for a living (e.g., worker, student, unemployed) and socio-economic status. Socio-economic status is measured on a scale from 0 (bottom end of the ladder; poor life conditions, revenue and work) to 4 (top end of the ladder; better life conditions, revenue and work). Social demographic variables are used as predictors for subsequent data imputations.

**Perception of social norms.** Participants' perception of social norms is assessed in two manners. First, we measure the extend to which each participant perceived that other members of their group use cannabis more or less frequently. This norm is measured with a single item: "In my opinion, when cannabis will be legal, the frequency at which (group) use cannabis will…" on a scale of 0 (decrease) to 4 (increase). After the first time of measure, we rephrase the item as follows "In my opinion, since cannabis is legal, the frequency at which (group) use cannabis has…". We also measure the perceived valence of cannabis legalization and use it as an approximation of the injunctive norm. Such perception is measured with the single item: "Do you think the changes regarding the legalization of cannabis are negative or positive?" with a scale of 0 (very negative) to 4 (very positive). We acknowledge that this latter item does not measure precisely the injunctive norm. Future study should measure the valence of the group instead of personal valence. For the present study, we will rely on personal valence. Both items were used in previous studies (e.g., de la Sablonnière & Tougas, 2008; de la Sablonnière, Tougas, & Lortie-Lussier, 2009) and have the potential to catch people's perception during a social change.

**Need for safety.** To measure need for safety, we selected three items of Strong and Fiebert (1987) scale of needs. The present scale is built on the theory of the hierarchy of needs of Maslow (1954, 1968). The three items selected are the following: "I live in a lawful, orderly society", "I feel safe in my neighbourhood and in my house" and "I have a stable lifestyle; I know what will happen next". Each item was answered on a scale of 0 (Strongly disagree) to 4 (Strongly agree). Internal consistency between is adequate across all the measure times ($\alpha_{T1}$ = .77, $\alpha_{T2}$ = .79, $\alpha_{T3}$ = .81). For each participant, scores were aggregated by doing the mean of the items.

**Action.** We measure action with a single item: “I followed political debates (e.g., in the media) surrounding cannabis legalization,” measured on a scale from 0 (Strongly disagree) to 4 (Strongly agree). With this item, we wish to capture the extend to which participants reach for information about cannabis legalization. By reaching for more information about cannabis legalization, people could modify their internal state as to integrate or not cannabis into their identity.

**Cannabis integration.** To measure the different states of cannabis integration of each participant, we used six items from Yampolsky and colleagues (2016)’ Multicultural Identity Integration scale (MULTIIS). A single item measures the stage of categorization: “At the moment, I identify exclusively to my (group) identity”. Two items measure the stage of compartmentation: “At the moment, my (group) identity and my cannabis identity represent separate parts of who I am” et “At the moment, the differences between my (group) identity and my cannabis identity cannot be reconciled”. Finally, three items measure the stage of integration: “At the moment, my (group) identity and my cannabis identity are linked”, “At the moment, my (group) identity includes my cannabis identity” and “At the moment, I perceive similarities between my (group) identity and my cannabis identity”. Items are measured on a scale from 0 (strongly disagree) to 4 (strongly agree). All items were adapted to the context of cannabis legalization. A brief description was provided to our participants to describe what is a “cannabis identity”. Internal consistency between items is adequate ($r_{T1}$ = .75, $r_{T2}$ = .71, $r_{T3}$ = .75 for compartmentation and $\alpha_{T1}$ = .94, $\alpha_{T2}$ = .94, $\alpha_{T3}$ = .94 for integration). Internal consistency was performed with Spearman-Brown for compartmentation.

**Identification to cannabis users.** We measure the extend to which participant relate themselves to cannabis users with three items from Cameron (2004): “Currently, I identity with cannabis users”, “Currently, I have a lot in common with cannabis users” and “Currently, being a cannabis user is an important part of who I am”. Items are measured on a scale from 0 (strongly disagree) to 4 (strongly agree). Internal consistency is adequate ($\alpha_{T1}$ = .88, $\alpha_{T2}$ = .88, $\alpha_{T3}$ = .89).

**Bayesian Operations of the Bayesian Model of Identity Integration**

The result of the BMII *P(identity|perception)* is basically the multiplication of a prior with evidence (see Formula 1). To perform such operation, we need to operationalize the prior *P(identity)* and the evidence *P(perception|identity)*. The term *∑P(perception|identity)P(identity)* is the marginal probability. It does not play a key role in the process of identity change; the marginal probability only ensure that the result will sum to 1.0 (which is a rule of probability – probability cannot go over 100%). Both prior and evidence distributions of probabilities used in the BMII were given the form of a normal distribution. The shape of normal distribution allows only a single value to be the most credible one. We argue that this particular value, centred in the middle of the normal curve, represent the idea of each participant in either their prior or evidence. To account for the uncertainty, the normal distribution allocates probabilities to values surrounding the most probable one. Probabilities decrease more and more as we come across distant values. To form normal distributions for both prior and evidence distributions, two parameters must be specified: the mean and the standard deviation for each distribution. The way these two parameters were chosen is fundamental for the simulation of the BMII and should thus be discussed for each prior and evidences.

$$p(identity|\text{perception}) = \frac{P(perception|\text{identity})P(identity)}{\sum P(perception|\text{identity})P(identity)} \quad \textbf{Formula 1}$$

**Cannabis Integration**

Prior distributions of cannabis integration is made with the score of each participant in the three items of the cannabis integration scale. Only scores of the first questionnaire are used for the prior, since they represent our starting point for the subsequent simulations of the BMII. The mean of the cannabis integration scores receives the highest probability and the normal distribution is formed around this value. The standard deviation is assessed using two kinds of variation. First, the variation of the scores on the cannabis integration items is considered. Participants who did not provide the exact score of the three items of cannabis integration present variation that we can assess as standard deviation. This standard deviation is taken into account for building prior distribution. In addition, every participant is given extra values of standard deviation decided on an arbitrary basis. Scores of SD = 0.1, 0.5, 1.0, 1.5 and 2.0 are added to the standard deviation found among each participant cannabis integration scores. The goal of this additional standard deviation is to understand how the BMII will work if the prior was strong (small standard deviation) or more uncertain (large standard deviation). Strong prior gives little opportunity to be modified by the evidence, while uncertain prior can be easily modified by evidences. For our hypotheses, we used an additional standard deviation of 1.0.

Evidence distributions represent the probability to perceive a social norm, to experience a certain degree of need or to produce a certain action according to levels of cannabis integration. So, for each value of cannabis integration, there is a probability distribution to perceive a social norm, to experience a certain degree of need or to produce a certain action. For instance, people who did not integrate cannabis into their identity, may perceive cannabis legalization as more negative than people who have integrated cannabis into their identity. Evidence distributions should thus be different depending on the prior cannabis integration score. Once again, means and standard deviation parameters were needed to form the normal distributions of each evidence distribution. Means were given along a theory-driven process for both perception variables. For these variables, a linear model was used to assess the relation between the internal states and perception. For frequency of cannabis used by other members of our group, we authors, discussed potential direction and strength of the relationship based on our expertise and previous studies that have measured the variables of identity and social norms, or related variables (see, Rise et al., 2010; Sparks & Shepherd, 1992). A slope of $r = .29$ was decided. For valency of cannabis legalization, we used the slope of $r = .40$ based on the same theoretical process and studies. With correlation formula ($y = ax + b$), we found the means to construct every evidence distribution. For instance, the mean of the evidence distribution when valency equals 0 is y = .40(0) + 0 = 0. So, people who perceived very negatively cannabis legalization (valency = 0) should not have integrated cannabis into their group identity (result of the mean = 0). Values of 0.1, 0.5, 1.0, 1.5, 2.0 are used to create variation in the normal distributions of the evidence. For our hypothesis, we used an additional standard deviation of 1.5.

Strength of relation between evidence of need and action and cannabis integration were calculated on a different optic. We based the strength of these relationships on our own data. So, we calculated correlation between both need and action, and cannabis integration and used it on the regression formula to get the means of every evidence distribution. Age, since it is our control variable, has not received any calculation for its strength of relation with prior. Age will not belong into its own BMII but will substitute evidence of existing BMII.

Mathematically, the BMII takes the form of a multiplication between the prior distribution of probabilities and two evidence distributions of probabilities (times 2 and 3). Since prior distributions are multiplied by the evidence, the probabilities previously allocated for cannabis integration will come to a change. The multiplication operation results in another distribution of probabilities called the *posterior* distribution. Posterior distributions spread new probabilities across every value of cannabis integration for each participant. Means of every posterior distribution become our best prediction on the level of cannabis integration for every participant.

To see if our prediction on cannabis integration score is adequate, we need to compare every predicted score of the BMII (mean of every posterior distribution) with the real score reported by our participants. Real scores are the actual values of cannabis integration given by our participants at the end of the survey.

**Identification to Cannabis Users**

To assess identification to cannabis users through the BMII, we rely on a similar procedure as for cannabis integration into people's group. Normal distributions of probabilities on the level of identification to cannabis users are built for every participant. Scores on the three items of identification are used to calculate the mean and the standard deviation of the normal distribution. Additional values are given to the standard deviation. Values of 0.1, 0.5, 1.0, 1.5 and 2.0 are added to the variation between items of each of our participants.

Evidence distributions are built according to the relation between each variable of evidence and the variable of identification. The relation serves to find the means of each evidence distribution. Values of 0.1, 0.5, 1.0, 1.5 and 2.0 are given to the standard deviation of each evidence distribution.

The multiplication of each participant prior distribution with their corresponding evidence distribution produce a distribution of probabilities around a certain value of identification (posterior distribution). We use this value and compare it with the value of identification to cannabis users reported by each participant in their final questionnaire. Regression tests are used to compare both predicted and actual results of identification.

**Stages of Cannabis Integration**

In our final set of analyses, we consider the three stages of identity integration: categorization, compartmentation and integration. People are complex agent that may fit somewhere between stages. So, for every participant, we consider the probability that they found themselves into each of the three stages. Those probabilities should sum to 1 and will be the basis on which we build our prior distribution. To get those probabilities, we relied on participants computed scores on each stage of identity integration at time 1. We divided each score of stages by the sum of the stages. For instance, if a participant provides scores of 2 for categorization, 3.5 for compartmentation and 4 for integration, the total amount is 9,5 (2 + 3.5 + 4 = 9.5). Each score divided by the total will give us probabilities of 0.21 for categorization, 0.37 for compartmentation and 0.42 for integration.

We then build distribution of probabilities for evidence. To do so, we calculate the relation between scores of our three stages of cannabis integration and each evidence (both perceptions, need and action). We let our data shape the strength of each relation.

Correlation scores are performed to know the strength of the association between each evidence and the prior. For instance, the relation between perception of valence and categorization is r = .13. This score is used with the function y = ax + b. In this function, y is the score we try to find, a is the strength of the relation (.13), x is the different possible scores of perception (0, 1, 2, 3 and 4) and b equals zero since we use a standardized correlation coefficient. We transform every score into probabilities and calculate the conditional probability over our internal states. This mean, we took the sum of every probability into one stage of internal state and transform those probabilities as to sum them to 1.

The resulting matrix provides probabilities for every distribution of evidence. The next step consists of the multiplication of every participant prior to the correct distribution of evidence. The multiplication of our prior with the evidence (and the application of a correction to sum the probability to 1) give rise to posterior distributions on the stages of cannabis integration for every participant. We compare these probabilities with the probabilities calculated on the third and final questionnaire.

## Results

### Preliminary Analyses

Like most longitudinal studies, the present study present missing values across time. From 1 682 participants at time 1, 867 completed the two subsequent questionnaires. To delete participants with missing values could bias our analyses (Enders, 2010), so we imputed the missing data. We did so with the use of package AMELIA (Honaker et al., 2010) with the software R. We included our variables of interest in the computation process (e.g., internal states, evidence) and 4 sociodemographic variables: age, gender, highest diploma achieved and socio-economic status. We argue that sociodemographic variables could explain to some extent why some people did not respond to subsequent questionnaires. A total of 50 imputed data sets were programed into AMELIA. The BMII was run on each valid imputed data set and results were pooled as to converge results on one value. For the pooling method, we used package MICE (van Buuren et al., 2015). So, the output of

AMELIA was converted into a “mids” object; which can be used by MICE package for pooling results. Readers can find our script in the annexe.

**Main Analyses: Can we predict cannabis integration?**

All simulations of the BMII were run with R (see annexe for our script). Every simulation provides a posterior value of cannabis integration for each of our participant. We call these values “predicted scores”. Predicted scores are assumed to be the scores on cannabis integration at time 3. So, through BMII simulations, every participant receives a predicted score on cannabis integration. We use predicted scores as predictors inside regression tests that predict the actual score of cannabis integration given in the third and final questionnaire. Regression analyses inform us on the strength and direction of our predictions. The stronger the regression coefficient, the better our prediction.

Simulations of the BMII predict positively scores of cannabis integration at time 3. Regression of the BMII with cannabis integration at time 3 is $\beta = .26$, $p < .001$, 95% CI [.20, .31] for frequency of cannabis use by other members of participants’ group as evidence, $\beta = .28$, $p < .001$, 95% CI [.22, .33] for valence of cannabis legalization as evidence, $\beta = .26$, $p < .001$, 95% CI [.20, .31] for need for safety as evidence and $\beta = .26$, $p < .001$, 95% CI [.20, .31] for the action to reach information about cannabis legalization as evidence. All these simulations of BMII were applied with a degree of uncertainty of 1.0 for prior and 1.5 for evidence. The first four lines of Figure 3 shows the confidence interval of our predictions.

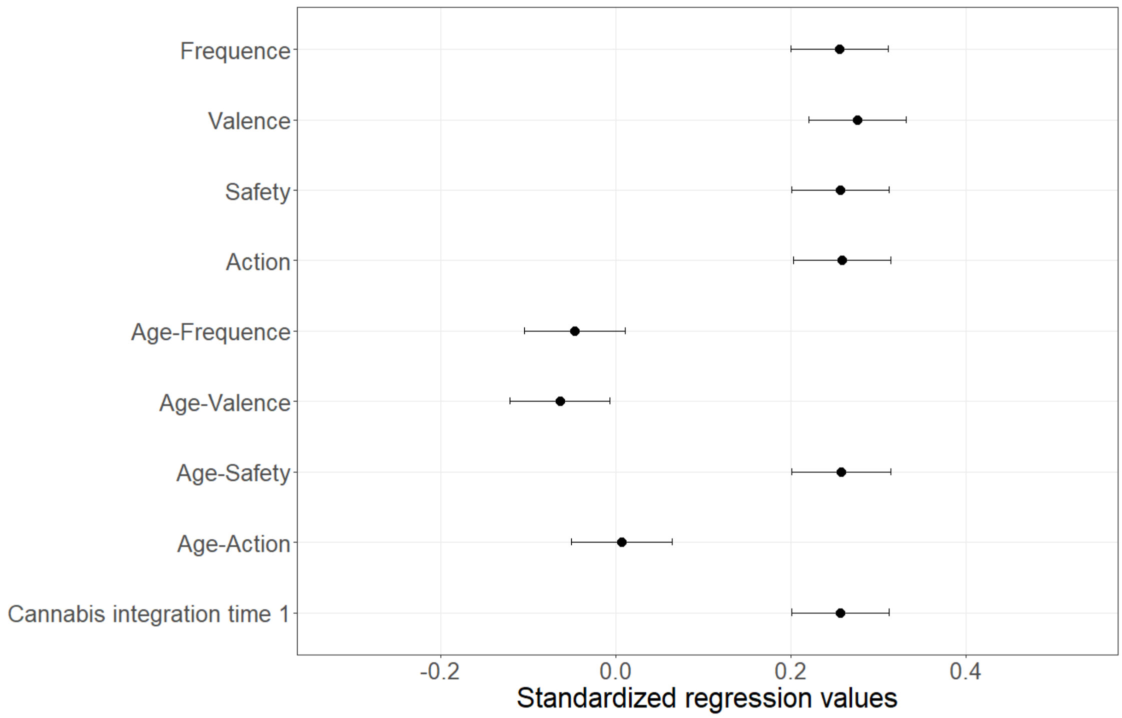


*Figure 5 Confidence intervals of predictions of cannabis integration into people's group at time 3 by simulations of the BMII. Each simulation is made with an additional uncertainty of 1.0 for priors and 1.5 for evidences.*

We then compared the four main simulations of the BMII with simulations made with a control variable (age of participants). To do so, we need to preserve the way each BMII were conceived (the relation between evidence and prior remains the same) and only substitute the variable of evidence by age. For instance, the BMII with frequency of cannabis use by others has an association of $r$ = .29 between its prior and evidence. We preserve $r$ = .29 with the BMII using age as evidence. The same apply to other simulations of the BMII. We preserve a relation of $r$ = .40 for valence of cannabis change, $r$ = .00 for the need for safety and $r$ = .14 for the action to reach information about cannabis legalization.

Simulations of the BMII with the four main variables of evidence better predict cannabis integration then simulation of the BMII with the control variable of age, except for one case: when we used age in the BMII structured for the need for safety. Simulations of the BMII predict at β = -.04, p = .102, 95% CI [-.11, .01] when age was substitute into the model of frequency of cannabis use by members of participants' group, at β = -.06, p = .026, 95% CI [-.12, -.01] into the model of valence of cannabis legalization, at β = .26, p

$< .001$, 95% CI [.20, .31] for need for safety and at $\beta = .01$, $p = .802$, 95% CI [-.05, .06] for the action of reaching information in media about cannabis legalization. All these simulations of BMII were applied with a degree of uncertainty of 1.0 for prior and 1.5 for evidence. Lines 5 to 8 in Figure 3 shows confidence interval of predictions made with age as a control variable.

BMII simulations show weaker prediction when we substitute frequency of cannabis uses by others, valence of cannabis legalization and action by age. On the other hand, when we substitute safety by age, we obtain a similar degree of prediction of internal states at time 3 as the simulation of BMII made with safety. When we take a closer look at the way BMII are constructed, we realize that evidence of safety does not influence cannabis integration ($r = .00$). So, the evidence of safety does not modify prior levels of cannabis integration. From a mathematical point of view, when the relation between evidence and prior is 0.0 ($r = .00$), every distribution of evidences will be the similar. Consequently, every distribution of evidence will modify priors the same way. Since every score of prior will be modified in the same way, the relative position of each participant on the scores produced by the BMII will remain the same as their relative position on the variable of cannabis integration at time 1. As a result, the efficacy of both variables to predict cannabis integration at time 3 will be similar. Since the BMII with need for safety produce the same change of priors, the substitution of need for safety by age will not bring a difference in the output of the simulations. That could explain why we get a similar prediction of internal states at time 3 whether we use need for safety or age.

The BMII appears to be an as good predictor of cannabis integration scores at time 3 than cannabis scores at time 1; $\beta = .26$, $p < .001$, 95% CI [.20, .31]. The last line of Figure 3 shows confidence interval of the present prediction test.

Four our final tests with cannabis integration in people's group as our internal state variable, we run 25 times models of the BMII with different values of uncertainty for prior (0.1, 0.5, 1.0, 1.5 and 2.0) and evidences (same values as for priors). All in all, prediction of cannabis at time 3 seems to be better when prior has a weak uncertainty and when evidence has a strong uncertainty. Tables 3 to 6 shows the different run of the BMII.

**Table 2**

*Regressions between BMII simulations with frequency of cannabis use as evidence and cannabis integration at time 3*

| Additional standard deviation for prior | Standard deviation for evidence | Regressions between predicted cannabis integration scores and actual scores at time 3 | P value | 95% Confidence Intervals |
|---|---|---|---|---|
| | 0.1 | .19 | < .001 | [.13, .24] |
| | 0.5 | .25 | < .001 | [.19, .30] |
| 0.1 | 1.0 | .26 | <.001 | [.20, .31] |
| | 1.5 | .26 | <.001 | [.20, .31] |
| | 2.0 | .26 | <.001 | [.20, .31] |
| | 0.1 | .01 | .590 | [-.04, .07] |
| | 0.5 | .22 | < .001 | [.17, .28] |
| 0.5 | 1.0 | .25 | < .001 | [.20, .31] |
| | 1.5 | .26 | < .001 | [.20, .31] |
| | 2.0 | .26 | < .001 | [.20, .31] |
| | 0.1 | .00 | .884 | [-.06, .05] |
| | 0.5 | .13 | < .001 | [.07, .18] |
| 1.0 | 1.0 | .24 | < .001 | [.19, .30] |
| | 1.5 | .26 | < .001 | [.20, .31] |
| | 2.0 | .26 | < .001 | [.20, .31] |
| | 0.1 | -.01 | .659 | [-.07, .04] |
| | 0.5 | .06 | .027 | [.01, .12] |
| 1.5 | 1.0 | .20 | < .001 | [.14, .25] |
| | 1.5 | .24 | < .001 | [.19, .30] |
| | 2.0 | .25 | < .001 | [.20, .31] |
| | 0.1 | -.02 | .557 | [-.07, .04] |
| | 0.5 | .03 | .270 | [-.02, .09] |
| 2.0 | 1.0 | .14 | < .001 | [.09, .20] |
| | 1.5 | .22 | < .001 | [.16, .27] |
| | 2.0 | .24 | < .001 | [.19, .30] |

**Table 3**

*Regressions between BMII simulations with valence of cannabis legalization use as evidence and cannabis integration at time 3*

| Additional standard deviation for prior | Standard deviation for evidence | Regressions between predicted cannabis integration scores and actual scores at time 3 | P-value | 95% Confidence Intervals |
|---|---|---|---|---|
| | 0.1 | .25 | < .001 | [.20, .31] |
| | 0.5 | .25 | < .001 | [.20, .31] |
| 0.1 | 1.0 | .26 | < .001 | [.21, .32] |
| | 1.5 | .26 | < .001 | [.21, .32] |
| | 2.0 | .26 | < .001 | [.20, .32] |
| | 0.1 | .18 | < .001 | [.13, .24] |
| | 0.5 | .26 | < .001 | [.21, .32] |
| 0.5 | 1.0 | .27 | < .001 | [.21, .32] |
| | 1.5 | .27 | < .001 | [.21, .32] |
| | 2.0 | .26 | < .001 | [.21, .32] |
| | 0.1 | .18 | < .001 | [.12, .23] |
| | 0.5 | .22 | < .001 | [.16, .27] |
| 1.0 | 1.0 | .27 | < .001 | [.22, .33] |
| | 1.5 | .28 | < .001 | [.22, .33] |
| | 2.0 | .27 | < .001 | [.22, .33] |
| | 0.1 | .18 | < .001 | [.12, .23] |
| | 0.5 | .19 | < .001 | [.14, .25] |
| 1.5 | 1.0 | .25 | < .001 | [.19, .30] |
| | 1.5 | .28 | < .001 | [.22, .33] |
| | 2.0 | .28 | < .001 | [.23, .34] |
| | 0.1 | .17 | < .001 | [.12, .23] |
| | 0.5 | .18 | < .001 | [.13, .24] |
| 2.0 | 1.0 | .23 | < .001 | [.17, .28] |
| | 1.5 | .27 | < .001 | [.21, .32] |
| | 2.0 | .28 | < .001 | [.23, .34] |

**Table 4**

*Regressions between BMII simulations with need for safety as evidence and cannabis integration at time 3*

| Additional standard deviation for prior | Standard deviation for evidence | Regressions between predicted cannabis integration scores and actual scores at time 3 | P-value | 95% Confidence Intervals |
|---|---|---|---|---|
| | 0.1 | .26 | < .001 | [.20, .31] |
| | 0.5 | .26 | < .001 | [.20, .31] |
| 0.1 | 1.0 | .26 | < .001 | [.20, .31] |
| | 1.5 | .26 | < .001 | [.20, .31] |
| | 2.0 | .26 | < .001 | [.20, .31] |
| | 0.1 | .26 | < .001 | [.20, .31] |
| | 0.5 | .26 | < .001 | [.20, .31] |
| 0.5 | 1.0 | .26 | < .001 | [.20, .31] |
| | 1.5 | .26 | < .001 | [.20, .31] |
| | 2.0 | .26 | < .001 | [.20, .31] |
| | 0.1 | .25 | < .001 | [.20, .31] |
| | 0.5 | .26 | < .001 | [.20, .31] |
| 1.0 | 1.0 | .26 | < .001 | [.20, .31] |
| | 1.5 | .26 | < .001 | [.20, .31] |
| | 2.0 | .26 | < .001 | [.20, .31] |
| | 0.1 | .23 | < .001 | [.17, .29] |
| | 0.5 | .26 | < .001 | [.20, .31] |
| 1.5 | 1.0 | .26 | < .001 | [.20, .31] |
| | 1.5 | .26 | < .001 | [.20, .31] |
| | 2.0 | .26 | < .001 | [.20, .31] |
| | 0.1 | .19 | < .001 | [.14, .25] |
| | 0.5 | .26 | < .001 | [.20, .31] |
| 2.0 | 1.0 | .26 | < .001 | [.20, .31] |
| | 1.5 | .26 | < .001 | [.20, .31] |
| | 2.0 | .26 | < .001 | [.20, .31] |

**Table 5**

*Regressions between BMII simulations with action use as evidence and cannabis integration at time 3*

| Additional standard deviation for prior | Standard deviation for evidence | Regressions between predicted cannabis integration scores and actual scores at time 3 | P-value | 95% Confidence Intervals |
|---|---|---|---|---|
| 0.1 | 0.1 | .19 | < .001 | [.14, .25] |
| | 0.5 | .25 | < .001 | [.19, .31] |
| | 1.0 | .26 | < .001 | [.20, .31] |
| | 1.5 | .26 | < .001 | [.20, .31] |
| | 2.0 | .26 | < .001 | [.20, .31] |
| 0.5 | 0.1 | .07 | .014 | [.01, .13] |
| | 0.5 | .24 | < .001 | [.19, .30] |
| | 1.0 | .26 | < .001 | [.20, .31] |
| | 1.5 | .26 | < .001 | [.20, .31] |
| | 2.0 | .26 | < .001 | [.20, .31] |
| 1.0 | 0.1 | .04 | .156 | [-.02, .10] |
| | 0.5 | .20 | < .001 | [.15, .26] |
| | 1.0 | .26 | < .001 | [.20, .31] |
| | 1.5 | .26 | < .001 | [.20, .31] |
| | 2.0 | .26 | < .001 | [.20, .31] |
| 1.5 | 0.1 | .03 | .292 | [-.03, .09] |
| | 0.5 | .15 | < .001 | [.09, .20] |
| | 1.0 | .24 | < .001 | [.19, .30] |
| | 1.5 | .26 | < .001 | [.20, .31] |
| | 2.0 | .26 | < .001 | [.20, .31] |
| 2.0 | 0.1 | .02 | .382 | [-.03, .08] |
| | 0.5 | .11 | < .001 | [.06, .17] |
| | 1.0 | .22 | < .001 | [.16, .28] |
| | 1.5 | .25 | < .001 | [.20, .31] |
| | 2.0 | .26 | < .001 | [.20, .31] |

### Identification to cannabis users

We repeat analyses of cannabis integration into people's group on the internal state of identification to cannabis users. In this optic, cannabis users form an identity to which participant can feel related to. We aim to model people's dynamic process of identification change. Again, the four main evidence used in the BMII predict positively levels of identification to cannabis users at time 3. Predicted scores of BMII simulations predict identification to cannabis users at $\beta = .34$, $p < .001$, 95% CI [.29, .40] for frequency of cannabis use by other members of people's group as evidence, β = .41, p < .001, 95% CI [.36, .46] for valence of cannabis legalization as evidence, β = .37, p < .001, 95% CI [.32, .43] for need for safety as evidence and β = .37, p < .001, 95% CI [.31, .42] for action to reach information about cannabis legalization in the media. All these simulations of BMII are applied with a degree of uncertainty of 1.0 for prior and 1.5 for evidence. First four lines of Figure 4 shows confidence interval of the present predictions.

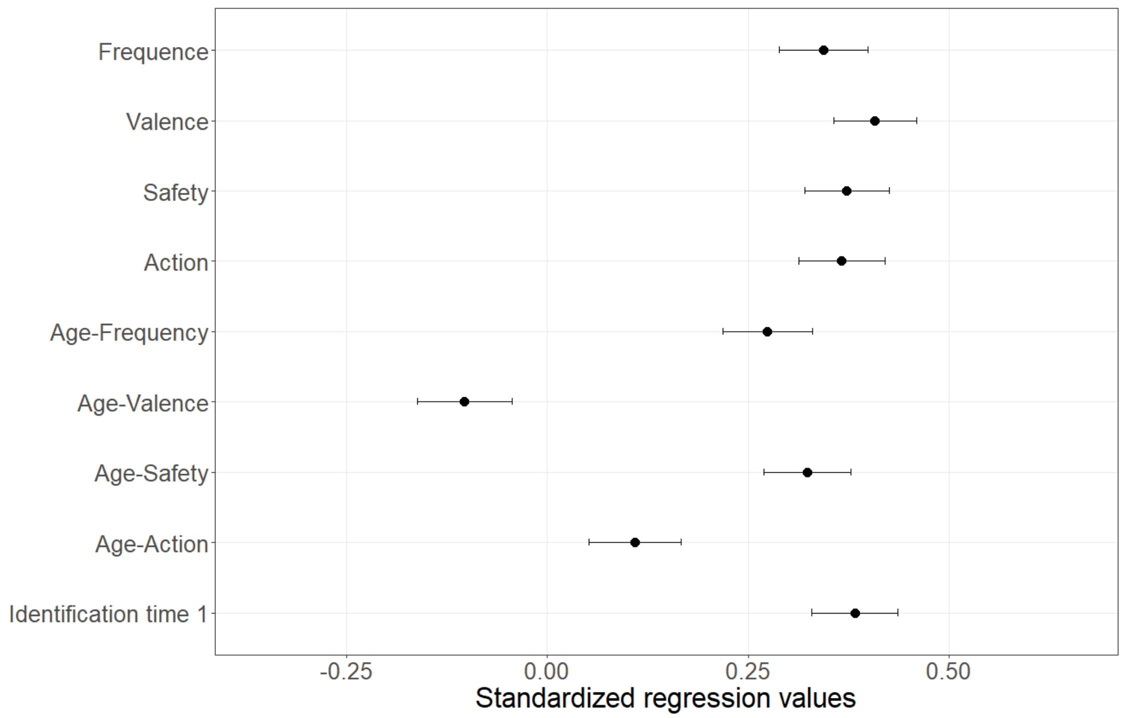


*Figure 4. Confidence intervals of predictions of identification to cannabis users at time 3 by simulations of the BMII. Each simulation is made with an additional uncertainty of 1.0 for priors and 1.5 for evidence.*

When we substitute evidences of BMII simulations with age, we obtain weaker regression coefficients of identification to cannabis users at time 3 for BMII made with valence of cannabis legalization and action. However, when we substitute frequency of cannabis use by others and safety with age, we obtain similar regression coefficients. Regression is β = .27, p < .001, 95% CI [.22, .33] when age is substituted into the model of frequency of cannabis use by members of participants' group, at β = -.10, p = .026, 95% CI [-.16, -.04] into the model of valence of cannabis legalization, at β = .32, p < .001, 95% CI [.27, .38] for need for safety and at β = .11, p = .802, 95% CI [.05, .17] for the action of reaching information in media about cannabis legalization.

Again, evidences of valence of cannabis legalization and action appears to predict less cannabis integration at time 3 when they are substitute with age. Here, substitution of frequency of cannabis use by others by age does not affect drastically predictions of cannabis at time 3. When we investigate the relation between both evidences and identification to cannabis users at time 1, we obtain similar coefficient of regression ($r$ = -.18; for frequency of cannabis use by others and $r$ = -.15 for age). So, when we substitute the evidence of frequency of cannabis use by others with evidence that hold a similar influence on prior, we should expect a small difference in our prediction of cannabis integration at time 3. This is what our results show.

We then look at the power of prediction of identification to cannabis users at time 1 with itself at time 3. The four main simulations of the BMII seems to be as good predictor of identification to cannabis users at time 3 then identification to cannabis users at time 1; β = .38, $p$ = .802, 95% CI [.33, .44]. All these simulations of BMII are applied with a degree of uncertainty of 1.0 for prior and 1.5 for evidence. The last five lines of Figure 4 shows prediction of cannabis integration at time 3 with simulations of the BMII with age (lines 5 to 8) and identification to cannabis users at time 1 (last line).

We perform 100 more simulations with the BMII on identification to cannabis users, using different values of uncertainty for priors and evidence. The BMII seems to better predict identification to cannabis users when prior has a weak uncertainty and evidences have a high uncertainty. Tables 6 to 9 shows results of every run.

**Table 6**

*Regressions between BMII simulations with frequency of cannabis use by others use as evidence and identification to cannabis users at time 3*

| Additional standard deviation for prior | Standard deviation for evidence | Regressions between predicted scores of identification to cannabis users and actual scores at time 3 | P-value | 95% Confidence Intervals |
|---|---|---|---|---|
| 0.1 | 0.1 | .23 | < .001 | [.17, .28] |
| | 0.5 | .33 | < .001 | [.28, .39] |
| | 1.0 | .36 | < .001 | [.31, .42] |
| | 1.5 | .37 | < .001 | [.32, .43] |
| | 2.0 | .37 | < .001 | [.32, .43] |
| 0.5 | 0.1 | -.08 | .014 | [-.14, -.02] |
| | 0.5 | .30 | < .001 | [.25, .35] |
| | 1.0 | .35 | < .001 | [.30, .40] |
| | 1.5 | .36 | < .001 | [.31, .42] |
| | 2.0 | .37 | < .001 | [.32, .42] |
| 1.0 | 0.1 | -.13 | < .001 | [-.19, -.07] |
| | 0.5 | .20 | < .001 | [.14, .26] |
| | 1.0 | .32 | < .001 | [.26, .37] |
| | 1.5 | .35 | < .001 | [.29, .40] |
| | 2.0 | .36 | < .001 | [.30, .41] |
| 1.5 | 0.1 | -.13 | < .001 | [-.19, -.07] |
| | 0.5 | -.04 | .164 | [-.10, .02] |
| | 1.0 | .21 | < .001 | [.15, .27] |
| | 1.5 | .30 | < .001 | [.24, .35] |
| | 2.0 | .33 | < .001 | [.28, .38] |
| 2.0 | 0.1 | -.13 | < .001 | [-.19, -.07] |
| | 0.5 | -.09 | .003 | [-.15, -.03] |
| | 1.0 | .06 | .041 | [.00, .12] |
| | 1.5 | .20 | < .001 | [.14, .26] |
| | 2.0 | .27 | < .001 | [.22, .33] |

**Table 7**

*Regressions between BMII simulations with valence of cannabis legalization as evidence and identification to cannabis users at time 3*

| Additional standard deviation for prior | Standard deviation for evidence | Regressions between predicted scores of identification to cannabis users and actual scores at time 3 | P-value | 95 % Confidence Intervals |
|---|---|---|---|---|
| 0.1 | 0.1 | .39 | < .001 | [.35, .45] |
| | 0.5 | .39 | < .001 | [.33, .44] |
| | 1.0 | .39 | < .001 | [.34, .45] |
| | 1.5 | .39 | < .001 | [.34, .45] |
| | 2.0 | .39 | < .001 | [.34, .44] |
| 0.5 | 0.1 | .35 | < .001 | [.29, .40] |
| | 0.5 | .40 | < .001 | [.34, .45] |
| | 1.0 | .40 | < .001 | [.34, .45] |
| | 1.5 | .40 | < .001 | [.34, .45] |
| | 2.0 | .39 | < .001 | [.34, .45] |
| 1.0 | 0.1 | .30 | < .001 | [.25, .35] |
| | 0.5 | .36 | < .001 | [.31, .41] |
| | 1.0 | .40 | < .001 | [.35, .45] |
| | 1.5 | .41 | < .001 | [.36, .46] |
| | 2.0 | .41 | < .001 | [.36, .46] |
| 1.5 | 0.1 | .28 | < .001 | [.22, .33] |
| | 0.5 | .33 | < .001 | [.27, .38] |
| | 1.0 | .38 | < .001 | [.33, .44] |
| | 1.5 | .41 | < .001 | [.36, .46] |
| | 2.0 | .42 | < .001 | [.37, .47] |
| 2.0 | 0.1 | .26 | < .001 | [.21, .31] |
| | 0.5 | .31 | < .001 | [.25, .37] |
| | 1.0 | .36 | < .001 | [.31, .42] |
| | 1.5 | .39 | < .001 | [.34, .45] |
| | 2.0 | .42 | < .001 | [.37, .47] |

**Table 8**
*Regressions between BMII simulations with need for safety as evidence and identification to cannabis users at time 3*

| Additional standard deviation for prior | Standard deviation for evidence | Regressions between predicted scores of identification to cannabis users and actual scores at time 3 | P-value | 95% Confidence Intervals |
|---|---|---|---|---|
| | 0.1 | .22 | < .001 | [.16, .27] |
| | 0.5 | .36 | < .001 | [.31, .42] |
| 0.1 | 1.0 | .38 | < .001 | [.32, .43] |
| | 1.5 | .38 | < .001 | [.32, .43] |
| | 2.0 | .38 | < .001 | [.32, .43] |
| | 0.1 | -.02 | .384 | [-.07, .03] |
| | 0.5 | .35 | < .001 | [.30, .40] |
| 0.5 | 1.0 | .37 | < .001 | [.32, .43] |
| | 1.5 | .37 | < .001 | [.32, .43] |
| | 2.0 | .37 | < .001 | [.32, .43] |
| | 0.1 | -.04 | .126 | [-.09, .01] |
| | 0.5 | .33 | < .001 | [.28, .38] |
| 1.0 | 1.0 | .38 | < .001 | [.32, .43] |
| | 1.5 | .37 | < .001 | [.32, .43] |
| | 2.0 | .37 | < .001 | [.32, .42] |
| | 0.1 | -.04 | .095 | [-.09, .01] |
| | 0.5 | .28 | < .001 | [.23, .34] |
| 1.5 | 1.0 | .38 | < .001 | [.33, .43] |
| | 1.5 | .38 | < .001 | [.32, .43] |
| | 2.0 | .37 | < .001 | [.32, .43] |
| | 0.1 | -.04 | .087 | [-.09, .01] |
| | 0.5 | .23 | < .001 | [.18, .29] |
| 2.0 | 1.0 | .38 | < .001 | [.33, .43] |
| | 1.5 | .38 | < .001 | [.33, .44] |
| | 2.0 | .38 | < .001 | [.33, .43] |

**Table 9**

*Regressions between BMII simulations with action use as evidence and identification to cannabis users at time 3*

| Additional standard deviation for prior | Standard deviation for evidence | Regressions between predicted scores of identification to cannabis users and actual scores at time 3 | P-value | 95% Confidence Intervals |
|---|---|---|---|---|
| 0.1 | 0.1 | .23 | < .001 | [.18, .29] |
| | 0.5 | .37 | < .001 | [.31, .42] |
| | 1.0 | .37 | < .001 | [.32, .43] |
| | 1.5 | .38 | < .001 | [.32, .43] |
| | 2.0 | .38 | < .001 | [.32, .43] |
| 0.5 | 0.1 | .07 | .017 | [.01, .12] |
| | 0.5 | .35 | < .001 | [.30, .40] |
| | 1.0 | .37 | < .001 | [.32, .42] |
| | 1.5 | .37 | < .001 | [.32, .42] |
| | 2.0 | .37 | < .001 | [.32, .42] |
| 1.0 | 0.1 | .02 | .574 | [-.04, .07] |
| | 0.5 | .31 | < .001 | [.26, .37] |
| | 1.0 | .36 | < .001 | [.31, .42] |
| | 1.5 | .37 | < .001 | [.31, .42] |
| | 2.0 | .37 | < .001 | [.31, .42] |
| 1.5 | 0.1 | .00 | .970 | [-.06, .05] |
| | 0.5 | .24 | < .001 | [.18, .29] |
| | 1.0 | .35 | < .001 | [.30, .41] |
| | 1.5 | .36 | < .001 | [.31, .42] |
| | 2.0 | .37 | < .001 | [.31, .42] |
| 2.0 | 0.1 | -.01 | .760 | [-.06, .05] |
| | 0.5 | .16 | < .001 | [.11, .22] |
| | 1.0 | .33 | < .001 | [.27, .38] |
| | 1.5 | .36 | < .001 | [.31, .41] |
| | 2.0 | .37 | < .001 | [.31, .42] |

## Stages of Cannabis Integration Into People's Group

In order to better understand cannabis integration dynamic process along with categorization and compartmentation stages, we conceptualize internal states as probabilities of cannabis integration stages. Participants can find themselves into three stages of identity integration (categorization, compartmentation and integration). Those stages are uncertain for each of our participant and are thus conceptualizing probabilistically. Here, we are interested in the reallocation of probabilities across the three different stages of identity integration through simulations of the BMII.

Each simulation of the present conception of BMII will produce probabilities for our three stages of identity integration. To validate if our predictions are adequate, we compare our predicted scores with the actual probabilities calculated at time 3. To find time 3 probabilities, we divided scores of categorization, compartmentation and integration by the sum of all three for every participant. The outcomes of all BMII simulations predict positively all three stages of identity integration. Outcomes of the BMII with frequency of cannabis use by others as evidence predicts probabilities of categorization at $\beta = .14$, $p < .001$, 95% CI [.08, .19], probabilities of compartmentation at $\beta = .14$, $p < .001$, 95% CI [.08, .19] and probabilities of integration at $\beta = .20$, $p < .001$, 95% CI [.15, .26]. Outcomes of BMII with valence of cannabis legalization as evidence predicts probabilities of categorization at $\beta = .12$, $p < .001$, 95% CI [.06, .18], probabilities of compartmentation at $\beta = .13$, $p < .001$, 95% CI [.07, .18] and probabilities of integration at $\beta = .20$, $p < .001$, 95% CI [.14, .26]. Outcomes from BMII with need for safety as evidence predicts probabilities of categorization at $\beta = .11$, $p < .001$, 95% CI [.05, .17], probabilities of compartmentation at $\beta = .14$ $p < .001$, 95% CI [.09, .20] and probabilities of integration at $\beta = .23$, $p < .001$, 95% CI [.17, .28]. Finally, outcomes of the BMII with the variable of action predict probabilities of categorization at $\beta = .09$, $p = .001$, 95% CI [.04, .15], probabilities of compartmentation at $\beta = .11$, $p < .001$, 95% CI [.05, .17] and probabilities of integration at $\beta = .18$, $p < .001$, 95% CI [.12, .24]. We also calculate the regression coefficient of each probability of stages at time 1 with their corresponding stages at time 3. Predictions across probabilities at times 1 and 3 are $\beta = .20$, $p < .001$, 95% CI [.14, .26] for categorization, $\beta = .22$, $p < .001$, 95% CI [.16, .27] for compartmentation and $\beta = .26$, $p < .001$, 95% CI [.20, .31] for integration. Figures 5 to 8 shows respectively confidence interval for each BMII simulation made with frequency of cannabis use by others, valence of cannabis legalization, need for safety and action. The first three lines of every figure are our prediction, the last three are the prediction of probabilities of stages at time 3 by probabilities of stages at time 1

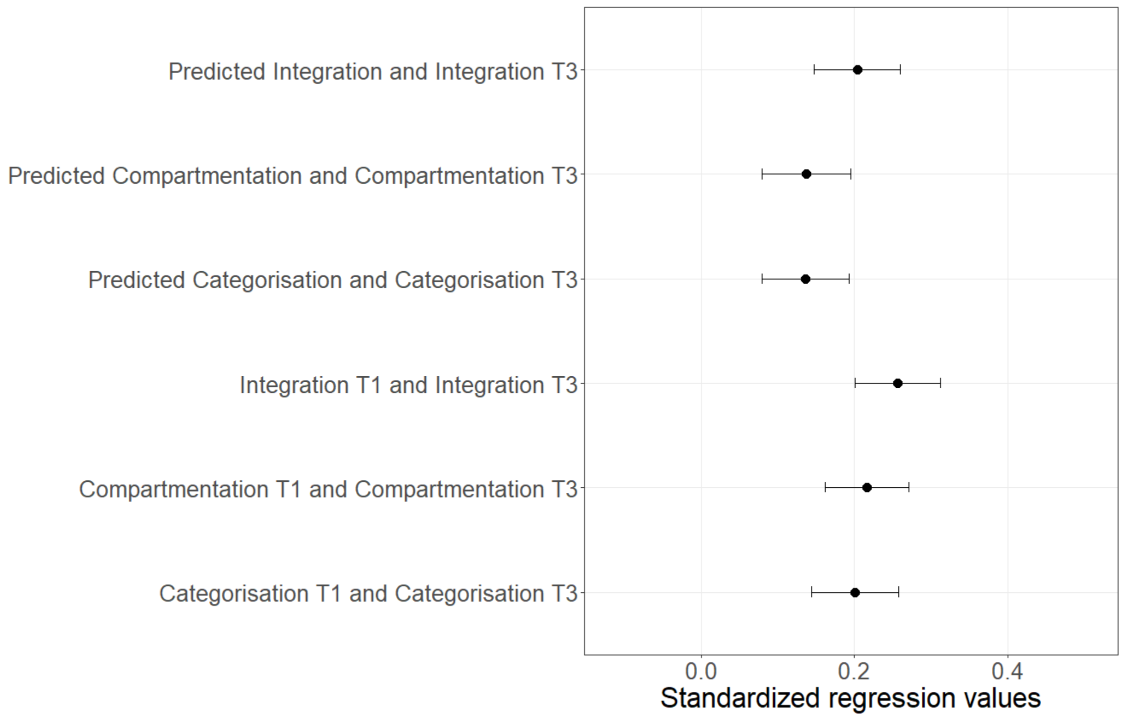


*Figure 5. Confidence intervals for regression tests run with frequency of cannabis use by others as evidence*

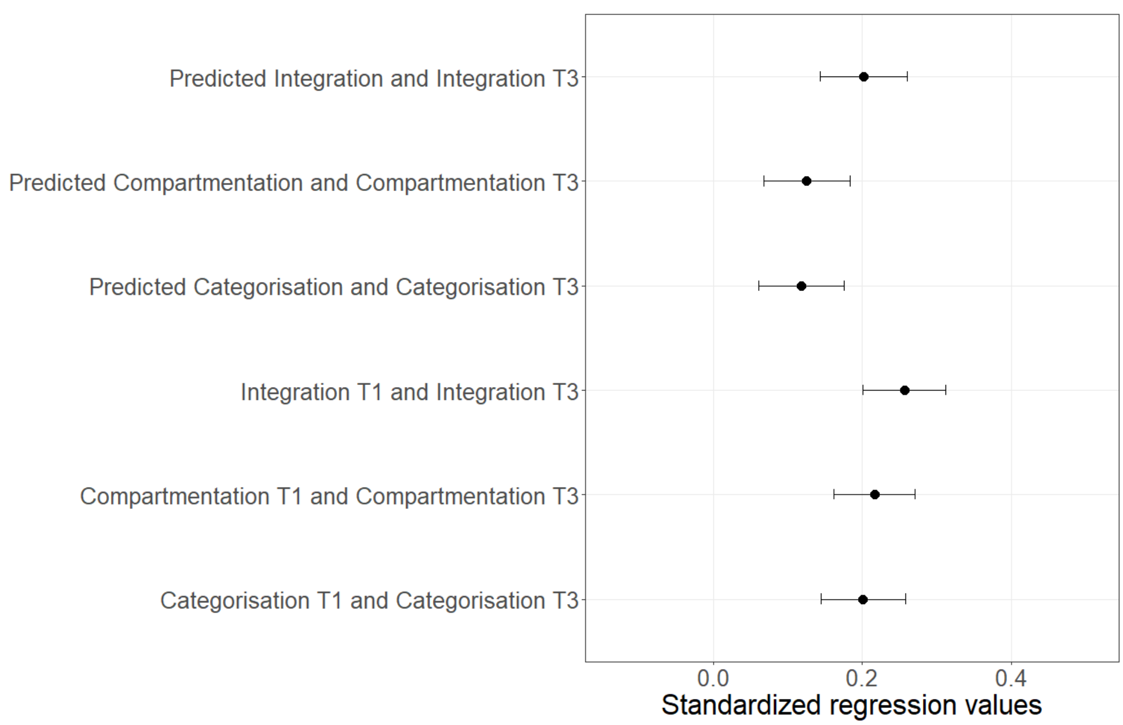


*Figure 6. Confidence intervals for regression tests run with* Valence of cannabis legalization *as evidence*

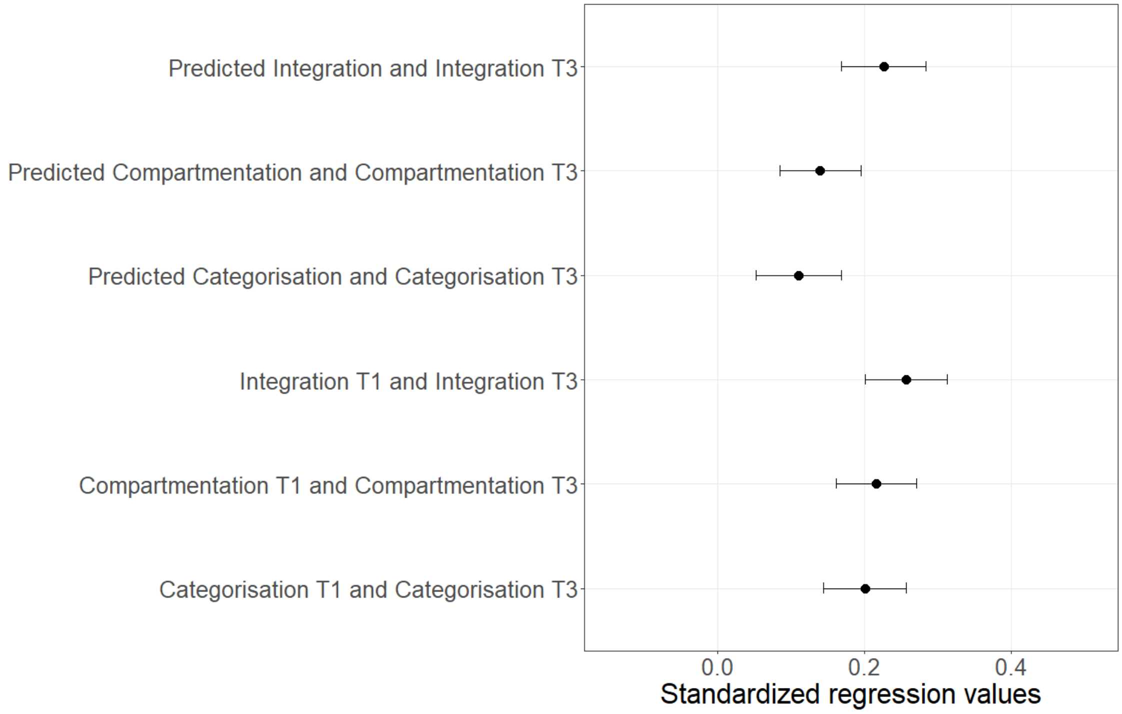


*Figure 7. Confidence intervals for regression tests run with* need of safety *as evidence*

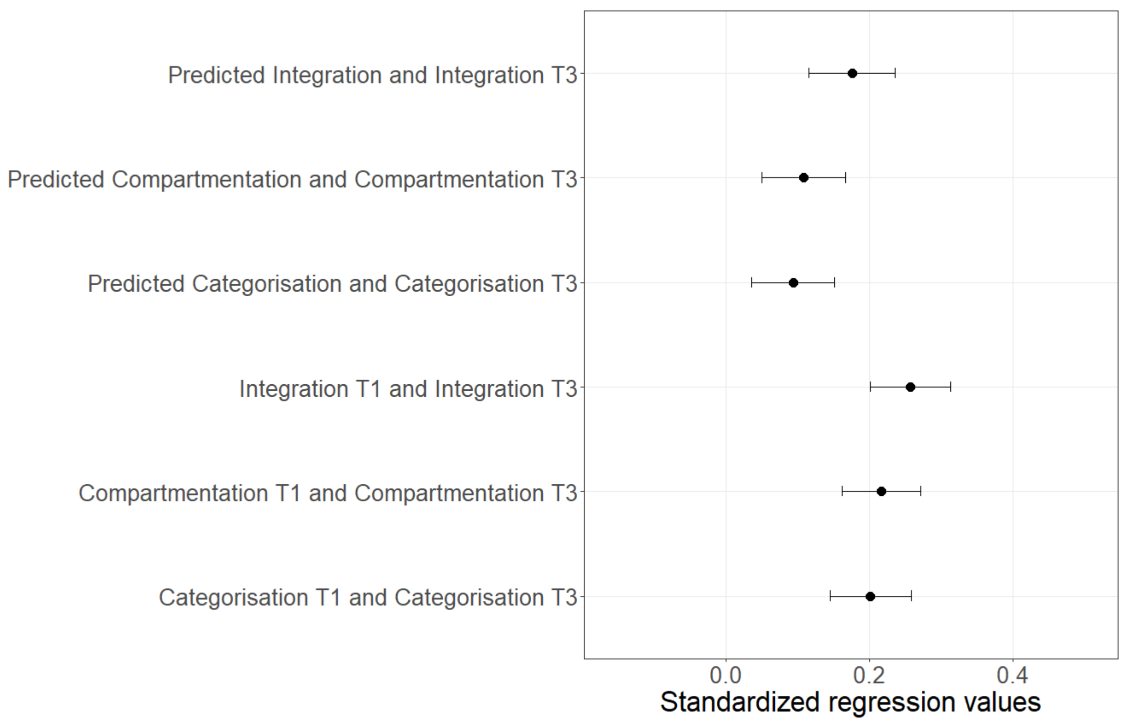


*Figure 8. Confidence intervals for regression tests run with* action *as evidence*

## Discussion

The present study introduces the Bayesian Model of Identity Integration (BMII); a new model to conceptualize and measure identity change in time. Our model provides a mathematical Bayesian frame to operationalize identity integration in time. More specifically, the formulas in use allow us to transform the internal states (identities) of people into new internal states. We can thereby understand and approximate how people change their level of identity integration. The BMII is flexible across internal states. We can use the BMII to measure schemas integration, personal identity integration and social identity integration. We could also quantify the degree of identification change to a certain group. Through this study, we aim to understand how Canadians will change their internal states in the context of cannabis legalization. To do so, we apply the BMII to cannabis integration into people's group across three times of measure.

In the context of cannabis legalization, we found evidence that the BMII predicts positively further states of cannabis integration. The outcomes of BMII simulations made with evidence of frequency of cannabis use by others, valence of cannabis legalization, need for safety and action of searching media for information regarding cannabis legalization predict positively cannabis integration at time 3. Such results support our hypotheses 1 to 4 and encourage the suitability of our model to explain and predict internal states. The BMII offers a more dynamic perspective of Amiot and colleagues' (2007) perspective of identity integration. With the BMII, we can understand the internal mechanisms responsible for identity change. Such understanding could lead to promising avenues in our understanding of identity integration. The BMII also inform models of neuroscience and machine learning fields (Firston, 2009; Friston et al., 2013; Friston et al., 2017). The BMII take a step further into the investigation of dynamic internal process. The present study takes interest in more complex human process than figuring out what we see or hear; we examine how people will figure out who they are.

Results seems to support that the BMII is a dynamic process that adapts itself to the context it finds itself in. Evidence that does not inform our internal states are disregarded; they don't modify the internal states. For instance, the strength of relation binding evidence for need for safety and cannabis integration was null. So, need for safety should not inform our internal state of cannabis integration. Yet, our simulations show that predicted scores coming from the BMII with the use of need for safety as evidence, predict well future scores of cannabis integration. In this case, the BMII gave very little importance to the evidence of the need for safety for future prediction of cannabis integration. Not all evidence that comes to our attention should be informative of our internal states. In these situations, we should rely more strongly on prior internal states to predict future internal states.

Since the choice of evidence matters for BMII simulations, we will discuss the choice of evidence of the present study. More precisely, we will discuss the need for safety as an inadequate evidence in the BMII. The relation between safety and cannabis integration is null ($r$ = .00) and weak with identification to cannabis users ($r$ = -.08). According to our theoretical reasoning, the role of needs should moderate the relation between evidence and prior. However, in our analyses, we apply need for safety as evidence. By doing so, we were able to investigate the way each element of the BMII (perceptions, needs and actions) influence internal states along the same process. From what our results show, needs should not be considered as evidence of internal state change. However, needs may still moderate the relation between evidence and prior. Future studies of the BMII should conceptualize a way that needs will moderate the strength of influence of perceptions on our internal states. One avenue for this could be to adjust the degree of uncertainty of evidences according to needs. We know that evidence with a high uncertainty should not modify our prior very much. On the other hand, evidence with low degree of uncertainty will modify our prior. So, if needs should moderate the strength of evidence on prior, they should moderate the degree of uncertainty of evidences. To perform such investigations, researchers should discuss what are the perceptions, needs and internal states at use and how needs would moderate the relationship between perceptions and internal states. With this information in hand, researchers could create their own BMII and perform simulations in it.

The way we conceive internal states and evidence matters in the BMII. Not every internal state will be influenced by the same evidence. Results from simulations of the BMII made with stages of cannabis integration support the necessity to specify how internal states and evidence will work together. In the present study, we investigate the independent role of four evidences on three different stages of cannabis integration. Even if we specify the proper strength (based on correlation tests) between evidence and each stage, results show that predictions of internal stages at time 3 by the BMII were slightly less accurate than the ones of internal stages at time 1 (see Figures 5 to 8). Stages of identity integration are mostly a cognitive representation of ourselves in relation to our world. For instance, in categorization people reject one of the identities of their world. In compartmentation, people identify themselves with one identity in a certain social context and to another identity in other social context. In integration stage, people resolve conflicts between their identities and can identify themselves to all their identity all the time (see, Amiot et al., 2007 for a full description of stages). So, through these stages, people do not hold the same understanding of who they are. What they perceive or do could have different impacts on their stage of identity integration. As such, different kinds of perceptions could influence one stage more than the others. Such consideration for different perceptions will be important for optimal use of the BMII. Future research should explore what kinds of perceptions is related to each stage of identity integration. Such studies could inform how we will operationalize the BMII.

Over 100 simulations were made with different degrees of uncertainty regarding priors and evidence. These simulations attempt to understand how degree of uncertainty comes to modify BMII predictions of future internal states. Results seem to show that a more certain prior gives better prediction of later internal states. The worst predictive scenario is when priors are very uncertain, and evidence are very certain. It appears that evidence, even if linked correlated strongly to priors ($r$ = .40 for valence of change and cannabis integration) should not receive more certitude than priors. Priors are central for the prediction of future internal states.

**What does the BMII bring to Current Knowledge of the Self?**

We should agree from the start that the self is a complex process. Many theories and ways to understand and define the self have been proposed. Each of these perspectives is relevant to understand how people manage their identities and reach a self-definition. We argue that the BMII can offer more precision to existing theories. We will discuss three main theories of the self and discuss how the BMII could complete these theories.

From a motivational perspective (see, theory of self-determination; Deci & Ryan, 1985, 2000), the self integrates new identities for the service of three psychological needs: relatedness, autonomy and competency (Ryan & Deci, 2000). Relatedness is the need to feel connected with others, care about them and feel cared for (Baumeister & Leary, 1995; Deci & Ryan, 2000). So, by integrating new identities, people should adopt roles, beliefs and practices recognized and valued by others and, ultimately, feel more connected to them (Ryan & Deci, 2014). Autonomy is defined as the desire to organize our self-concept and to have activities that are concordant with who we are (Deci & Ryan, 2000). With identity integration people can choose with their own volition the kinds of interests and values that will define their lifestyle (Ryan & Deci, 2014). According to these authors, such liberty of choice should satisfy their need for autonomy. Finally, the need of competence is defined as feeling effective in what we are doing and feeling we own the activity we perform (Deci & Ryan, 1985; Ryan & Deci, 2017). Identity integration should provide new skills and knowledge that will make people more effective, competent and adapted (Ryan & Deci, 2014). In sum, the identities we integrate should fulfil our psychological needs. However, not all identities can do so. According to the theory of self-determination, people can wear different identities for different reasons. For instance, a 15-year-old boy could play hockey and identify accordingly because he feels pressure by friends and parents to do so. In this context, the identity of a hockey player would not fulfill the young man psychological needs. On the other hand, if the young man chooses to play hockey because he appreciates the sport, the identity of a hockey player will surely fulfill his psychological needs. The theory of self-determination is currently lacking on a main point: it is yet unclear by which process needs will participate in identity integration. The BMII may bring answers to this point. Our model considers needs as a fundamental aspect of identity integration. We argue that needs filter the perceptions that will come to our attention. So, when people reach for information into their environment as to integrate a new identity, they do so according to their needs. If people are in need to relate to others, they will probably perceive good aspects of others and neglected the bad aspects. If people need to feel autonomous, they will likely be more aware of perceptions that fit with their own self instead of identities pressured by others. In some cases, people could also be reactant to what others encourages even if they share others' viewpoint (Brehm & Brehm, 2013). So, reactance pushes people to take the opposite side of others as to gain some liberty and be free of their own choices. Finally, people will surely drive their attention and be more aware of perception that fits their competences.

For qualitative researchers, the self is mainly a storyteller (see, McAdams, 2001; McAdams & McLean, 2013). Across our lives, each and every one of us comes around some life experiences that shape the person we are. Such experiences are remembered as stories that we can share with others and use to define ourselves (McAdams & McLean, 2013). Qualitative researchers have used several procedures to analyze people's narrative. For instance, to look at the clarity of one's group historical story could inform us about the clarity of one's identity (Usborne & Taylor, 2010) and well-being (de la Sablonnière et al., 2011). If the narrative of people is disorganized and difficult to understand, these people could have difficulties to structure a sense of who they are (Usborne & Taylor, 2010). In such qualitative context, the BMII could offer insight on the process through which people form their stories. The BMII explain how we understand our environment and how we react in it. According to our understanding of the world, we will perform certain actions and let our perceptions inform ourselves if our actions were appropriate. The process through which we understand our world (and ourselves along the way) can approximate the way people form their stories. As such, the BMII could be used as a framework for more structure interview interested in the way people become who they are.

From a cognitive perspective, the self is a highly complex structure of identities and schemas (Markus, 1977). If people have reached a balance sense of themselves, their identities and schemas should be linked together in a coherent organization. According to this optic, studying one identity becomes questionable, since every identity is related and influenced by other aspects of our self. Bentley and colleagues (2019) have developed a software based on identity mapping: the online Social Identity Mapping (oSIM). Identity mapping engage participants to create and link their identity into a network (Cruwys et al., 2016). So, starting with a blank space, participants can draw their identities, link them one to others and give strength to these links. With this tool, researcher can measure more faithfully the dynamic between every element of someone's self. However, such tools do not explain how people will change themselves in time. The BMII could supplement this method with a dynamic process of identities change. More studies on the BMII are necessitated before we can extend its process to the whole self.

**Limitations**

Our study presents some limitations that, if address, could benefit our understanding of the BMII and dynamic processes of identity integration. First of all, we did not measure the BMII to its full extent. Our analyses are limited to the impact of one evidence (be it perceptions, need or action) on internal states. However, the BMII should be run with all three evidence in the process of internal states changes. To do so, we need to create mathematical operations as to unite perceptions, action and need into the same evidence that will change internal states of people. Our team is currently working on probabilistic formulas to quantify the impact of our action on our perceptions and the role of moderator of our needs. With such mathematical frame, we would be able to run the entire element of the BMII at once.

Our second limitation concern the context of change of cannabis legalization. Through many years, cannabis has become more and more accepted in Canada. Before its legalization, cannabis was decriminalized and allowed for therapeutic use. So, the legalization of cannabis might not be a big change, but rather the subsequent step to a better acceptance of the drug. To this end, people could already be familiar with cannabis and have integrated it to some extent into their self and identity. So, cannabis integration may have brought a small change into people's internal state which could have limited our predictions with the BMII.

**Theoretical, Methodological and Practical Implications**

The present study has three main implications. From a theoretical perspective, the BMII brings a new vision of internal processes of the self and identity integration. With the BMII, we can conceptualize the process through which people shape who they are. Day-by-day we encounter information that change or validate who we are. Such information can be as simple as going to work. Being at work, seeing our work environment and doing the action of working validate our identity of workers and, to some extent, our self. The BMII offers an avenue to explain the iterative process by which people become and maintain who they are through their perceptions and actions in their environment.

The second implication of the present study rest on a methodological basis. The BMII offers a way to understand and quantify change. Such dynamic methods could bring new understandings of people internal processes. We base our methods on Bayesian operations. So, we conceived people's internal states as probabilities that change across new evidence. When the prior is subjected to new evidence, it transforms itself into a posterior. Bayesian operations conceptualize every step of changes: internal states before the change (prior), information that represent the change (evidence) and internal states after the change (posterior).

Finally, the BMII has an essential practical implication for social workers and governments. Social workers could use the BMII as a tool to better understand people experience identity crisis issues. On another hand, governments could benefit from a process that informs them about how people are going to integrate any changes planned.

## Conclusion

To conclude, the BMII is still at an embryonic phase of its conception. Our results seem to support, the goodness of prediction of BMII simulations. However, the power of prediction of the BMII could be upgraded. The goal of future studies will be to investigate mathematical formulas to link perceptions, actions and needs into a single evidence in the simulation of the BMII and upgrade prediction of the BMII of future internal states.

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# Discussion générale

Le présent mémoire discute de l'élaboration d'un processus dynamique de l'intégration identitaire. L'objectif est de comprendre et d'opérationnaliser les processus internes responsables du changement identitaire. À l'aide d'une première étude (article 1), nous avons expliqué et décrit les fondements du MBII. Une seconde étude (article 2) a permis de tester notre modèle dans un contexte de changement social; celui de la légalisation du cannabis au Canada. Nous allons discuter des résultats obtenus lors de cette seconde étude, puis des implications et limitations de notre étude et des directions futures.

**Résultats de l'article 2**

Au sein du second article, nous avons testé pour la première fois le MBII dans un contexte de changement social: la légalisation du cannabis au Canada. Afin d'établir une première connaissance des processus du MBII, nous avons étudié un seul processus sur toutes les variables clés du MBII. Plus précisément, nous avons considéré les perceptions, le besoin de sécurité et l'action de s'informer sur la légalisation du cannabis comme des évidences. Nous jugeons cette étape nécessaire afin de comprendre les fondements du MBII. Grâce à ces analyses, nous pouvons comprendre comment les états internes changent lorsque nous utilisons une perception, un besoin ou une action comme évidence.

Trois résultats principaux ressortent de notre article 2. Premièrement, le MBII réussit à prédire positivement l'intégration identitaire future de nos participants. Avec des tests de régressions, nous nous sommes attardés sur la force de prédictions des scores produits par le MBII avec les scores d'intégration rapportée par les participants au dernier temps de mesure (temps 3); tous ont donné des prédictions positives et considérables pour la poursuite de nos recherches sur le MBII.

Deuxièmement, nous avons comparé des simulations du MBII fait avec une variable contrôle (l'âge de nos participants) afin de constater si les prédictions seraient reliées aux scores d'intégrations du cannabis au temps 3. Les résultats étaient mitigés. Nous observons que les deux types de perceptions (lorsque remplacé par la variable d'âge) prédisent moins efficacement l'intégration identitaire au temps 3. Des résultats similaires sont observés lorsqu'on substitue l'action par l'âge. Par contre, lorsque nous remplaçons le besoin de sécurité par l'âge, la prédiction demeure de la même ampleur. En regardant plus attentivement la manière dont les simulations du MBII ont été conçues, nous pouvons constater que le besoin de sécurité n'informe aucunement nos états internes. Plus précisément, l'évidence du besoin de sécurité vient modifier nos états internes de la même manière. Les participants ayant un faible besoin de sécurité subiront la même modification de leurs états internes que les personnes ayant un fort sentiment de sécurité. Comme tous les scores d'états internes a priori ont été modifiés de la même manière, la prédiction des états internes au temps 3 par le MBII demeure similaire à la prédiction des états internes au temps 3 par les états internes au temps 1. Ainsi, lorsque nous remplaçons une variable qui ne modifie pas nos états internes (besoin de sécurité), par une variable tierce (âge), le résultat demeure le même. Cette observation nous amène à considérer la manière dont nous utilisons le MBII. Nous devons nous assurer que les variables d'évidence viennent modifier notre a priori, sinon le modèle est inefficace.

Troisièmement, le pouvoir prédictif du MBII ne parvenait pas à dépasser celui des états internes au temps 1. Donc, la valeur du coefficient de régression entre les scores produit par le MBII et les scores d'intégration identitaire au temps 3 était équivalente aux coefficients de régressions entre les scores d'intégration identitaire au temps 1 et ceux au temps 3. Nous avons comparé ces deux types de prédictions, car nous jugions important de savoir si les résultats du MBII peuvent prédire les états futurs d'intégration identitaire au-delà d'un autre prédicteur. Les résultats ne supportent pas cette conclusion; le MBII prédit aussi bien les scores d'intégration au temps 3 que les scores d'intégration au temps 1.

**Le MBII est-il un bon modèle?**

Le présent projet de mémoire n'a étudié qu'une petite facette du MBII. Nous nous sommes intéressés à connaitre la manière dont les perceptions venaient modifier nos niveaux d’intégration identitaires. Nous n’avons donc pas considéré comment chacune des variables du MBII venait s’influencer selon la théorie de l’étude 1.

Dans l’ensemble, les résultats de l’étude 2 supportent le MBII. Nous arrivons à prédire les niveaux d’intégration du cannabis de nos participants au temps 3 grâce à notre modèle Bayésien. Lorsque nous considérons une variable contrôle tel que l’âge de nos participants, nous obtenons des relations nulles. Ces résultats supportent notre modèle. Finalement, lorsque nous comparons nos prédictions faites avec le modèle Bayésien avec les prédictions du temps 1 (Figure 3) nous obtenons des prédictions équivalentes. Donc, notre modèle est un aussi bon prédicteur des niveaux d’intégration au temps 3 que l’état a priori d’intégration identitaire (temps 1). Bien que notre modèle n’arrive pas à se démarquer lors de cette dernière comparaison, nous jugeons que les résultats demeurent encourageants. En effet, les prédictions du MBII sont positives et ne sont pas plus faibles que le modèle de comparaison. La capacité du MBII à prédire plus fortement les niveaux d’intégration identitaire pourrait être limitée par notre considération limitée des processus du MBII.

Selon les résultats obtenus à l’étude 2, nous ne parvenons pas encore à expliquer l’ensemble des niveaux d’intégration identitaire de nos participants. Nous argumentons qu’une considération plus exhaustive du MBII permettrait d’aller chercher une meilleure prédiction des niveaux d’intégration de nos participants. Le défi des recherches futures sera de concevoir une méthode Bayésienne pouvant considérer l’ensemble des variables du MBII. Ce modèle devra considérer l’impact de chacune des variables sur les autres. Dans l’étude 2, nous avons considéré l’impact de chacune des variables (perceptions, besoins et actions) sur les niveaux d’intégration identitaire de nos participants. Les modélisations futures devront considérer que les besoins ont plutôt un rôle modérateur sur la relation entre les perceptions et les niveaux d’intégration identitaire, et que les actions ont un impact sur l’environnement. Une modélisation complète et fidèle avec notre théorie pourrait permettre une meilleure prédiction des niveaux d’intégration identitaire.

**Le MBII vient-il compléter la théorie du modèle cognitif-développemental de l'intégration identitaire?**

Le MBII a pour but d'expliquer et de mesurer le changement identitaire. Plus précisément, le MBII devrait pouvoir expliquer comment une personne augmente ou diminue son niveau d'intégration identitaire et comment une personne change d'état identitaire (p. ex., passer de l'étape de la catégorisation à l'étape de la compartimentation). L'étude 2 a étudié ces deux phénomènes. Dans les deux cas, nous parvenons à atteindre des prédictions positives. Toutefois, lorsque nous comparons la force des prédictions du MBII à la force de prédiction des niveaux d'intégration au temps 1, nous nous apercevons que les prédictions du MBII sont aussi bonnes, sinon légèrement moins, que les modèles comparatifs.

Lorsque nous nous intéressons au changement du niveau d'intégration identitaire, les prédictions du MBII sont aussi bonnes que celles du modèle comparatif. En ce sens, nous considérons que nos résultats soutiennent les processus dynamiques du MBII pouvant opérer au sein de la théorie d'Amiot et collègues.

Dans le second cas, lorsque nous nous intéressons au changement d'étape d'intégration identitaire, les prédictions du MBII sont plus faibles que le modèle comparatif. Encore une fois, notre considération partielle du MBII pourrait être la cause de nos faibles prédictions. Toutefois, nous considérons une limite alternative. Lorsque nous avons mesuré le changement d'étape d'intégration identitaire à l'étude 2, nous avons considéré pour chaque participant leur probabilité d'être sur chacune des trois étapes d'intégration. Cette mesure pourrait ne pas être fidèle aux états internes des personnes. Les recherches futures devraient considérer les étapes d'intégration comme étant exclusives; les participants appartiennent à une seule étape du processus d'intégration.

Dans l'ensemble, nous demeurons confiants que le MBII puisse capter les processus dynamiques derrière l'intégration identitaire telle que rapportée par Amiot et collègues (2007). L'ensemble des résultats de l'étude 2 sont encourageants étant donné que nous n'avons considéré qu'une partie du MBII dans notre modélisation. Les recherches futures devront relever un second défi; c'est-à-dire conceptualiser la manière la plus fidèle de mesurer les états d'intégration identitaire.

**Implications théorique et méthodologique**

Notre compréhension des processus d'intégration identitaire est déficiente. Nous conceptualisons le soi comme une entité dynamique (Markus & Wurf, 1987), pourtant nous décrivons les processus d'intégration identitaire de manière largement statique. Le processus itératif utilisé par les personnes pour changer leur identité demeure peu compris. Le champ de la psychologie sociale a besoin de se redéfinir et d'explorer de nouvelles approches pour décrire plus fidèlement l'expérience dynamique et complexe des êtres humains. Le MBII est un premier pas vers des processus plus dynamiques de l'intégration identitaire. Nous considérons que le MBII a le potentiel d'ouvrir une porte vers de nouvelles études des processus internes reliés aux identités et au concept de soi. Plus encore, le MBII offre des méthodes pour tester le changement d'identité à travers le temps. Nous avons basé nos méthodes sur des opérations bayésiennes. Ces dernières ont l'avantage de considérer les états internes des personnes de manière probabiliste et de pouvoir mesure le changement de ces états.

**Implications pratiques**

Le MBII s'adresse à plusieurs acteurs autres que les chercheurs en psychologie sociale. Les gouvernements de par le monde peuvent bénéficier de notre modèle afin de comprendre comment leur population fait face à un changement. À titre d'exemple, la pandémie de la Covid-19 a forcé plusieurs gouvernements à imposer des mesures drastiques sur leurs citoyens. Ceux-ci pourraient s'opposer à de telles contraintes et ressentir une diminution de leur bien-être. Le MBII pourrait représenter un outil pratique pour les gouvernements afin de mesurer et de comprendre comment leur population peut s'adapter aux changements.

Les professionnels de la santé, travailleurs sociaux et psychologues peuvent aussi bénéficier du MBII dans leur profession. Les patients aux prises avec une crise identitaire peuvent représenter un défi de taille pour les professionnels de la santé mentale. Avec un outil comme le BMII, les psychologues pourraient avoir une meilleure compréhension du processus permettant à leurs clients d'intégrer une nouvelle identité.

**Limites et directions futures**

Notre étude demeure limitée sur deux points. Premièrement, nous avons mesuré l'efficacité du MBII dans le contexte de la légalisation du cannabis au Canada. Nous avons argumenté que ce contexte représentait un changement social. Toutefois, en raison de la diminution des conséquences reliées à la possession de cannabis, la légalisation pourrait être perçue comme une étape subséquente d'un processus d'intégration du cannabis au Canada plutôt qu'un changement. À cet effet, les changements identitaires reliés au cannabis pourraient ne pas avoir été si importants et, donc, difficiles à modéliser avec le MBII. Les études subséquentes devraient considérer un phénomène ayant apporté des changements plus drastiques dans le mode de vie de leurs participants. Sur ce point, notre équipe de recherche a conduit une étude sur le changement identitaire lors de la Covid-19. L'étude est toujours en cours.

Deuxièmement, notre manière de modéliser le changement identitaire avec le MBII n'est pas fidèle à notre conception théorique du MBII. Nous avons testé certaines parties du MBII, sans considérer le processus complet. Bien que nous justifiions notre choix de méthode par un désir de comprendre les bases du modèle avant d'étudier son entièreté, le produit des simulations du MBII pourrait donner des résultats moins efficaces pour prédire l'intégration identitaire. Ceci pourrait expliquer pourquoi les prédictions entre les produits du MBII et les états internes au temps 3 n'arrivent pas à dépasser les prédictions des états internes au temps 3 par les états internes au temps 1.

**Conclusion**

Le MBII est un premier pas vers une approche dynamique des processus d'intégration identitaire. Plusieurs études seront nécessaires pour construire une compréhension solide du MBII et, par extension, des processus cognitifs dynamiques. Les études futures doivent avant tout s'intéresser à une conceptualisation du MBII qui unira tous ses aspects.

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# Annexe A : Script R pour l’intégration du cannabis dans l’identité de groupe (article 2)

```
# ----  Packages ----

library(haven)
library(Amelia)
library(reshape2)
library(dplyr)
library(ggplot2)
library(na.tools)
library(psych)
library(mice)

# ---- Data ----

df <- read_sav("D:/Cannabis/R/CannabisNew/CannabisMergedAll.sav")

set.seed(10802020)

# ---- Matrix of Variables ----

Cannabis <- df[ ,c("respid", "Int_2", "Int_3", "Int_4",
                   "IntT2_2", "IntT2_3", "IntT2_4",
                   "IntT3_2", "IntT3_3", "IntT3_4",
                   "GInt_2", "GInt_3", "GInt_4",
                   "GIntT2_2", "GIntT2_3", "GIntT2_4",
                   "GIntT3_2", "GIntT3_3", "GIntT3_4",
                   "IdentifyPot", "CommonPot", "ImpPot",
                   "IdentifyPotT2", "CommonPotT2", "ImpPotT2",
                   "IdentifyPotT3", "CommonPotT3", "ImpPotT3",
                   "GFrequency", "GFrequencyT2", "GFrequencyT3",
                   "Cat", "CatT2", "CatT3",
                   "Comp_1", "CompT2_1", "CompT3_1",
                   "Comp_2", "CompT2_2", "CompT3_2",
                   "GCat", "GCatT2", "GCatT3",
                   "GComp_1", "GCompT2_1", "GCompT3_1",
                   "GComp_2", "GCompT2_2", "GCOmpT3_2",
                   "Neg_Pos", "Neg_PosT2", "Neg_PosT3",
                   "Safety_1", "SafetyT2_1", "SafetyT3_1",
                   "Safety_2", "SafetyT2_2", "SafetyT3_2",
                   "Safety_3", "SafetyT2_3", "SafetyT3_3",
                   "SuiviPot", "SuiviPotT2", "SuiviPotT3",
                   "Age", "Gender", "Diploma", "Situation",
"life_cond")]

Cannabis$GintT1 <- rowMeans(Cannabis[,c("GInt_2", "GInt_3",
"GInt_4")])
```

```
Cannabis$IdenT1 <- rowMeans(Cannabis[,c("IdentifyPot",
"CommonPot", "ImpPot")])
Cannabis$SafetyT1 <- rowMeans(Cannabis[,c("Safety_1", "Safety_2",
"Safety_3")])

Cannabis[,"AgeT2"] <- Cannabis[,"Age"]
Cannabis[,"AgeT3"] <- Cannabis[,"Age"]
Cannabis[,"GenderT2"] <- Cannabis[,"Gender"]
Cannabis[,"GenderT3"] <- Cannabis[,"Gender"]
Cannabis[,"DiplomaT2"] <- Cannabis[,"Diploma"]
Cannabis[,"DiplomaT3"] <- Cannabis[,"Diploma"]
Cannabis[,"SituationT2"] <- Cannabis[,"Situation"]
Cannabis[,"SituationT3"] <- Cannabis[,"Situation"]
Cannabis[,"life_condT2"] <- Cannabis[,"life_cond"]
Cannabis[,"life_condT3"] <- Cannabis[,"life_cond"]

Int_2 <- melt(Cannabis,  id.vars = "respid", measure.vars =
c("Int_2", "IntT2_2", "IntT3_2"))
Int_2 <- Int_2[order(Int_2$respid),]
Int_3 <- melt(Cannabis,  id.vars = "respid", measure.vars =
c("Int_3", "IntT2_3", "IntT3_3"))
Int_3 <- Int_3[order(Int_3$respid),]
Int_4 <- melt(Cannabis,  id.vars = "respid", measure.vars =
c("Int_4", "IntT2_4", "IntT3_4"))
Int_4 <- Int_4[order(Int_4$respid),]

Cat <- melt(Cannabis,  id.vars = "respid", measure.vars =
c("Cat", "CatT2", "CatT3"))
Cat <- Cat[order(Cat$respid),]

Comp_1 <- melt(Cannabis,  id.vars = "respid", measure.vars =
c("Comp_1", "CompT2_1", "CompT3_1"))
Comp_1 <- Comp_1[order(Comp_1$respid),]
Comp_2 <- melt(Cannabis,  id.vars = "respid", measure.vars =
c("Comp_2", "CompT2_2", "CompT3_2"))
Comp_2 <- Comp_2[order(Comp_2$respid),]

GCat <- melt(Cannabis,  id.vars = "respid", measure.vars =
c("GCat", "GCatT2", "GCatT3"))
GCat <- GCat[order(GCat$respid),]

GComp_1 <- melt(Cannabis,  id.vars = "respid", measure.vars =
c("GComp_1", "GCompT2_1", "GCompT3_1"))
GComp_1 <- GComp_1[order(GComp_1$respid),]
GComp_2 <- melt(Cannabis,  id.vars = "respid", measure.vars =
c("GComp_2", "GCompT2_2", "GCOmpT3_2"))
GComp_2 <- GComp_2[order(GComp_2$respid),]

GInt_2 <- melt(Cannabis,  id.vars = "respid", measure.vars =
c("GInt_2", "GIntT2_2", "GIntT3_2"))
GInt_2 <- GInt_2[order(GInt_2$respid),]
```

```
GInt_3 <- melt(Cannabis,  id.vars = "respid", measure.vars =
c("GInt_3", "GIntT2_3", "GIntT3_3"))
GInt_3 <- GInt_3[order(GInt_3$respid),]
GInt_4 <- melt(Cannabis,  id.vars = "respid", measure.vars =
c("GInt_4", "GIntT2_4", "GIntT3_4"))
GInt_4 <- GInt_4[order(GInt_4$respid),]

Iden_1 <- melt(Cannabis,  id.vars = "respid", measure.vars =
c("IdentifyPot", "IdentifyPotT2", "IdentifyPotT3"))
Iden_1 <- Iden_1[order(Iden_1$respid),]
Iden_2 <- melt(Cannabis,  id.vars = "respid", measure.vars =
c("CommonPot", "CommonPotT2", "CommonPotT3"))
Iden_2 <- Iden_2[order(Iden_2$respid),]
Iden_3 <- melt(Cannabis,  id.vars = "respid", measure.vars =
c("ImpPot", "ImpPotT2", "ImpPotT3"))
Iden_3 <- Iden_3[order(Iden_3$respid),]

GFrequency <- melt(Cannabis,  id.vars = "respid", measure.vars =
c("GFrequency", "GFrequencyT2", "GFrequencyT3"))
GFrequency <- GFrequency[order(GFrequency$respid),]

Valence <- melt(Cannabis,  id.vars = "respid", measure.vars =
c("Neg_Pos", "Neg_PosT2", "Neg_PosT3"))
Valence <- Valence[order(Valence$respid),]

Safety_1 <- melt(Cannabis,  id.vars = "respid", measure.vars =
c("Safety_1", "SafetyT2_1", "SafetyT3_1"))
Safety_1 <- Safety_1[order(Safety_1$respid),]
Safety_2 <- melt(Cannabis,  id.vars = "respid", measure.vars =
c("Safety_2", "SafetyT2_2", "SafetyT3_2"))
Safety_2 <- Safety_2[order(Safety_2$respid),]
Safety_3 <- melt(Cannabis,  id.vars = "respid", measure.vars =
c("Safety_3", "SafetyT2_3", "SafetyT3_3"))
Safety_3 <- Safety_3[order(Safety_3$respid),]

SuiviPot <- melt(Cannabis,  id.vars = "respid", measure.vars =
c("SuiviPot", "SuiviPotT2", "SuiviPotT3"))
SuiviPot <- SuiviPot[order(SuiviPot$respid),]

Gender <- melt(Cannabis,  id.vars = "respid", measure.vars =
c("Gender", "GenderT2", "GenderT3"))
Gender <- Gender[order(Gender$respid),]

Diploma <- melt(Cannabis,  id.vars = "respid", measure.vars =
c("Diploma", "DiplomaT2", "DiplomaT3"))
Diploma <- Diploma[order(Diploma$respid),]

life_cond <- melt(Cannabis,  id.vars = "respid", measure.vars =
c("life_cond", "life_condT2", "life_condT3"))
life_cond <- life_cond[order(life_cond$respid),]
```

```
Age <- melt(Cannabis,  id.vars = "respid", measure.vars =
c("Age", "AgeT2", "AgeT3"))
Age <- Age[order(Age$respid),]

Long <- cbind(Int_2[,1], Int_2[,2], Int_2[,3], Int_3[,3],
Int_4[,3],
              GInt_2[,3], GInt_3[,3], GInt_4[,3],
              Iden_1[,3], Iden_2[,3], Iden_3[,3],
              Cat[,3], Comp_1[,3], Comp_2[,3],
              GCat[,3], GComp_1[,3], GComp_2[,3],
              GFrequency[,3], Valence[,3],
              Safety_1[,3], Safety_2[,3], Safety_3[,3],
SuiviPot[,3],
              Gender[,3], Diploma[,3], life_cond[,3], Age[,3])

# We attribute names to our column.
colnames(Long) <- c("respid", "Temps",
                    "Int_2", "Int_3", "Int_4",
                    "GInt_2", "GInt_3", "GInt_4",
                    "Iden_1", "Iden_2", "Iden_3",
                    "Cat", "Comp_1", "Comp_2",
                    "GCat", "GComp_1", "GComp_2",
                    "GFrequency", "Valence",
                    "Safety_1", "Safety_2", "Safety_3",
"SuiviPot",
                    "Gender", "Diploma", "life_cond", "Age")


# ---- Imputation ----

# Matrix that specifies the border of our variables. Our
variables were measures on a scale from 0 to 4.
# First column is the number of the variable
# Column 2 and 3 are respectively the lower and upper border of
the variables.
# The matrix "x" will be used in the following script with
AMELIA.
x <- matrix(1, nrow = 21, ncol = 3)
x[,1] <- c(3:23)
x[,2] <- 0
x[,3] <- 4

# AMELIA - Imputation
amelia_fit <- amelia(Long, m = 50,
                     idvars = "respid", ts = "Temps", polytime =
2,
                     noms = c("Gender", "Diploma", "life_cond"),
                     ords = c("Int_2", "Int_3", "Int_4",
                              "GInt_2", "GInt_3", "GInt_4",
                              "Iden_1", "Iden_2", "Iden_3",
                              "Cat", "Comp_1", "Comp_2",
                              "GCat", "GComp_1", "GComp_2",
```

```
                              "GFrequency", "Valence",
                              "Safety_1", "Safety_2", "Safety_3",
"SuiviPot"),
                     incheck = TRUE,
                     bounds = x)

# ---- ** Multiple datasets ----

# We will stock every simulations into "a".
a <- amelia_fit$imputations
# We remove imputations that did not work.
a <- a[-which_na(amelia_fit$imputations)]

# for every imputation, we will transform the long dataframe into
a wide dataframe.
mydata <- list()
for (i in 1:length(a)){

Int_2I <- matrix(a[[i]][,3], nrow = nrow(Cannabis), ncol = 3,
byrow = TRUE)
Int_3I <- matrix(a[[i]][,4], nrow = nrow(Cannabis), ncol = 3,
byrow = TRUE)
Int_4I <- matrix(a[[i]][,5], nrow = nrow(Cannabis), ncol = 3,
byrow = TRUE)

GInt_2I <- matrix(a[[i]][,6], nrow = nrow(Cannabis), ncol = 3,
byrow = TRUE)
GInt_3I <- matrix(a[[i]][,7], nrow = nrow(Cannabis), ncol = 3,
byrow = TRUE)
GInt_4I <- matrix(a[[i]][,8], nrow = nrow(Cannabis), ncol = 3,
byrow = TRUE)

Iden_1I <- matrix(a[[i]][,9], nrow = nrow(Cannabis), ncol = 3,
byrow = TRUE)
Iden_2I <- matrix(a[[i]][,10], nrow = nrow(Cannabis), ncol = 3,
byrow = TRUE)
Iden_3I <- matrix(a[[i]][,11], nrow = nrow(Cannabis), ncol = 3,
byrow = TRUE)

Cat <- matrix(a[[i]][,12], nrow = nrow(Cannabis), ncol = 3, byrow
= TRUE)
Comp_1 <- matrix(a[[i]][,13], nrow = nrow(Cannabis), ncol = 3,
byrow = TRUE)
Comp_2 <- matrix(a[[i]][,14], nrow = nrow(Cannabis), ncol = 3,
byrow = TRUE)

GCat <- matrix(a[[i]][,15], nrow = nrow(Cannabis), ncol = 3,
byrow = TRUE)
GComp_1 <- matrix(a[[i]][,16], nrow = nrow(Cannabis), ncol = 3,
byrow = TRUE)
GComp_2 <- matrix(a[[i]][,17], nrow = nrow(Cannabis), ncol = 3,
byrow = TRUE)
```

```
GFrequencyI <- matrix(a[[i]][,18], nrow = nrow(Cannabis), ncol =
3, byrow = TRUE)
ValenceI <- matrix(a[[i]][,19], nrow = nrow(Cannabis), ncol = 3,
byrow = TRUE)

Safety_1I <- matrix(a[[i]][,20], nrow = nrow(Cannabis), ncol = 3,
byrow = TRUE)
Safety_2I <- matrix(a[[i]][,21], nrow = nrow(Cannabis), ncol = 3,
byrow = TRUE)
Safety_3I <- matrix(a[[i]][,22], nrow = nrow(Cannabis), ncol = 3,
byrow = TRUE)

SuiviPotI <- matrix(a[[i]][,23], nrow = nrow(Cannabis), ncol = 3,
byrow = TRUE)

mydata[[i]] <- cbind(Cannabis$respid, Int_2I, Int_3I, Int_4I,
                       GInt_2I, GInt_3I, GInt_4I,
                       Iden_1I, Iden_2I, Iden_3I,
                       Cat, Comp_1, Comp_2 , GCat, GComp_1,
GComp_2,
                       GFrequencyI, ValenceI,
                       Safety_1I, Safety_2I, Safety_3I,
SuiviPotI)

colnames(mydata[[i]]) <- c("respid",
                             "Int_2", "IntT2_2", "IntT3_2",
                             "Int_3", "IntT2_3", "IntT3_3",
                             "Int_4", "IntT2_4", "IntT3_4",
                             "GInt_2", "GIntT2_2", "GIntT3_2",
                             "GInt_3", "GIntT2_3", "GIntT3_3",
                             "GInt_4", "GIntT2_4", "GIntT3_4",
                             "Iden_1", "IdenT2_1", "IdenT3_1",
                             "Iden_2", "IdenT2_2", "IdenT3_2",
                             "Iden_3", "IdenT2_3", "IdenT3_3",
                             "CatT1", "CatT2", "CatT3",
                             "CompT1_1", "CompT2_1", "CompT3_1",
                             "CompT1_2", "CompT2_2", "CompT3_2",
                             "GCatT1", "GCatT2", "GCatT3",
                             "GCompT1_1", "GCompT2_1",
"GCompT3_1",
                             "GCompT1_2", "GCompT2_2",
"GCompT3_2",
                             "GFrequency", "GFrequencyT2",
"GFrequencyT3",
                             "Valence", "ValenceT2", "ValenceT3",
                             "Safety_1", "SafetyT2_1",
"SafetyT3_1",
                             "Safety_2", "SafetyT2_2",
"SafetyT3_2",
                             "Safety_3", "SafetyT2_3",
"SafetyT3_3",
```

```
                             "SuiviPot", "SuiviPotT2",
"SuiviPotT3")

  i <- i + 1

}

# ---- Compute ----

# We compute scores.
for (i in 1:length(mydata)){
  mydata[[i]] <- cbind(mydata[[i]], rowMeans(mydata[[i]][,
c("IntT3_2", "IntT3_3", "IntT3_4")]),
                       rowMeans(mydata[[i]][, c("GIntT3_2",
"GIntT3_3", "GIntT3_4")]),
                       rowMeans(mydata[[i]][, c("IdenT3_1",
"IdenT3_2", "IdenT3_3")]),
                       rowMeans(mydata[[i]][, c("GCompT3_1",
"GCompT3_2")]),
                       rowMeans(mydata[[i]][, c("SafetyT2_1",
"SafetyT2_2", "SafetyT2_2")]),
                       rowMeans(mydata[[i]][, c("SafetyT3_1",
"SafetyT3_2", "SafetyT3_2")]),
                       Cannabis$Age, Cannabis$Age, Cannabis$Age +
1)

# We attribute new names for our computations
colnames(mydata[[i]]) <- c("respid",
                             "Int_2", "IntT2_2", "IntT3_2",
                             "Int_3", "IntT2_3", "IntT3_3",
                             "Int_4", "IntT2_4", "IntT3_4",
                             "GInt_2", "GIntT2_2", "GIntT3_2",
                             "GInt_3", "GIntT2_3", "GIntT3_3",
                             "GInt_4", "GIntT2_4", "GIntT3_4",
                             "Iden_1", "IdenT2_1", "IdenT3_1",
                             "Iden_2", "IdenT2_2", "IdenT3_2",
                             "Iden_3", "IdenT2_3", "IdenT3_3",
                             "CatT1", "CatT2", "CatT3",
                             "CompT1_1", "CompT2_1", "CompT3_1",
                             "CompT1_2", "CompT2_2", "CompT3_2",
                             "GCatT1", "GCatT2", "GCatT3",
                             "GCompT1_1", "GCompT2_1",
"GCompT3_1",
                             "GCompT1_2", "GCompT2_2",
"GCompT3_2",
                             "GFrequency", "GFrequencyT2",
"GFrequencyT3",
                             "Valence", "ValenceT2", "ValenceT3",
                             "Safety_1", "SafetyT2_1",
"SafetyT3_1",
                             "Safety_2", "SafetyT2_2",
"SafetyT3_2",
```

```
                             "Safety_3", "SafetyT2_3",
"SafetyT3_3",
                             "SuiviPot", "SuiviPotT2",
"SuiviPotT3",
                             "IntT3", "GIntT3", "IdenT3",
"GCompT3",
                             "SafetyT2", "SafetyT3",
                             "Age", "AgeT2", "AgeT3")

  i <- i + 1
}
# ---- Codes ----

# we attribute degree of uncertainty for both prior and evidence
sdprior <- 1
sdlikelihood <- 1.5
# We specify the strength of relation between prior and evidence
aF <- .29
aV <- .40
aS <- cor(Cannabis[, c("GintT1", "SafetyT1")])[2,1]
aA <- cor(Cannabis[, c("GintT1", "SuiviPot")])[2,1]

# ---- Matrix of prediction ----

# We create matrix into which predicted scores of the BMII will
go. Each column of the matrix are predicted scores of
# one imputation set and each row are the participants.
PredictionM1 <- matrix(NA, nrow = nrow(Cannabis), ncol =
length(mydata))
PredictionM2 <- matrix(NA, nrow = nrow(Cannabis), ncol =
length(mydata))
PredictionM3 <- matrix(NA, nrow = nrow(Cannabis), ncol =
length(mydata))
PredictionM4 <- matrix(NA, nrow = nrow(Cannabis), ncol =
length(mydata))
PredictionM1a <- matrix(NA, nrow = nrow(Cannabis), ncol =
length(mydata))
PredictionM2a <- matrix(NA, nrow = nrow(Cannabis), ncol =
length(mydata))
PredictionM3a <- matrix(NA, nrow = nrow(Cannabis), ncol =
length(mydata))
PredictionM4a <- matrix(NA, nrow = nrow(Cannabis), ncol =
length(mydata))

# ---- CrÃ©ation matrice likelihood ----

# We create a matrix of likelihood (refered to as "evidence" in
the text) for each evidence.

# Frequency of cannabis use by other members of our group.
likelihoodF <- matrix(0, nrow = 41, ncol = 41)
```

```
colnames(likelihoodF) <- c("0.0", "0.1", "0.2", "0.3", "0.4",
"0.5", "0.6", "0.7", "0.8", "0.9", "1.0", "1.1", "1.2", "1.3",
"1.4", "1.5", "1.6", "1.7", "1.8", "1.9", "2.0", "2.1", "2.2",
"2.3", "2.4", "2.5", "2.6", "2.7", "2.8", "2.9", "3.0", "3.1",
"3.2", "3.3", "3.4", "3.5", "3.6", "3.7", "3.8", "3.9", "4.0")
rownames(likelihoodF) <- c("0.0", "0.1", "0.2", "0.3", "0.4",
"0.5", "0.6", "0.7", "0.8", "0.9", "1.0", "1.1", "1.2", "1.3",
"1.4", "1.5", "1.6", "1.7", "1.8", "1.9", "2.0", "2.1", "2.2",
"2.3", "2.4", "2.5", "2.6", "2.7", "2.8", "2.9", "3.0", "3.1",
"3.2", "3.3", "3.4", "3.5", "3.6", "3.7", "3.8", "3.9", "4.0")
for (i in 1:nrow(likelihoodF)){
  x <- rownames(likelihoodF)[i]
  x <- as.numeric(x) # scores de perception
  fx <- (aF * x) # scores de perception moyen pour chaque score
de schÃ©mas.
  sd <- sdlikelihood # on impose une variance, une distribution
d'incertitude, autour de la moyenne de perception
  y <- seq(0,4,0.1)
  likelihoodF[i,] <- dnorm(y, fx, sd, log = FALSE)
  i <- i + 1
}

colsum <- colSums(likelihoodF)
for (i in 1:ncol(likelihoodF)){
  likelihoodF[,i] <- likelihoodF[,i]/colsum[i]
  i <- i + 1
}

# Valence of cannabis legalization
likelihoodV <- matrix(0, nrow = 41, ncol = 41)
colnames(likelihoodV) <- c("0.0", "0.1", "0.2", "0.3", "0.4",
"0.5", "0.6", "0.7", "0.8", "0.9", "1.0", "1.1", "1.2", "1.3",
"1.4", "1.5", "1.6", "1.7", "1.8", "1.9", "2.0", "2.1", "2.2",
"2.3", "2.4", "2.5", "2.6", "2.7", "2.8", "2.9", "3.0", "3.1",
"3.2", "3.3", "3.4", "3.5", "3.6", "3.7", "3.8", "3.9", "4.0")
rownames(likelihoodV) <- c("0.0", "0.1", "0.2", "0.3", "0.4",
"0.5", "0.6", "0.7", "0.8", "0.9", "1.0", "1.1", "1.2", "1.3",
"1.4", "1.5", "1.6", "1.7", "1.8", "1.9", "2.0", "2.1", "2.2",
"2.3", "2.4", "2.5", "2.6", "2.7", "2.8", "2.9", "3.0", "3.1",
"3.2", "3.3", "3.4", "3.5", "3.6", "3.7", "3.8", "3.9", "4.0")
for (i in 1:nrow(likelihoodV)){
  x <- rownames(likelihoodV)[i]
  x <- as.numeric(x) # scores de perception
  fx <- (aV * x) # scores de perception moyen pour chaque score
de schÃ©mas.
  sd <- sdlikelihood # on impose une variance, une distribution
d'incertitude, autour de la moyenne de perception
  y <- seq(0,4,0.1)
  likelihoodV[i,] <- dnorm(y, fx, sd, log = FALSE)
  i <- i + 1
}
```

```
colsum <- colSums(likelihoodV)
for (i in 1:ncol(likelihoodV)){
  likelihoodV[,i] <- likelihoodV[,i]/colsum[i]
  i <- i + 1
}

# Need for safety
likelihoodS <- matrix(0, nrow = 41, ncol = 41)
colnames(likelihoodS) <- c("0.0", "0.1", "0.2", "0.3", "0.4",
"0.5", "0.6", "0.7", "0.8", "0.9", "1.0", "1.1", "1.2", "1.3",
"1.4", "1.5", "1.6", "1.7", "1.8", "1.9", "2.0", "2.1", "2.2",
"2.3", "2.4", "2.5", "2.6", "2.7", "2.8", "2.9", "3.0", "3.1",
"3.2", "3.3", "3.4", "3.5", "3.6", "3.7", "3.8", "3.9", "4.0")
rownames(likelihoodS) <- c("0.0", "0.1", "0.2", "0.3", "0.4",
"0.5", "0.6", "0.7", "0.8", "0.9", "1.0", "1.1", "1.2", "1.3",
"1.4", "1.5", "1.6", "1.7", "1.8", "1.9", "2.0", "2.1", "2.2",
"2.3", "2.4", "2.5", "2.6", "2.7", "2.8", "2.9", "3.0", "3.1",
"3.2", "3.3", "3.4", "3.5", "3.6", "3.7", "3.8", "3.9", "4.0")
for (i in 1:nrow(likelihoodS)){
  x <- rownames(likelihoodS)[i]
  x <- as.numeric(x) # scores de perception
  fx <- (aS * x) # scores de perception moyen pour chaque score
de schÃ©mas.
  sd <- sdlikelihood # on impose une variance, une distribution
d'incertitude, autour de la moyenne de perception
  y <- seq(0,4,0.1)
  likelihoodS[i,] <- dnorm(y, fx, sd, log = FALSE)
  i <- i + 1
}

colsum <- colSums(likelihoodS)
for (i in 1:ncol(likelihoodS)){
  likelihoodS[,i] <- likelihoodS[,i]/colsum[i]
  i <- i + 1
}

# Action
likelihoodA <- matrix(0, nrow = 41, ncol = 41)
colnames(likelihoodA) <- c("0.0", "0.1", "0.2", "0.3", "0.4",
"0.5", "0.6", "0.7", "0.8", "0.9", "1.0", "1.1", "1.2", "1.3",
"1.4", "1.5", "1.6", "1.7", "1.8", "1.9", "2.0", "2.1", "2.2",
"2.3", "2.4", "2.5", "2.6", "2.7", "2.8", "2.9", "3.0", "3.1",
"3.2", "3.3", "3.4", "3.5", "3.6", "3.7", "3.8", "3.9", "4.0")
rownames(likelihoodA) <- c("0.0", "0.1", "0.2", "0.3", "0.4",
"0.5", "0.6", "0.7", "0.8", "0.9", "1.0", "1.1", "1.2", "1.3",
"1.4", "1.5", "1.6", "1.7", "1.8", "1.9", "2.0", "2.1", "2.2",
"2.3", "2.4", "2.5", "2.6", "2.7", "2.8", "2.9", "3.0", "3.1",
"3.2", "3.3", "3.4", "3.5", "3.6", "3.7", "3.8", "3.9", "4.0")
for (i in 1:nrow(likelihoodA)){
  x <- rownames(likelihoodA)[i]
  x <- as.numeric(x) # scores de perception
```

```
  fx <- (aA * x) # scores de perception moyen pour chaque score
de schÃ©mas.
  sd <- sdlikelihood # on impose une variance, une distribution
d'incertitude, autour de la moyenne de perception
  y <- seq(0,4,0.1)
  likelihoodA[i,] <- dnorm(y, fx, sd, log = FALSE)
  i <- i + 1
}

colsum <- colSums(likelihoodA)
for (i in 1:ncol(likelihoodA)){
  likelihoodA[,i] <- likelihoodA[,i]/colsum[i]
  i <- i + 1
}

# Age with the structure of likelihood of frequency of cannabis
use by others.
# If you look at the formula fx, you see that the slope (aF) is
equal to one use with likelihood of frequency of cannabis use by
others
likelihoodAGE1 <- matrix(0, nrow = 92, ncol = 41)
colnames(likelihoodAGE1) <- c("0.0", "0.1", "0.2", "0.3", "0.4",
"0.5", "0.6", "0.7", "0.8", "0.9", "1.0", "1.1", "1.2", "1.3",
"1.4", "1.5", "1.6", "1.7", "1.8", "1.9", "2.0", "2.1", "2.2",
"2.3", "2.4", "2.5", "2.6", "2.7", "2.8", "2.9", "3.0", "3.1",
"3.2", "3.3", "3.4", "3.5", "3.6", "3.7", "3.8", "3.9", "4.0")
rownames(likelihoodAGE1) <- 1:92
for (i in 1:nrow(likelihoodAGE1)){
  x <- rownames(likelihoodAGE1)[i]
  x <- as.numeric(x) # scores de perception
  fx <- (aF * x) # scores de perception moyen pour chaque score
de schÃ©mas.
  sd <- sdlikelihood # on impose une variance, une distribution
d'incertitude, autour de la moyenne de perception
  y <- seq(0,4,0.1)
  likelihoodAGE1[i,] <- dnorm(y, fx, sd, log = FALSE)
  i <- i + 1
}

colsum <- colSums(likelihoodAGE1)
for (i in 1:ncol(likelihoodAGE1)){
  likelihoodAGE1[,i] <- likelihoodAGE1[,i]/colsum[i]
  i <- i + 1
}

# Age with the structure of likelihood of valence of cannabis
legalization.
likelihoodAGE2 <- matrix(0, nrow = 92, ncol = 41)
colnames(likelihoodAGE2) <- c("0.0", "0.1", "0.2", "0.3", "0.4",
"0.5", "0.6", "0.7", "0.8", "0.9", "1.0", "1.1", "1.2", "1.3",
"1.4", "1.5", "1.6", "1.7", "1.8", "1.9", "2.0", "2.1", "2.2",
```

```
"2.3", "2.4", "2.5", "2.6", "2.7", "2.8", "2.9", "3.0", "3.1",
"3.2", "3.3", "3.4", "3.5", "3.6", "3.7", "3.8", "3.9", "4.0")
rownames(likelihoodAGE2) <- 1:92
for (i in 1:nrow(likelihoodAGE2)){
  x <- rownames(likelihoodAGE2)[i]
  x <- as.numeric(x) # scores de perception
  fx <- (aV * x) # scores de perception moyen pour chaque score
de schÃ©mas.
  sd <- sdlikelihood # on impose une variance, une distribution
d'incertitude, autour de la moyenne de perception
  y <- seq(0,4,0.1)
  likelihoodAGE2[i,] <- dnorm(y, fx, sd, log = FALSE)
  i <- i + 1
}

colsum <- colSums(likelihoodAGE2)
for (i in 1:ncol(likelihoodAGE2)){
  likelihoodAGE2[,i] <- likelihoodAGE2[,i]/colsum[i]
  i <- i + 1
}

# Age with the structure of likelihood of need for security.
likelihoodAGE3 <- matrix(0, nrow = 92, ncol = 41)
colnames(likelihoodAGE3) <- c("0.0", "0.1", "0.2", "0.3", "0.4",
"0.5", "0.6", "0.7", "0.8", "0.9", "1.0", "1.1", "1.2", "1.3",
"1.4", "1.5", "1.6", "1.7", "1.8", "1.9", "2.0", "2.1", "2.2",
"2.3", "2.4", "2.5", "2.6", "2.7", "2.8", "2.9", "3.0", "3.1",
"3.2", "3.3", "3.4", "3.5", "3.6", "3.7", "3.8", "3.9", "4.0")
rownames(likelihoodAGE3) <- 1:92
for (i in 1:nrow(likelihoodAGE3)){
  x <- rownames(likelihoodAGE3)[i]
  x <- as.numeric(x) # scores de perception
  fx <- (aS * x) # scores de perception moyen pour chaque score
de schÃ©mas.
  sd <- sdlikelihood # on impose une variance, une distribution
d'incertitude, autour de la moyenne de perception
  y <- seq(0,4,0.1)
  likelihoodAGE3[i,] <- dnorm(y, fx, sd, log = FALSE)
  i <- i + 1
}

colsum <- colSums(likelihoodAGE3)
for (i in 1:ncol(likelihoodAGE3)){
  likelihoodAGE3[,i] <- likelihoodAGE3[,i]/colsum[i]
  i <- i + 1
}

# Age with the structure of likelihood of action.
likelihoodAGE4 <- matrix(0, nrow = 92, ncol = 41)
colnames(likelihoodAGE4) <- c("0.0", "0.1", "0.2", "0.3", "0.4",
"0.5", "0.6", "0.7", "0.8", "0.9", "1.0", "1.1", "1.2", "1.3",
"1.4", "1.5", "1.6", "1.7", "1.8", "1.9", "2.0", "2.1", "2.2",
```

```
"2.3", "2.4", "2.5", "2.6", "2.7", "2.8", "2.9", "3.0", "3.1",
"3.2", "3.3", "3.4", "3.5", "3.6", "3.7", "3.8", "3.9", "4.0")
rownames(likelihoodAGE4) <- 1:92
for (i in 1:nrow(likelihoodAGE4)){
  x <- rownames(likelihoodAGE4)[i]
  x <- as.numeric(x) # scores de perception
  fx <- (aA * x) # scores de perception moyen pour chaque score
de schÃ©mas.
  sd <- sdlikelihood # on impose une variance, une distribution
d'incertitude, autour de la moyenne de perception
  y <- seq(0,4,0.1)
  likelihoodAGE4[i,] <- dnorm(y, fx, sd, log = FALSE)
  i <- i + 1
}

colsum <- colSums(likelihoodAGE4)
for (i in 1:ncol(likelihoodAGE4)){
  likelihoodAGE4[,i] <- likelihoodAGE4[,i]/colsum[i]
  i <- i + 1
}

# ---- BMII Frequence ----

for (ii in 1:length(mydata)){

  mat <- matrix(mydata[[ii]][,c("respid", "GInt_2", "GInt_3",
"GInt_4", "GFrequency", "GFrequencyT2", "GFrequencyT3")], nrow =
nrow(mydata[[ii]]), ncol = 7)

  Post <- matrix(NA, ncol = 41, nrow = nrow(mat))
  colnames(Post) <- c("0.0", "0.1", "0.2", "0.3", "0.4", "0.5",
"0.6", "0.7", "0.8", "0.9", "1.0", "1.1", "1.2", "1.3", "1.4",
"1.5", "1.6", "1.7", "1.8", "1.9", "2.0", "2.1", "2.2", "2.3",
"2.4", "2.5", "2.6", "2.7", "2.8", "2.9", "3.0", "3.1", "3.2",
"3.3", "3.4", "3.5", "3.6", "3.7", "3.8", "3.9", "4.0")
  for (i in 1:nrow(mat)){
    # Prior
    mean <- mean(mat[i,c(2,3,4)])
    mean <- ifelse(is.na(mean) > 0, 0, mean)
    sd <- sd(mat[i,c(2,3,4)])
    sd <- sd + sdprior
    y <- seq(0,4,0.1)
    prior <- dnorm(y, mean, sd, log = FALSE)
    # Likelihood 1
    n <- mat[i,6] * 10 + 1
    prior2 <- prior * likelihoodF[n,]
    # Likelihood 2
    n2 <- mat[i,7] * 10 + 1
    Post[i,] <- prior2 * likelihoodF[n2,]
    # Posterior
    Sum <- sum(Post[i,])
    Post[i,] <- Post[i,] / Sum
```

```
    i <- i + 1
  }

  column <- 0.0
  for (i in 1:ncol(Post)){
    Post[,i] <- Post[,i]*column
    column <- column + 0.1
    i <- i + 1
  }


  for (i in 1:nrow(Post)){
    PredictionM1[i,ii] <- cbind(sum(Post[i,]))
    i <- i + 1
  }

  ii <- ii + 1

}

for (i in 1:length(mydata)){
  mydata[[i]] <- cbind(mydata[[i]], PredictionM1[,i])
  i <- i + 1
}

# ---- BMII Valence ----

for (ii in 1:length(mydata)){

  mat <- matrix(mydata[[ii]][,c("respid", "GInt_2", "GInt_3",
"GInt_4", "Valence", "ValenceT2", "ValenceT3")], nrow =
nrow(mydata[[ii]]), ncol = 7)

  Post <- matrix(NA, ncol = 41, nrow = nrow(mat))
  colnames(Post) <- c("0.0", "0.1", "0.2", "0.3", "0.4", "0.5",
"0.6", "0.7", "0.8", "0.9", "1.0", "1.1", "1.2", "1.3", "1.4",
"1.5", "1.6", "1.7", "1.8", "1.9", "2.0", "2.1", "2.2", "2.3",
"2.4", "2.5", "2.6", "2.7", "2.8", "2.9", "3.0", "3.1", "3.2",
"3.3", "3.4", "3.5", "3.6", "3.7", "3.8", "3.9", "4.0")
  for (i in 1:nrow(mat)){
    # Prior
    mean <- mean(mat[i,c(2,3,4)])
    mean <- ifelse(is.na(mean) > 0, 0, mean)
    sd <- sd(mat[i,c(2,3,4)])
    sd <- sd + sdprior
    y <- seq(0,4,0.1)
    prior <- dnorm(y, mean, sd, log = FALSE)
    # Likelihood 1
    n <- mat[i,6] * 10 + 1
    prior2 <- prior * likelihoodV[n,]
    # Likelihood 2
    n2 <- mat[i,7] * 10 + 1
```

```
    Post[i,] <- prior2 * likelihoodV[n2,]
    # Posterior
    Sum <- sum(Post[i,])
    Post[i,] <- Post[i,] / Sum
    i <- i + 1
  }

  column <- 0.0
  for (i in 1:ncol(Post)){
    Post[,i] <- Post[,i]*column
    column <- column + 0.1
    i <- i + 1
  }


  for (i in 1:nrow(Post)){
    PredictionM2[i,ii] <- cbind(sum(Post[i,]))
    i <- i + 1
  }

  ii <- ii + 1

}

for (i in 1:length(mydata)){
  mydata[[i]] <- cbind(mydata[[i]], PredictionM2[,i])
  i <- i + 1
}

# ---- BMII Safety ----


for (ii in 1:length(mydata)){

  mat <- matrix(mydata[[ii]][,c("respid", "GInt_2", "GInt_3",
"GInt_4", "SafetyT2", "SafetyT3")], nrow = nrow(mydata[[ii]]),
ncol = 7)

  Post <- matrix(NA, ncol = 41, nrow = nrow(mat))
  colnames(Post) <- c("0.0", "0.1", "0.2", "0.3", "0.4", "0.5",
"0.6", "0.7", "0.8", "0.9", "1.0", "1.1", "1.2", "1.3", "1.4",
"1.5", "1.6", "1.7", "1.8", "1.9", "2.0", "2.1", "2.2", "2.3",
"2.4", "2.5", "2.6", "2.7", "2.8", "2.9", "3.0", "3.1", "3.2",
"3.3", "3.4", "3.5", "3.6", "3.7", "3.8", "3.9", "4.0")
  for (i in 1:nrow(mat)){
    # Prior
    mean <- mean(mat[i,c(2,3,4)])
    mean <- ifelse(is.na(mean) > 0, 0, mean)
    sd <- sd(mat[i,c(2,3,4)])
    sd <- sd + sdprior
    y <- seq(0,4,0.1)
    prior <- dnorm(y, mean, sd, log = FALSE)
```

```
    # Likelihood 1
    n <- round(mat[i,5],1) * 10 + 1
    prior2 <- prior * likelihoodS[n,]
    # Likelihood 2
    n2 <- round(mat[i,6],1) * 10 + 1
    Post[i,] <- prior2 * likelihoodS[n2,]
    # Posterior
    Sum <- sum(Post[i,])
    Post[i,] <- Post[i,] / Sum
    i <- i + 1
  }

  column <- 0.0
  for (i in 1:ncol(Post)){
    Post[,i] <- Post[,i]*column
    column <- column + 0.1
    i <- i + 1
  }


  for (i in 1:nrow(Post)){
    PredictionM3[i,ii] <- cbind(sum(Post[i,]))
    i <- i + 1
  }

  ii <- ii + 1

}

for (i in 1:length(mydata)){
  mydata[[i]] <- cbind(mydata[[i]], PredictionM3[,i])
  i <- i + 1
}

# ---- BMII Action ----

for (ii in 1:length(mydata)){

  mat <- matrix(mydata[[ii]][,c("respid", "GInt_2", "GInt_3",
"GInt_4", "SuiviPot", "SuiviPotT2", "SuiviPotT3")], nrow =
nrow(mydata[[ii]]), ncol = 7)

  Post <- matrix(NA, ncol = 41, nrow = nrow(mat))
  colnames(Post) <- c("0.0", "0.1", "0.2", "0.3", "0.4", "0.5",
"0.6", "0.7", "0.8", "0.9", "1.0", "1.1", "1.2", "1.3", "1.4",
"1.5", "1.6", "1.7", "1.8", "1.9", "2.0", "2.1", "2.2", "2.3",
"2.4", "2.5", "2.6", "2.7", "2.8", "2.9", "3.0", "3.1", "3.2",
"3.3", "3.4", "3.5", "3.6", "3.7", "3.8", "3.9", "4.0")
  for (i in 1:nrow(mat)){
    # Prior
    mean <- mean(mat[i,c(2,3,4)])
    mean <- ifelse(is.na(mean) > 0, 0, mean)
```

```
    sd <- sd(mat[i,c(2,3,4)])
    sd <- sd + sdprior
    y <- seq(0,4,0.1)
    prior <- dnorm(y, mean, sd, log = FALSE)
    # Likelihood 1
    n <- mat[i,6] * 10 + 1
    prior2 <- prior * likelihoodA[n,]
    # Likelihood 2
    n2 <- mat[i,7] * 10 + 1
    Post[i,] <- prior2 * likelihoodA[n2,]
    # Posterior
    Sum <- sum(Post[i,])
    Post[i,] <- Post[i,] / Sum
    i <- i + 1
  }

  column <- 0.0
  for (i in 1:ncol(Post)){
    Post[,i] <- Post[,i]*column
    column <- column + 0.1
    i <- i + 1
  }


  for (i in 1:nrow(Post)){
    PredictionM4[i,ii] <- cbind(sum(Post[i,]))
    i <- i + 1
  }

  ii <- ii + 1

}

for (i in 1:length(mydata)){
  mydata[[i]] <- cbind(mydata[[i]], PredictionM4[,i])
  i <- i + 1
}

# ---- BMII AGE-Frequency ----

for (ii in 1:length(mydata)){

  mat <- matrix(mydata[[ii]][,c("respid", "GInt_2", "GInt_3",
"GInt_4", "Age", "AgeT2", "AgeT3")], nrow = nrow(mydata[[ii]]),
ncol = 7)

  Post <- matrix(NA, ncol = 41, nrow = nrow(mat))
  colnames(Post) <- c("0.0", "0.1", "0.2", "0.3", "0.4", "0.5",
"0.6", "0.7", "0.8", "0.9", "1.0", "1.1", "1.2", "1.3", "1.4",
"1.5", "1.6", "1.7", "1.8", "1.9", "2.0", "2.1", "2.2", "2.3",
"2.4", "2.5", "2.6", "2.7", "2.8", "2.9", "3.0", "3.1", "3.2",
"3.3", "3.4", "3.5", "3.6", "3.7", "3.8", "3.9", "4.0")
```

```
  for (i in 1:nrow(mat)){
    # Prior
    mean <- mean(mat[i,c(2,3,4)])
    mean <- ifelse(is.na(mean) > 0, 0, mean)
    sd <- sd(mat[i,c(2,3,4)])
    sd <- sd + sdprior
    y <- seq(0,4,0.1)
    prior <- dnorm(y, mean, sd, log = FALSE)
    # Likelihood 1
    n <- mat[i,6]
    prior2 <- prior * likelihoodAGE1[n,]
    # Likelihood 2
    n2 <- mat[i,7]
    Post[i,] <- prior2 * likelihoodAGE1[n2,]
    # Posterior
    Sum <- sum(Post[i,])
    Post[i,] <- Post[i,] / Sum
    i <- i + 1
  }

  column <- 0.0
  for (i in 1:ncol(Post)){
    Post[,i] <- Post[,i]*column
    column <- column + 0.1
    i <- i + 1
  }


  for (i in 1:nrow(Post)){
    PredictionM1a[i,ii] <- cbind(sum(Post[i,]))
    i <- i + 1
  }

  ii <- ii + 1

}

for (i in 1:length(mydata)){
  mydata[[i]] <- cbind(mydata[[i]], PredictionM1a[,i])
  i <- i + 1
}

# ---- BMII AGE-Valence ----

for (ii in 1:length(mydata)){

  mat <- matrix(mydata[[ii]][,c("respid", "GInt_2", "GInt_3",
"GInt_4", "Age", "AgeT2", "AgeT3")], nrow = nrow(mydata[[ii]]),
ncol = 7)

  Post <- matrix(NA, ncol = 41, nrow = nrow(mat))
```

```
  colnames(Post) <- c("0.0", "0.1", "0.2", "0.3", "0.4", "0.5",
"0.6", "0.7", "0.8", "0.9", "1.0", "1.1", "1.2", "1.3", "1.4",
"1.5", "1.6", "1.7", "1.8", "1.9", "2.0", "2.1", "2.2", "2.3",
"2.4", "2.5", "2.6", "2.7", "2.8", "2.9", "3.0", "3.1", "3.2",
"3.3", "3.4", "3.5", "3.6", "3.7", "3.8", "3.9", "4.0")
  for (i in 1:nrow(mat)){
    # Prior
    mean <- mean(mat[i,c(2,3,4)])
    mean <- ifelse(is.na(mean) > 0, 0, mean)
    sd <- sd(mat[i,c(2,3,4)])
    sd <- sd + sdprior
    y <- seq(0,4,0.1)
    prior <- dnorm(y, mean, sd, log = FALSE)
    # Likelihood 1
    n <- mat[i,6]
    prior2 <- prior * likelihoodAGE2[n,]
    # Likelihood 2
    n2 <- mat[i,7]
    Post[i,] <- prior2 * likelihoodAGE2[n2,]
    # Posterior
    Sum <- sum(Post[i,])
    Post[i,] <- Post[i,] / Sum
    i <- i + 1
  }

  column <- 0.0
  for (i in 1:ncol(Post)){
    Post[,i] <- Post[,i]*column
    column <- column + 0.1
    i <- i + 1
  }


  for (i in 1:nrow(Post)){
    PredictionM2a[i,ii] <- cbind(sum(Post[i,]))
    i <- i + 1
  }

  ii <- ii + 1

}

for (i in 1:length(mydata)){
  mydata[[i]] <- cbind(mydata[[i]], PredictionM2a[,i])
  i <- i + 1
}

# ---- BMII AGE-Safety ----

for (ii in 1:length(mydata)){
```

```
  mat <- matrix(mydata[[ii]][,c("respid", "GInt_2", "GInt_3",
"GInt_4", "Age", "AgeT2", "AgeT3")], nrow = nrow(mydata[[ii]]),
ncol = 7)

  Post <- matrix(NA, ncol = 41, nrow = nrow(mat))
  colnames(Post) <- c("0.0", "0.1", "0.2", "0.3", "0.4", "0.5",
"0.6", "0.7", "0.8", "0.9", "1.0", "1.1", "1.2", "1.3", "1.4",
"1.5", "1.6", "1.7", "1.8", "1.9", "2.0", "2.1", "2.2", "2.3",
"2.4", "2.5", "2.6", "2.7", "2.8", "2.9", "3.0", "3.1", "3.2",
"3.3", "3.4", "3.5", "3.6", "3.7", "3.8", "3.9", "4.0")
  for (i in 1:nrow(mat)){
    # Prior
    mean <- mean(mat[i,c(2,3,4)])
    mean <- ifelse(is.na(mean) > 0, 0, mean)
    sd <- sd(mat[i,c(2,3,4)])
    sd <- sd + sdprior
    y <- seq(0,4,0.1)
    prior <- dnorm(y, mean, sd, log = FALSE)
    # Likelihood 1
    n <- mat[i,6]
    prior2 <- prior * likelihoodAGE3[n,]
    # Likelihood 2
    n2 <- mat[i,7]
    Post[i,] <- prior2 * likelihoodAGE3[n2,]
    # Posterior
    Sum <- sum(Post[i,])
    Post[i,] <- Post[i,] / Sum
    i <- i + 1
  }

  column <- 0.0
  for (i in 1:ncol(Post)){
    Post[,i] <- Post[,i]*column
    column <- column + 0.1
    i <- i + 1
  }


  for (i in 1:nrow(Post)){
    PredictionM3a[i,ii] <- cbind(sum(Post[i,]))
    i <- i + 1
  }

  ii <- ii + 1

}

for (i in 1:length(mydata)){
  mydata[[i]] <- cbind(mydata[[i]], PredictionM3a[,i])
  i <- i + 1
}
```

```
# ---- BMII AGE-Action ----

for (ii in 1:length(mydata)){

  mat <- matrix(mydata[[ii]][,c("respid", "GInt_2", "GInt_3",
"GInt_4", "Age", "AgeT2", "AgeT3")], nrow = nrow(mydata[[ii]]),
ncol = 7)

  Post <- matrix(NA, ncol = 41, nrow = nrow(mat))
  colnames(Post) <- c("0.0", "0.1", "0.2", "0.3", "0.4", "0.5",
"0.6", "0.7", "0.8", "0.9", "1.0", "1.1", "1.2", "1.3", "1.4",
"1.5", "1.6", "1.7", "1.8", "1.9", "2.0", "2.1", "2.2", "2.3",
"2.4", "2.5", "2.6", "2.7", "2.8", "2.9", "3.0", "3.1", "3.2",
"3.3", "3.4", "3.5", "3.6", "3.7", "3.8", "3.9", "4.0")
  for (i in 1:nrow(mat)){
    # Prior
    mean <- mean(mat[i,c(2,3,4)])
    mean <- ifelse(is.na(mean) > 0, 0, mean)
    sd <- sd(mat[i,c(2,3,4)])
    sd <- sd + sdprior
    y <- seq(0,4,0.1)
    prior <- dnorm(y, mean, sd, log = FALSE)
    # Likelihood 1
    n <- mat[i,6]
    prior2 <- prior * likelihoodAGE4[n,]
    # Likelihood 2
    n2 <- mat[i,7]
    Post[i,] <- prior2 * likelihoodAGE4[n2,]
    # Posterior
    Sum <- sum(Post[i,])
    Post[i,] <- Post[i,] / Sum
    i <- i + 1
  }

  column <- 0.0
  for (i in 1:ncol(Post)){
    Post[,i] <- Post[,i]*column
    column <- column + 0.1
    i <- i + 1
  }


  for (i in 1:nrow(Post)){
    PredictionM4a[i,ii] <- cbind(sum(Post[i,]))
    i <- i + 1
  }

  ii <- ii + 1

}

for (i in 1:length(mydata)){
```

```
  mydata[[i]] <- cbind(mydata[[i]], PredictionM4a[,i])
  i <- i + 1
}


for (i in 1:length(mydata)){
  colnames(mydata[[i]]) <- c("respid",
                              "Int_2", "IntT2_2", "IntT3_2",
                              "Int_3", "IntT2_3", "IntT3_3",
                              "Int_4", "IntT2_4", "IntT3_4",
                              "GInt_2", "GIntT2_2", "GIntT3_2",
                              "GInt_3", "GIntT2_3", "GIntT3_3",
                              "GInt_4", "GIntT2_4", "GIntT3_4",
                              "Iden_1", "IdenT2_1", "IdenT3_1",
                              "Iden_2", "IdenT2_2", "IdenT3_2",
                              "Iden_3", "IdenT2_3", "IdenT3_3",
                              "CatT1", "CatT2", "CatT3",
                              "CompT1_1", "CompT2_1", "CompT3_1",
                              "CompT1_2", "CompT2_2", "CompT3_2",
                              "GCatT1", "GCatT2", "GCatT3",
                              "GCompT1_1", "GCompT2_1",
"GCompT3_1",
                              "GCompT1_2", "GCompT2_2",
"GCompT3_2",
                              "GFrequency", "GFrequencyT2",
"GFrequencyT3",
                              "Valence", "ValenceT2", "ValenceT3",
                              "Safety_1", "SafetyT2_1",
"SafetyT3_1",
                              "Safety_2", "SafetyT2_2",
"SafetyT3_2",
                              "Safety_3", "SafetyT2_3",
"SafetyT3_3",
                              "SuiviPot", "SuiviPotT2",
"SuiviPotT3",
                              "IntT3", "GIntT3", "IdenT3",
"GCompT3",
                              "Age", "AgeT2", "AgeT3",
                              "SafetyT2", "SafetyT3",
                              "PredictionM1", "PredictionM2",
"PredictionM3", "PredictionM4",
                              "PredictionM1a", "PredictionM2a",
"PredictionM3a", "PredictionM4a")

  i <- i + 1
}

# ---- Results ----

# Conversion of a list object into a mice object.
a.mids <- miceadds::datlist2mids(mydata)
```

```
fitM1 <- with(data = a.mids, exp = lm(scale(GIntT3) ~
scale(PredictionM1)))
MeanM1 <- summary(pool(fitM1))$estimate[2] # Mean SD
SDM1 <- summary(pool(fitM1))$std.error[2] # Pooled SD

fitM2 <- with(data = a.mids, exp = lm(scale(GIntT3) ~
scale(PredictionM2)))
MeanM2 <- summary(pool(fitM2))$estimate[2] # Mean SD
SDM2 <- summary(pool(fitM2))$std.error[2] # Pooled SD

fitM3 <- with(data = a.mids, exp = lm(scale(GIntT3) ~
scale(PredictionM3)))
MeanM3 <- summary(pool(fitM3))$estimate[2] # Mean SD
SDM3 <- summary(pool(fitM3))$std.error[2] # Pooled SD

fitM4 <- with(data = a.mids, exp = lm(scale(GIntT3) ~
scale(PredictionM4)))
MeanM4 <- summary(pool(fitM4))$estimate[2] # Mean SD
SDM4 <- summary(pool(fitM4))$std.error[2] # Pooled SD

fitM5 <- with(data = a.mids, exp = lm(scale(GIntT3) ~
scale(PredictionM1a)))
MeanM5 <- summary(pool(fitM5))$estimate[2] # Mean SD
SDM5 <- summary(pool(fitM5))$std.error[2] # Pooled SD

fitM6 <- with(data = a.mids, exp = lm(scale(GIntT3) ~
scale(PredictionM2a)))
MeanM6 <- summary(pool(fitM6))$estimate[2] # Mean SD
SDM6 <- summary(pool(fitM6))$std.error[2] # Pooled SD

fitM7 <- with(data = a.mids, exp = lm(scale(GIntT3) ~
scale(PredictionM3a)))
MeanM7 <- summary(pool(fitM7))$estimate[2] # Mean SD
SDM7 <- summary(pool(fitM7))$std.error[2] # Pooled SD

fitM8 <- with(data = a.mids, exp = lm(scale(GIntT3) ~
scale(PredictionM4a)))
MeanM8 <- summary(pool(fitM8))$estimate[2] # Mean SD
SDM8 <- summary(pool(fitM8))$std.error[2] # Pooled SD

fit2 <- with(data = a.mids, exp = lm(scale(GIntT3) ~
scale(Cannabis$GintT1)))
Mean <- summary(pool(fit2))$estimate[2] # Mean SD
SD <- summary(pool(fit2))$std.error[2] # Pooled SD

# Matrix for the figure
boxLabels = c("Frequence", "Valence", "Safety", "Action",
              "Age-Frequence", "Age-Valence", "Age-Safety", "Age-
Action",
              "Cannabis integration time 1")
allo <- data.frame(yAxis = length(boxLabels):1,
                   boxOdds = c(MeanM1,
```

```
                                MeanM2,
                                MeanM3,
                                MeanM4,
                                MeanM5,
                                MeanM6,
                                MeanM7,
                                MeanM8,
                                Mean),
                   boxCILow = c(MeanM1 - (2.01 * SDM1),
                                MeanM2 - (2.01 * SDM2),
                                MeanM3 - (2.01 * SDM3),
                                MeanM4 - (2.01 * SDM4),
                                MeanM5 - (2.01 * SDM5),
                                MeanM6 - (2.01 * SDM6),
                                MeanM7 - (2.01 * SDM7),
                                MeanM8 - (2.01 * SDM8),
                                Mean - (2.01 * SD)),
                   boxCIHigh = c(MeanM1 + (2.01 * SDM1),
                                 MeanM2 + (2.01 * SDM2),
                                 MeanM3 + (2.01 * SDM3),
                                 MeanM4 + (2.01 * SDM4),
                                 MeanM5 + (2.01 * SDM5),
                                 MeanM6 + (2.01 * SDM6),
                                 MeanM7 + (2.01 * SDM7),
                                 MeanM8 + (2.01 * SDM8),
                                 Mean + (2.01 * SD))
)

# Figure
ggplot(allo, aes(x = boxOdds, y = reorder(boxLabels, yAxis))) +
  geom_errorbarh(aes(xmax = boxCIHigh, xmin = boxCILow), size =
.2, height =
                   .1, color = "black") +
  geom_point(size = 3.5, color = "black") +
  scale_x_continuous(limits = c(min(allo$boxCILow) - .20,
max(allo$boxCIHigh) + .20)) +
  theme_bw()+
  theme(panel.grid.minor = element_blank(),
        text = element_text(size = 25)) +
  ylab("") +
  xlab("Standardized regression values")
```

# Annexe B : Script R pour l'identification aux consommateurs de cannabis (article 2)

```
# ----  Packages ----

library(haven)
library(Amelia)
library(reshape2)
library(dplyr)
library(ggplot2)
library(na.tools)
library(psych)
library(mice)

# ---- Data & seed ----

df <- read_sav("D:/Cannabis/R/CannabisNew/CannabisMergedAll.sav")

set.seed(10802020)

# ---- Matrix of Variables ----

# We create a matrix of the data used for the imputation.
Cannabis <- df[ ,c("respid", "Int_2", "Int_3", "Int_4",
                   "IntT2_2", "IntT2_3", "IntT2_4",
                   "IntT3_2", "IntT3_3", "IntT3_4",
                   "GInt_2", "GInt_3", "GInt_4",
                   "GIntT2_2", "GIntT2_3", "GIntT2_4",
                   "GIntT3_2", "GIntT3_3", "GIntT3_4",
                   "IdentifyPot", "CommonPot", "ImpPot",
                   "IdentifyPotT2", "CommonPotT2", "ImpPotT2",
                   "IdentifyPotT3", "CommonPotT3", "ImpPotT3",
                   "GFrequency", "GFrequencyT2", "GFrequencyT3",
                   "Cat", "CatT2", "CatT3",
                   "Comp_1", "CompT2_1", "CompT3_1",
                   "Comp_2", "CompT2_2", "CompT3_2",
                   "GCat", "GCatT2", "GCatT3",
                   "GComp_1", "GCompT2_1", "GCompT3_1",
                   "GComp_2", "GCompT2_2", "GCOmpT3_2",
                   "Neg_Pos", "Neg_PosT2", "Neg_PosT3",
                   "Safety_1", "SafetyT2_1", "SafetyT3_1",
                   "Safety_2", "SafetyT2_2", "SafetyT3_2",
                   "Safety_3", "SafetyT2_3", "SafetyT3_3",
                   "SuiviPot", "SuiviPotT2", "SuiviPotT3",
                   "Age", "Gender", "Diploma", "Situation",
"life_cond")]

# We compute variables that does not need to be impute.
```

```
Cannabis$GintT1 <- rowMeans(Cannabis[,c("GInt_2", "GInt_3",
"GInt_4")])
Cannabis$IdenT1 <- rowMeans(Cannabis[,c("IdentifyPot",
"CommonPot", "ImpPot")])
Cannabis$SafetyT1 <- rowMeans(Cannabis[,c("Safety_1", "Safety_2",
"Safety_3")])

# We create sociodemographic variables at time 2 and 3 for the
multiple imputation.
# We suppose that these sociodemographic variables will remain
the same across time.
Cannabis[,"AgeT2"] <- Cannabis[,"Age"]
Cannabis[,"AgeT3"] <- Cannabis[,"Age"]
Cannabis[,"GenderT2"] <- Cannabis[,"Gender"]
Cannabis[,"GenderT3"] <- Cannabis[,"Gender"]
Cannabis[,"DiplomaT2"] <- Cannabis[,"Diploma"]
Cannabis[,"DiplomaT3"] <- Cannabis[,"Diploma"]
Cannabis[,"SituationT2"] <- Cannabis[,"Situation"]
Cannabis[,"SituationT3"] <- Cannabis[,"Situation"]
Cannabis[,"life_condT2"] <- Cannabis[,"life_cond"]
Cannabis[,"life_condT3"] <- Cannabis[,"life_cond"]

# To use AMELIA, we need to use a "long" format of matrix. To do
so, we created several matrix for each variables.
# These matrix are in a long format. They will be join to one
another latter.
Int_2 <- melt(Cannabis,  id.vars = "respid", measure.vars =
c("Int_2", "IntT2_2", "IntT3_2"))
Int_2 <- Int_2[order(Int_2$respid),]
Int_3 <- melt(Cannabis,  id.vars = "respid", measure.vars =
c("Int_3", "IntT2_3", "IntT3_3"))
Int_3 <- Int_3[order(Int_3$respid),]
Int_4 <- melt(Cannabis,  id.vars = "respid", measure.vars =
c("Int_4", "IntT2_4", "IntT3_4"))
Int_4 <- Int_4[order(Int_4$respid),]

Cat <- melt(Cannabis,  id.vars = "respid", measure.vars =
c("Cat", "CatT2", "CatT3"))
Cat <- Cat[order(Cat$respid),]

Comp_1 <- melt(Cannabis,  id.vars = "respid", measure.vars =
c("Comp_1", "CompT2_1", "CompT3_1"))
Comp_1 <- Comp_1[order(Comp_1$respid),]
Comp_2 <- melt(Cannabis,  id.vars = "respid", measure.vars =
c("Comp_2", "CompT2_2", "CompT3_2"))
Comp_2 <- Comp_2[order(Comp_2$respid),]

GCat <- melt(Cannabis,  id.vars = "respid", measure.vars =
c("GCat", "GCatT2", "GCatT3"))
GCat <- GCat[order(GCat$respid),]
```

```
GComp_1 <- melt(Cannabis,  id.vars = "respid", measure.vars =
c("GComp_1", "GCompT2_1", "GCompT3_1"))
GComp_1 <- GComp_1[order(GComp_1$respid),]
GComp_2 <- melt(Cannabis,  id.vars = "respid", measure.vars =
c("GComp_2", "GCompT2_2", "GCOmpT3_2"))
GComp_2 <- GComp_2[order(GComp_2$respid),]

GInt_2 <- melt(Cannabis,  id.vars = "respid", measure.vars =
c("GInt_2", "GIntT2_2", "GIntT3_2"))
GInt_2 <- GInt_2[order(GInt_2$respid),]
GInt_3 <- melt(Cannabis,  id.vars = "respid", measure.vars =
c("GInt_3", "GIntT2_3", "GIntT3_3"))
GInt_3 <- GInt_3[order(GInt_3$respid),]
GInt_4 <- melt(Cannabis,  id.vars = "respid", measure.vars =
c("GInt_4", "GIntT2_4", "GIntT3_4"))
GInt_4 <- GInt_4[order(GInt_4$respid),]

Iden_1 <- melt(Cannabis,  id.vars = "respid", measure.vars =
c("IdentifyPot", "IdentifyPotT2", "IdentifyPotT3"))
Iden_1 <- Iden_1[order(Iden_1$respid),]
Iden_2 <- melt(Cannabis,  id.vars = "respid", measure.vars =
c("CommonPot", "CommonPotT2", "CommonPotT3"))
Iden_2 <- Iden_2[order(Iden_2$respid),]
Iden_3 <- melt(Cannabis,  id.vars = "respid", measure.vars =
c("ImpPot", "ImpPotT2", "ImpPotT3"))
Iden_3 <- Iden_3[order(Iden_3$respid),]

GFrequency <- melt(Cannabis,  id.vars = "respid", measure.vars =
c("GFrequency", "GFrequencyT2", "GFrequencyT3"))
GFrequency <- GFrequency[order(GFrequency$respid),]

Valence <- melt(Cannabis,  id.vars = "respid", measure.vars =
c("Neg_Pos", "Neg_PosT2", "Neg_PosT3"))
Valence <- Valence[order(Valence$respid),]

Safety_1 <- melt(Cannabis,  id.vars = "respid", measure.vars =
c("Safety_1", "SafetyT2_1", "SafetyT3_1"))
Safety_1 <- Safety_1[order(Safety_1$respid),]
Safety_2 <- melt(Cannabis,  id.vars = "respid", measure.vars =
c("Safety_2", "SafetyT2_2", "SafetyT3_2"))
Safety_2 <- Safety_2[order(Safety_2$respid),]
Safety_3 <- melt(Cannabis,  id.vars = "respid", measure.vars =
c("Safety_3", "SafetyT2_3", "SafetyT3_3"))
Safety_3 <- Safety_3[order(Safety_3$respid),]

SuiviPot <- melt(Cannabis,  id.vars = "respid", measure.vars =
c("SuiviPot", "SuiviPotT2", "SuiviPotT3"))
SuiviPot <- SuiviPot[order(SuiviPot$respid),]

Gender <- melt(Cannabis,  id.vars = "respid", measure.vars =
c("Gender", "GenderT2", "GenderT3"))
Gender <- Gender[order(Gender$respid),]
```

```
Diploma <- melt(Cannabis,  id.vars = "respid", measure.vars =
c("Diploma", "DiplomaT2", "DiplomaT3"))
Diploma <- Diploma[order(Diploma$respid),]

life_cond <- melt(Cannabis,  id.vars = "respid", measure.vars =
c("life_cond", "life_condT2", "life_condT3"))
life_cond <- life_cond[order(life_cond$respid),]

Age <- melt(Cannabis,  id.vars = "respid", measure.vars =
c("Age", "AgeT2", "AgeT3"))
Age <- Age[order(Age$respid),]

# We join the matrix into one long matrix.
Long <- cbind(Int_2[,1], Int_2[,2], Int_2[,3], Int_3[,3],
Int_4[,3],
              GInt_2[,3], GInt_3[,3], GInt_4[,3],
              Iden_1[,3], Iden_2[,3], Iden_3[,3],
              Cat[,3], Comp_1[,3], Comp_2[,3],
              GCat[,3], GComp_1[,3], GComp_2[,3],
              GFrequency[,3], Valence[,3],
              Safety_1[,3], Safety_2[,3], Safety_3[,3],
SuiviPot[,3],
              Gender[,3], Diploma[,3], life_cond[,3], Age[,3])

# We attribute names to our column.
colnames(Long) <- c("respid", "Temps",
                    "Int_2", "Int_3", "Int_4",
                    "GInt_2", "GInt_3", "GInt_4",
                    "Iden_1", "Iden_2", "Iden_3",
                    "Cat", "Comp_1", "Comp_2",
                    "GCat", "GComp_1", "GComp_2",
                    "GFrequency", "Valence",
                    "Safety_1", "Safety_2", "Safety_3",
"SuiviPot",
                    "Gender", "Diploma", "life_cond", "Age")


# ---- Imputation ----

# Matrix that specifies the border of our variables. Our
variables were measures on a scale from 0 to 4.
# First column is the number of the variable
# Column 2 and 3 are respectively the lower and upper border of
the variables.
# The matrix "x" will be used in the following script with
AMELIA.
x <- matrix(1, nrow = 21, ncol = 3)
x[,1] <- c(3:23)
x[,2] <- 0
x[,3] <- 4
```

```
# AMELIA - Imputation
amelia_fit <- amelia(Long, m = 50,
                     idvars = "respid", ts = "Temps", polytime =
2,
                     noms = c("Gender", "Diploma", "life_cond"),
                     ords = c("Int_2", "Int_3", "Int_4",
                              "GInt_2", "GInt_3", "GInt_4",
                              "Iden_1", "Iden_2", "Iden_3",
                              "Cat", "Comp_1", "Comp_2",
                              "GCat", "GComp_1", "GComp_2",
                              "GFrequency", "Valence",
                              "Safety_1", "Safety_2", "Safety_3",
"SuiviPot"),
                     incheck = TRUE,
                     bounds = x)

# ---- ** Multiple datasets ----

# We will stock every simulations into "a".
a <- amelia_fit$imputations
# We remove imputations that did not work.
a <- a[-which_na(amelia_fit$imputations)]

# for every imputation, we will transform the long dataframe into
a wide dataframe.
mydata <- list()
for (i in 1:length(a)){

Int_2I <- matrix(a[[i]][,3], nrow = nrow(Cannabis), ncol = 3,
byrow = TRUE)
Int_3I <- matrix(a[[i]][,4], nrow = nrow(Cannabis), ncol = 3,
byrow = TRUE)
Int_4I <- matrix(a[[i]][,5], nrow = nrow(Cannabis), ncol = 3,
byrow = TRUE)

GInt_2I <- matrix(a[[i]][,6], nrow = nrow(Cannabis), ncol = 3,
byrow = TRUE)
GInt_3I <- matrix(a[[i]][,7], nrow = nrow(Cannabis), ncol = 3,
byrow = TRUE)
GInt_4I <- matrix(a[[i]][,8], nrow = nrow(Cannabis), ncol = 3,
byrow = TRUE)

Iden_1I <- matrix(a[[i]][,9], nrow = nrow(Cannabis), ncol = 3,
byrow = TRUE)
Iden_2I <- matrix(a[[i]][,10], nrow = nrow(Cannabis), ncol = 3,
byrow = TRUE)
Iden_3I <- matrix(a[[i]][,11], nrow = nrow(Cannabis), ncol = 3,
byrow = TRUE)

Cat <- matrix(a[[i]][,12], nrow = nrow(Cannabis), ncol = 3, byrow
= TRUE)
```

```
Comp_1 <- matrix(a[[i]][,13], nrow = nrow(Cannabis), ncol = 3,
byrow = TRUE)
Comp_2 <- matrix(a[[i]][,14], nrow = nrow(Cannabis), ncol = 3,
byrow = TRUE)

GCat <- matrix(a[[i]][,15], nrow = nrow(Cannabis), ncol = 3,
byrow = TRUE)
GComp_1 <- matrix(a[[i]][,16], nrow = nrow(Cannabis), ncol = 3,
byrow = TRUE)
GComp_2 <- matrix(a[[i]][,17], nrow = nrow(Cannabis), ncol = 3,
byrow = TRUE)

GFrequencyI <- matrix(a[[i]][,18], nrow = nrow(Cannabis), ncol =
3, byrow = TRUE)
ValenceI <- matrix(a[[i]][,19], nrow = nrow(Cannabis), ncol = 3,
byrow = TRUE)

Safety_1I <- matrix(a[[i]][,20], nrow = nrow(Cannabis), ncol = 3,
byrow = TRUE)
Safety_2I <- matrix(a[[i]][,21], nrow = nrow(Cannabis), ncol = 3,
byrow = TRUE)
Safety_3I <- matrix(a[[i]][,22], nrow = nrow(Cannabis), ncol = 3,
byrow = TRUE)

SuiviPotI <- matrix(a[[i]][,23], nrow = nrow(Cannabis), ncol = 3,
byrow = TRUE)

mydata[[i]] <- cbind(Cannabis$respid, Int_2I, Int_3I, Int_4I,
                       GInt_2I, GInt_3I, GInt_4I,
                       Iden_1I, Iden_2I, Iden_3I,
                       Cat, Comp_1, Comp_2 , GCat, GComp_1,
GComp_2,
                       GFrequencyI, ValenceI,
                       Safety_1I, Safety_2I, Safety_3I,
SuiviPotI)

colnames(mydata[[i]]) <- c("respid",
                             "Int_2", "IntT2_2", "IntT3_2",
                             "Int_3", "IntT2_3", "IntT3_3",
                             "Int_4", "IntT2_4", "IntT3_4",
                             "GInt_2", "GIntT2_2", "GIntT3_2",
                             "GInt_3", "GIntT2_3", "GIntT3_3",
                             "GInt_4", "GIntT2_4", "GIntT3_4",
                             "Iden_1", "IdenT2_1", "IdenT3_1",
                             "Iden_2", "IdenT2_2", "IdenT3_2",
                             "Iden_3", "IdenT2_3", "IdenT3_3",
                             "CatT1", "CatT2", "CatT3",
                             "CompT1_1", "CompT2_1", "CompT3_1",
                             "CompT1_2", "CompT2_2", "CompT3_2",
                             "GCatT1", "GCatT2", "GCatT3",
                             "GCompT1_1", "GCompT2_1",
"GCompT3_1",
```

```
                              "GCompT1_2", "GCompT2_2",
"GCompT3_2",
                              "GFrequency", "GFrequencyT2",
"GFrequencyT3",
                              "Valence", "ValenceT2", "ValenceT3",
                              "Safety_1", "SafetyT2_1",
"SafetyT3_1",
                              "Safety_2", "SafetyT2_2",
"SafetyT3_2",
                              "Safety_3", "SafetyT2_3",
"SafetyT3_3",
                              "SuiviPot", "SuiviPotT2",
"SuiviPotT3")

  i <- i + 1

}

# ---- Compute ----

# We compute scores.
for (i in 1:length(mydata)){
  mydata[[i]] <- cbind(mydata[[i]], rowMeans(mydata[[i]][,
c("IntT3_2", "IntT3_3", "IntT3_4")]),
                       rowMeans(mydata[[i]][, c("GIntT3_2",
"GIntT3_3", "GIntT3_4")]),
                       rowMeans(mydata[[i]][, c("IdenT3_1",
"IdenT3_2", "IdenT3_3")]),
                       rowMeans(mydata[[i]][, c("GCompT3_1",
"GCompT3_2")]),
                       rowMeans(mydata[[i]][, c("SafetyT2_1",
"SafetyT2_2", "SafetyT2_2")]),
                       rowMeans(mydata[[i]][, c("SafetyT3_1",
"SafetyT3_2", "SafetyT3_2")]),
                       Cannabis$Age, Cannabis$Age, Cannabis$Age +
1)

# We attribute new names for our computations
colnames(mydata[[i]]) <- c("respid",
                              "Int_2", "IntT2_2", "IntT3_2",
                              "Int_3", "IntT2_3", "IntT3_3",
                              "Int_4", "IntT2_4", "IntT3_4",
                              "GInt_2", "GIntT2_2", "GIntT3_2",
                              "GInt_3", "GIntT2_3", "GIntT3_3",
                              "GInt_4", "GIntT2_4", "GIntT3_4",
                              "Iden_1", "IdenT2_1", "IdenT3_1",
                              "Iden_2", "IdenT2_2", "IdenT3_2",
                              "Iden_3", "IdenT2_3", "IdenT3_3",
                              "CatT1", "CatT2", "CatT3",
                              "CompT1_1", "CompT2_1", "CompT3_1",
                              "CompT1_2", "CompT2_2", "CompT3_2",
                              "GCatT1", "GCatT2", "GCatT3",
```

```
                                 "GCompT1_1", "GCompT2_1",
"GCompT3_1",
                                 "GCompT1_2", "GCompT2_2",
"GCompT3_2",
                                 "GFrequency", "GFrequencyT2",
"GFrequencyT3",
                                 "Valence", "ValenceT2", "ValenceT3",
                                 "Safety_1", "SafetyT2_1",
"SafetyT3_1",
                                 "Safety_2", "SafetyT2_2",
"SafetyT3_2",
                                 "Safety_3", "SafetyT2_3",
"SafetyT3_3",
                                 "SuiviPot", "SuiviPotT2",
"SuiviPotT3",
                                 "IntT3", "GIntT3", "IdenT3",
"GCompT3",
                                 "SafetyT2", "SafetyT3",
                                 "Age", "AgeT2", "AgeT3")

  i <- i + 1
}

# ---- Codes ----

# we attribute degree of uncertainty for both prior and evidence
sdprior <- 1
sdlikelihood <- 1.5
# We specify the strength of relation between prior and evidence
aF <- cor(Cannabis[, c("IdenT1", "GFrequency")])
aV <- cor(Cannabis[, c("IdenT1", "Neg_Pos")])
aS <- cor(Cannabis[, c("IdenT1", "SafetyT1")])[2,1]
aA <- cor(Cannabis[, c("IdenT1", "SuiviPot")])[2,1]

# ---- Matrix of prediction ----

# We create matrix into which predicted scores of the BMII will
go. Each column of the matrix are predicted scores of
# one imputation set and each row are the participants.
PredictionM1 <- matrix(NA, nrow = nrow(Cannabis), ncol =
length(mydata))
PredictionM2 <- matrix(NA, nrow = nrow(Cannabis), ncol =
length(mydata))
PredictionM3 <- matrix(NA, nrow = nrow(Cannabis), ncol =
length(mydata))
PredictionM4 <- matrix(NA, nrow = nrow(Cannabis), ncol =
length(mydata))
PredictionM1a <- matrix(NA, nrow = nrow(Cannabis), ncol =
length(mydata))
PredictionM2a <- matrix(NA, nrow = nrow(Cannabis), ncol =
length(mydata))
```

```
PredictionM3a <- matrix(NA, nrow = nrow(Cannabis), ncol =
length(mydata))
PredictionM4a <- matrix(NA, nrow = nrow(Cannabis), ncol =
length(mydata))

# ---- Likelihood Matrix ----

# We create a matrix of likelihood (refered to as "evidence" in
the text) for each evidence.

# Frequency of cannabis use by other members of our group.
likelihoodF <- matrix(0, nrow = 41, ncol = 41)
colnames(likelihoodF) <- c("0.0", "0.1", "0.2", "0.3", "0.4",
"0.5", "0.6", "0.7", "0.8", "0.9", "1.0", "1.1", "1.2", "1.3",
"1.4", "1.5", "1.6", "1.7", "1.8", "1.9", "2.0", "2.1", "2.2",
"2.3", "2.4", "2.5", "2.6", "2.7", "2.8", "2.9", "3.0", "3.1",
"3.2", "3.3", "3.4", "3.5", "3.6", "3.7", "3.8", "3.9", "4.0")
rownames(likelihoodF) <- c("0.0", "0.1", "0.2", "0.3", "0.4",
"0.5", "0.6", "0.7", "0.8", "0.9", "1.0", "1.1", "1.2", "1.3",
"1.4", "1.5", "1.6", "1.7", "1.8", "1.9", "2.0", "2.1", "2.2",
"2.3", "2.4", "2.5", "2.6", "2.7", "2.8", "2.9", "3.0", "3.1",
"3.2", "3.3", "3.4", "3.5", "3.6", "3.7", "3.8", "3.9", "4.0")
for (i in 1:nrow(likelihoodF)){
  x <- rownames(likelihoodF)[i]
  x <- as.numeric(x) # scores de perception
  fx <- (aF * x) # scores de perception moyen pour chaque score
de schÃ©mas.
  sd <- sdlikelihood # on impose une variance, une distribution
d'incertitude, autour de la moyenne de perception
  y <- seq(0,4,0.1)
  likelihoodF[i,] <- dnorm(y, fx, sd, log = FALSE)
  i <- i + 1
}

colsum <- colSums(likelihoodF)
for (i in 1:ncol(likelihoodF)){
  likelihoodF[,i] <- likelihoodF[,i]/colsum[i]
  i <- i + 1
}

# Valence of cannabis legalization
likelihoodV <- matrix(0, nrow = 41, ncol = 41)
colnames(likelihoodV) <- c("0.0", "0.1", "0.2", "0.3", "0.4",
"0.5", "0.6", "0.7", "0.8", "0.9", "1.0", "1.1", "1.2", "1.3",
"1.4", "1.5", "1.6", "1.7", "1.8", "1.9", "2.0", "2.1", "2.2",
"2.3", "2.4", "2.5", "2.6", "2.7", "2.8", "2.9", "3.0", "3.1",
"3.2", "3.3", "3.4", "3.5", "3.6", "3.7", "3.8", "3.9", "4.0")
rownames(likelihoodV) <- c("0.0", "0.1", "0.2", "0.3", "0.4",
"0.5", "0.6", "0.7", "0.8", "0.9", "1.0", "1.1", "1.2", "1.3",
"1.4", "1.5", "1.6", "1.7", "1.8", "1.9", "2.0", "2.1", "2.2",
"2.3", "2.4", "2.5", "2.6", "2.7", "2.8", "2.9", "3.0", "3.1",
"3.2", "3.3", "3.4", "3.5", "3.6", "3.7", "3.8", "3.9", "4.0")
```

```
for (i in 1:nrow(likelihoodV)){
  x <- rownames(likelihoodV)[i]
  x <- as.numeric(x) # scores de perception
  fx <- (aV * x) # scores de perception moyen pour chaque score
de schÃ©mas.
  sd <- sdlikelihood # on impose une variance, une distribution
d'incertitude, autour de la moyenne de perception
  y <- seq(0,4,0.1)
  likelihoodV[i,] <- dnorm(y, fx, sd, log = FALSE)
  i <- i + 1
}

colsum <- colSums(likelihoodV)
for (i in 1:ncol(likelihoodV)){
  likelihoodV[,i] <- likelihoodV[,i]/colsum[i]
  i <- i + 1
}

# Need for security
likelihoodS <- matrix(0, nrow = 41, ncol = 41)
colnames(likelihoodS) <- c("0.0", "0.1", "0.2", "0.3", "0.4",
"0.5", "0.6", "0.7", "0.8", "0.9", "1.0", "1.1", "1.2", "1.3",
"1.4", "1.5", "1.6", "1.7", "1.8", "1.9", "2.0", "2.1", "2.2",
"2.3", "2.4", "2.5", "2.6", "2.7", "2.8", "2.9", "3.0", "3.1",
"3.2", "3.3", "3.4", "3.5", "3.6", "3.7", "3.8", "3.9", "4.0")
rownames(likelihoodS) <- c("0.0", "0.1", "0.2", "0.3", "0.4",
"0.5", "0.6", "0.7", "0.8", "0.9", "1.0", "1.1", "1.2", "1.3",
"1.4", "1.5", "1.6", "1.7", "1.8", "1.9", "2.0", "2.1", "2.2",
"2.3", "2.4", "2.5", "2.6", "2.7", "2.8", "2.9", "3.0", "3.1",
"3.2", "3.3", "3.4", "3.5", "3.6", "3.7", "3.8", "3.9", "4.0")
for (i in 1:nrow(likelihoodS)){
  x <- rownames(likelihoodS)[i]
  x <- as.numeric(x) # scores de perception
  fx <- (aS * x) # scores de perception moyen pour chaque score
de schÃ©mas.
  sd <- sdlikelihood # on impose une variance, une distribution
d'incertitude, autour de la moyenne de perception
  y <- seq(0,4,0.1)
  likelihoodS[i,] <- dnorm(y, fx, sd, log = FALSE)
  i <- i + 1
}

colsum <- colSums(likelihoodS)
for (i in 1:ncol(likelihoodS)){
  likelihoodS[,i] <- likelihoodS[,i]/colsum[i]
  i <- i + 1
}

# Action
likelihoodA <- matrix(0, nrow = 41, ncol = 41)
colnames(likelihoodA) <- c("0.0", "0.1", "0.2", "0.3", "0.4",
"0.5", "0.6", "0.7", "0.8", "0.9", "1.0", "1.1", "1.2", "1.3",
```

```
"1.4", "1.5", "1.6", "1.7", "1.8", "1.9", "2.0", "2.1", "2.2",
"2.3", "2.4", "2.5", "2.6", "2.7", "2.8", "2.9", "3.0", "3.1",
"3.2", "3.3", "3.4", "3.5", "3.6", "3.7", "3.8", "3.9", "4.0")
rownames(likelihoodA) <- c("0.0", "0.1", "0.2", "0.3", "0.4",
"0.5", "0.6", "0.7", "0.8", "0.9", "1.0", "1.1", "1.2", "1.3",
"1.4", "1.5", "1.6", "1.7", "1.8", "1.9", "2.0", "2.1", "2.2",
"2.3", "2.4", "2.5", "2.6", "2.7", "2.8", "2.9", "3.0", "3.1",
"3.2", "3.3", "3.4", "3.5", "3.6", "3.7", "3.8", "3.9", "4.0")
for (i in 1:nrow(likelihoodA)){
  x <- rownames(likelihoodA)[i]
  x <- as.numeric(x) # scores de perception
  fx <- (aA * x) # scores de perception moyen pour chaque score
de schÃ©mas.
  sd <- sdlikelihood # on impose une variance, une distribution
d'incertitude, autour de la moyenne de perception
  y <- seq(0,4,0.1)
  likelihoodA[i,] <- dnorm(y, fx, sd, log = FALSE)
  i <- i + 1
}

colsum <- colSums(likelihoodA)
for (i in 1:ncol(likelihoodA)){
  likelihoodA[,i] <- likelihoodA[,i]/colsum[i]
  i <- i + 1
}

# Age with the structure of likelihood of frequency of cannabis
use by others.
# If you look at the formula fx, you see that the slope (aF) is
equal to one use with likelihood of frequency of cannabis use by
others
likelihoodAGE1 <- matrix(0, nrow = 92, ncol = 41)
colnames(likelihoodAGE1) <- c("0.0", "0.1", "0.2", "0.3", "0.4",
"0.5", "0.6", "0.7", "0.8", "0.9", "1.0", "1.1", "1.2", "1.3",
"1.4", "1.5", "1.6", "1.7", "1.8", "1.9", "2.0", "2.1", "2.2",
"2.3", "2.4", "2.5", "2.6", "2.7", "2.8", "2.9", "3.0", "3.1",
"3.2", "3.3", "3.4", "3.5", "3.6", "3.7", "3.8", "3.9", "4.0")
rownames(likelihoodAGE1) <- 1:92
for (i in 1:nrow(likelihoodAGE1)){
  x <- rownames(likelihoodAGE1)[i]
  x <- as.numeric(x) # scores de perception
  fx <- (aF * x) # scores de perception moyen pour chaque score
de schÃ©mas.
  sd <- sdlikelihood # on impose une variance, une distribution
d'incertitude, autour de la moyenne de perception
  y <- seq(0,4,0.1)
  likelihoodAGE1[i,] <- dnorm(y, fx, sd, log = FALSE)
  i <- i + 1
}

colsum <- colSums(likelihoodAGE1)
for (i in 1:ncol(likelihoodAGE1)){
```

```
  likelihoodAGE1[,i] <- likelihoodAGE1[,i]/colsum[i]
  i <- i + 1
}

# Age with the structure of likelihood of valence of cannabis
legalization.
likelihoodAGE2 <- matrix(0, nrow = 92, ncol = 41)
colnames(likelihoodAGE2) <- c("0.0", "0.1", "0.2", "0.3", "0.4",
"0.5", "0.6", "0.7", "0.8", "0.9", "1.0", "1.1", "1.2", "1.3",
"1.4", "1.5", "1.6", "1.7", "1.8", "1.9", "2.0", "2.1", "2.2",
"2.3", "2.4", "2.5", "2.6", "2.7", "2.8", "2.9", "3.0", "3.1",
"3.2", "3.3", "3.4", "3.5", "3.6", "3.7", "3.8", "3.9", "4.0")
rownames(likelihoodAGE2) <- 1:92
for (i in 1:nrow(likelihoodAGE2)){
  x <- rownames(likelihoodAGE2)[i]
  x <- as.numeric(x) # scores de perception
  fx <- (aV * x) # scores de perception moyen pour chaque score
de schÃ©mas.
  sd <- sdlikelihood # on impose une variance, une distribution
d'incertitude, autour de la moyenne de perception
  y <- seq(0,4,0.1)
  likelihoodAGE2[i,] <- dnorm(y, fx, sd, log = FALSE)
  i <- i + 1
}

colsum <- colSums(likelihoodAGE2)
for (i in 1:ncol(likelihoodAGE2)){
  likelihoodAGE2[,i] <- likelihoodAGE2[,i]/colsum[i]
  i <- i + 1
}

# Age with the structure of likelihood of need for security.
likelihoodAGE3 <- matrix(0, nrow = 92, ncol = 41)
colnames(likelihoodAGE3) <- c("0.0", "0.1", "0.2", "0.3", "0.4",
"0.5", "0.6", "0.7", "0.8", "0.9", "1.0", "1.1", "1.2", "1.3",
"1.4", "1.5", "1.6", "1.7", "1.8", "1.9", "2.0", "2.1", "2.2",
"2.3", "2.4", "2.5", "2.6", "2.7", "2.8", "2.9", "3.0", "3.1",
"3.2", "3.3", "3.4", "3.5", "3.6", "3.7", "3.8", "3.9", "4.0")
rownames(likelihoodAGE3) <- 1:92
for (i in 1:nrow(likelihoodAGE3)){
  x <- rownames(likelihoodAGE3)[i]
  x <- as.numeric(x) # scores de perception
  fx <- (aS * x) # scores de perception moyen pour chaque score
de schÃ©mas.
  sd <- sdlikelihood # on impose une variance, une distribution
d'incertitude, autour de la moyenne de perception
  y <- seq(0,4,0.1)
  likelihoodAGE3[i,] <- dnorm(y, fx, sd, log = FALSE)
  i <- i + 1
}

colsum <- colSums(likelihoodAGE3)
```

```
for (i in 1:ncol(likelihoodAGE3)){
  likelihoodAGE3[,i] <- likelihoodAGE3[,i]/colsum[i]
  i <- i + 1
}

# Age with the structure of likelihood of action.
likelihoodAGE4 <- matrix(0, nrow = 92, ncol = 41)
colnames(likelihoodAGE4) <- c("0.0", "0.1", "0.2", "0.3", "0.4",
"0.5", "0.6", "0.7", "0.8", "0.9", "1.0", "1.1", "1.2", "1.3",
"1.4", "1.5", "1.6", "1.7", "1.8", "1.9", "2.0", "2.1", "2.2",
"2.3", "2.4", "2.5", "2.6", "2.7", "2.8", "2.9", "3.0", "3.1",
"3.2", "3.3", "3.4", "3.5", "3.6", "3.7", "3.8", "3.9", "4.0")
rownames(likelihoodAGE4) <- 1:92
for (i in 1:nrow(likelihoodAGE4)){
  x <- rownames(likelihoodAGE4)[i]
  x <- as.numeric(x) # scores de perception
  fx <- (aA * x) # scores de perception moyen pour chaque score
de schÃ©mas.
  sd <- sdlikelihood # on impose une variance, une distribution
d'incertitude, autour de la moyenne de perception
  y <- seq(0,4,0.1)
  likelihoodAGE4[i,] <- dnorm(y, fx, sd, log = FALSE)
  i <- i + 1
}

colsum <- colSums(likelihoodAGE4)
for (i in 1:ncol(likelihoodAGE4)){
  likelihoodAGE4[,i] <- likelihoodAGE4[,i]/colsum[i]
  i <- i + 1
}

# ---- BMII Frequence ----

for (ii in 1:length(mydata)){

  mat <- matrix(mydata[[ii]][,c("respid", "Iden_1", "Iden_2",
"Iden_3", "GFrequency", "GFrequencyT2", "GFrequencyT3")], nrow =
nrow(mydata[[ii]]), ncol = 7)

  Post <- matrix(NA, ncol = 41, nrow = nrow(mat))
  colnames(Post) <- c("0.0", "0.1", "0.2", "0.3", "0.4", "0.5",
"0.6", "0.7", "0.8", "0.9", "1.0", "1.1", "1.2", "1.3", "1.4",
"1.5", "1.6", "1.7", "1.8", "1.9", "2.0", "2.1", "2.2", "2.3",
"2.4", "2.5", "2.6", "2.7", "2.8", "2.9", "3.0", "3.1", "3.2",
"3.3", "3.4", "3.5", "3.6", "3.7", "3.8", "3.9", "4.0")
  for (i in 1:nrow(mat)){
    # Prior
    mean <- mean(mat[i,c(2,3,4)])
    mean <- ifelse(is.na(mean) > 0, 0, mean)
    sd <- sd(mat[i,c(2,3,4)])
    sd <- sd + sdprior
    y <- seq(0,4,0.1)
```

```
    prior <- dnorm(y, mean, sd, log = FALSE)
    # Likelihood 1
    n <- mat[i,6] * 10 + 1
    prior2 <- prior * likelihoodF[n,]
    # Likelihood 2
    n2 <- mat[i,7] * 10 + 1
    Post[i,] <- prior2 * likelihoodF[n2,]
    # Posterior
    Sum <- sum(Post[i,])
    Post[i,] <- Post[i,] / Sum
    i <- i + 1
  }

  column <- 0.0
  for (i in 1:ncol(Post)){
    Post[,i] <- Post[,i]*column
    column <- column + 0.1
    i <- i + 1
  }


  for (i in 1:nrow(Post)){
    PredictionM1[i,ii] <- cbind(sum(Post[i,]))
    i <- i + 1
  }

  ii <- ii + 1

}

for (i in 1:length(mydata)){
  mydata[[i]] <- cbind(mydata[[i]], PredictionM1[,i])
  i <- i + 1
}

# ---- BMII Valence ----

for (ii in 1:length(mydata)){

  mat <- matrix(mydata[[ii]][,c("respid", "Iden_1", "Iden_2",
"Iden_3", "Valence", "ValenceT2", "ValenceT3")], nrow =
nrow(mydata[[ii]]), ncol = 7)

  Post <- matrix(NA, ncol = 41, nrow = nrow(mat))
  colnames(Post) <- c("0.0", "0.1", "0.2", "0.3", "0.4", "0.5",
"0.6", "0.7", "0.8", "0.9", "1.0", "1.1", "1.2", "1.3", "1.4",
"1.5", "1.6", "1.7", "1.8", "1.9", "2.0", "2.1", "2.2", "2.3",
"2.4", "2.5", "2.6", "2.7", "2.8", "2.9", "3.0", "3.1", "3.2",
"3.3", "3.4", "3.5", "3.6", "3.7", "3.8", "3.9", "4.0")
  for (i in 1:nrow(mat)){
    # Prior
    mean <- mean(mat[i,c(2,3,4)])
```

```
    mean <- ifelse(is.na(mean) > 0, 0, mean)
    sd <- sd(mat[i,c(2,3,4)])
    sd <- sd + sdprior
    y <- seq(0,4,0.1)
    prior <- dnorm(y, mean, sd, log = FALSE)
    # Likelihood 1
    n <- mat[i,6] * 10 + 1
    prior2 <- prior * likelihoodV[n,]
    # Likelihood 2
    n2 <- mat[i,7] * 10 + 1
    Post[i,] <- prior2 * likelihoodV[n2,]
    # Posterior
    Sum <- sum(Post[i,])
    Post[i,] <- Post[i,] / Sum
    i <- i + 1
  }

  column <- 0.0
  for (i in 1:ncol(Post)){
    Post[,i] <- Post[,i]*column
    column <- column + 0.1
    i <- i + 1
  }


  for (i in 1:nrow(Post)){
    PredictionM2[i,ii] <- cbind(sum(Post[i,]))
    i <- i + 1
  }

  ii <- ii + 1

}

for (i in 1:length(mydata)){
  mydata[[i]] <- cbind(mydata[[i]], PredictionM2[,i])
  i <- i + 1
}

# ---- BMII Safety ----


for (ii in 1:length(mydata)){

  mat <- matrix(mydata[[ii]][,c("respid", "Iden_1", "Iden_2",
"Iden_3", "SafetyT2", "SafetyT3")], nrow = nrow(mydata[[ii]]),
ncol = 7)

  Post <- matrix(NA, ncol = 41, nrow = nrow(mat))
  colnames(Post) <- c("0.0", "0.1", "0.2", "0.3", "0.4", "0.5",
"0.6", "0.7", "0.8", "0.9", "1.0", "1.1", "1.2", "1.3", "1.4",
"1.5", "1.6", "1.7", "1.8", "1.9", "2.0", "2.1", "2.2", "2.3",
```

```
"2.4", "2.5", "2.6", "2.7", "2.8", "2.9", "3.0", "3.1", "3.2",
"3.3", "3.4", "3.5", "3.6", "3.7", "3.8", "3.9", "4.0")
  for (i in 1:nrow(mat)){
    # Prior
    mean <- mean(mat[i,c(2,3,4)])
    mean <- ifelse(is.na(mean) > 0, 0, mean)
    sd <- sd(mat[i,c(2,3,4)])
    sd <- sd + sdprior
    y <- seq(0,4,0.1)
    prior <- dnorm(y, mean, sd, log = FALSE)
    # Likelihood 1
    n <- round(mat[i,5],1) * 10 + 1
    prior2 <- prior * likelihoodS[n,]
    # Likelihood 2
    n2 <- round(mat[i,6],1) * 10 + 1
    Post[i,] <- prior2 * likelihoodS[n2,]
    # Posterior
    Sum <- sum(Post[i,])
    Post[i,] <- Post[i,] / Sum
    i <- i + 1
  }

  column <- 0.0
  for (i in 1:ncol(Post)){
    Post[,i] <- Post[,i]*column
    column <- column + 0.1
    i <- i + 1
  }


  for (i in 1:nrow(Post)){
    PredictionM3[i,ii] <- cbind(sum(Post[i,]))
    i <- i + 1
  }

  ii <- ii + 1

}

for (i in 1:length(mydata)){
  mydata[[i]] <- cbind(mydata[[i]], PredictionM3[,i])
  i <- i + 1
}

# ---- BMII Action ----

for (ii in 1:length(mydata)){

  mat <- matrix(mydata[[ii]][,c("respid", "Iden_1", "Iden_2",
"Iden_3", "SuiviPot", "SuiviPotT2", "SuiviPotT3")], nrow =
nrow(mydata[[ii]]), ncol = 7)
```

```
  Post <- matrix(NA, ncol = 41, nrow = nrow(mat))
  colnames(Post) <- c("0.0", "0.1", "0.2", "0.3", "0.4", "0.5",
"0.6", "0.7", "0.8", "0.9", "1.0", "1.1", "1.2", "1.3", "1.4",
"1.5", "1.6", "1.7", "1.8", "1.9", "2.0", "2.1", "2.2", "2.3",
"2.4", "2.5", "2.6", "2.7", "2.8", "2.9", "3.0", "3.1", "3.2",
"3.3", "3.4", "3.5", "3.6", "3.7", "3.8", "3.9", "4.0")
  for (i in 1:nrow(mat)){
    # Prior
    mean <- mean(mat[i,c(2,3,4)])
    mean <- ifelse(is.na(mean) > 0, 0, mean)
    sd <- sd(mat[i,c(2,3,4)])
    sd <- sd + sdprior
    y <- seq(0,4,0.1)
    prior <- dnorm(y, mean, sd, log = FALSE)
    # Likelihood 1
    n <- mat[i,6] * 10 + 1
    prior2 <- prior * likelihoodA[n,]
    # Likelihood 2
    n2 <- mat[i,7] * 10 + 1
    Post[i,] <- prior2 * likelihoodA[n2,]
    # Posterior
    Sum <- sum(Post[i,])
    Post[i,] <- Post[i,] / Sum
    i <- i + 1
  }

  column <- 0.0
  for (i in 1:ncol(Post)){
    Post[,i] <- Post[,i]*column
    column <- column + 0.1
    i <- i + 1
  }


  for (i in 1:nrow(Post)){
    PredictionM4[i,ii] <- cbind(sum(Post[i,]))
    i <- i + 1
  }

  ii <- ii + 1

}

for (i in 1:length(mydata)){
  mydata[[i]] <- cbind(mydata[[i]], PredictionM4[,i])
  i <- i + 1
}

# ---- BMII AGE-Frequency ----

for (ii in 1:length(mydata)){
```

```
  mat <- matrix(mydata[[ii]][,c("respid", "Iden_1", "Iden_2",
"Iden_3", "Age", "AgeT2", "AgeT3")], nrow = nrow(mydata[[ii]]),
ncol = 7)

  Post <- matrix(NA, ncol = 41, nrow = nrow(mat))
  colnames(Post) <- c("0.0", "0.1", "0.2", "0.3", "0.4", "0.5",
"0.6", "0.7", "0.8", "0.9", "1.0", "1.1", "1.2", "1.3", "1.4",
"1.5", "1.6", "1.7", "1.8", "1.9", "2.0", "2.1", "2.2", "2.3",
"2.4", "2.5", "2.6", "2.7", "2.8", "2.9", "3.0", "3.1", "3.2",
"3.3", "3.4", "3.5", "3.6", "3.7", "3.8", "3.9", "4.0")
  for (i in 1:nrow(mat)){
    # Prior
    mean <- mean(mat[i,c(2,3,4)])
    mean <- ifelse(is.na(mean) > 0, 0, mean)
    sd <- sd(mat[i,c(2,3,4)])
    sd <- sd + sdprior
    y <- seq(0,4,0.1)
    prior <- dnorm(y, mean, sd, log = FALSE)
    # Likelihood 1
    n <- mat[i,6]
    prior2 <- prior * likelihoodAGE1[n,]
    # Likelihood 2
    n2 <- mat[i,7]
    Post[i,] <- prior2 * likelihoodAGE1[n2,]
    # Posterior
    Sum <- sum(Post[i,])
    Post[i,] <- Post[i,] / Sum
    i <- i + 1
  }

  column <- 0.0
  for (i in 1:ncol(Post)){
    Post[,i] <- Post[,i]*column
    column <- column + 0.1
    i <- i + 1
  }


  for (i in 1:nrow(Post)){
    PredictionM1a[i,ii] <- cbind(sum(Post[i,]))
    i <- i + 1
  }

  ii <- ii + 1

}

for (i in 1:length(mydata)){
  mydata[[i]] <- cbind(mydata[[i]], PredictionM1a[,i])
  i <- i + 1
}
```

```
# ---- BMII AGE-Valence ----

for (ii in 1:length(mydata)){

  mat <- matrix(mydata[[ii]][,c("respid", "Iden_1", "Iden_2",
"Iden_3", "Age", "AgeT2", "AgeT3")], nrow = nrow(mydata[[ii]]),
ncol = 7)

  Post <- matrix(NA, ncol = 41, nrow = nrow(mat))
  colnames(Post) <- c("0.0", "0.1", "0.2", "0.3", "0.4", "0.5",
"0.6", "0.7", "0.8", "0.9", "1.0", "1.1", "1.2", "1.3", "1.4",
"1.5", "1.6", "1.7", "1.8", "1.9", "2.0", "2.1", "2.2", "2.3",
"2.4", "2.5", "2.6", "2.7", "2.8", "2.9", "3.0", "3.1", "3.2",
"3.3", "3.4", "3.5", "3.6", "3.7", "3.8", "3.9", "4.0")
  for (i in 1:nrow(mat)){
    # Prior
    mean <- mean(mat[i,c(2,3,4)])
    mean <- ifelse(is.na(mean) > 0, 0, mean)
    sd <- sd(mat[i,c(2,3,4)])
    sd <- sd + sdprior
    y <- seq(0,4,0.1)
    prior <- dnorm(y, mean, sd, log = FALSE)
    # Likelihood 1
    n <- mat[i,6]
    prior2 <- prior * likelihoodAGE2[n,]
    # Likelihood 2
    n2 <- mat[i,7]
    Post[i,] <- prior2 * likelihoodAGE2[n2,]
    # Posterior
    Sum <- sum(Post[i,])
    Post[i,] <- Post[i,] / Sum
    i <- i + 1
  }

  column <- 0.0
  for (i in 1:ncol(Post)){
    Post[,i] <- Post[,i]*column
    column <- column + 0.1
    i <- i + 1
  }


  for (i in 1:nrow(Post)){
    PredictionM2a[i,ii] <- cbind(sum(Post[i,]))
    i <- i + 1
  }

  ii <- ii + 1

}

for (i in 1:length(mydata)){
```

```
  mydata[[i]] <- cbind(mydata[[i]], PredictionM2a[,i])
  i <- i + 1
}

# ---- BMII AGE-Safety ----

for (ii in 1:length(mydata)){

  mat <- matrix(mydata[[ii]][,c("respid", "Iden_1", "Iden_2",
"Iden_3", "Age", "AgeT2", "AgeT3")], nrow = nrow(mydata[[ii]]),
ncol = 7)

  Post <- matrix(NA, ncol = 41, nrow = nrow(mat))
  colnames(Post) <- c("0.0", "0.1", "0.2", "0.3", "0.4", "0.5",
"0.6", "0.7", "0.8", "0.9", "1.0", "1.1", "1.2", "1.3", "1.4",
"1.5", "1.6", "1.7", "1.8", "1.9", "2.0", "2.1", "2.2", "2.3",
"2.4", "2.5", "2.6", "2.7", "2.8", "2.9", "3.0", "3.1", "3.2",
"3.3", "3.4", "3.5", "3.6", "3.7", "3.8", "3.9", "4.0")
  for (i in 1:nrow(mat)){
    # Prior
    mean <- mean(mat[i,c(2,3,4)])
    mean <- ifelse(is.na(mean) > 0, 0, mean)
    sd <- sd(mat[i,c(2,3,4)])
    sd <- sd + sdprior
    y <- seq(0,4,0.1)
    prior <- dnorm(y, mean, sd, log = FALSE)
    # Likelihood 1
    n <- mat[i,6]
    prior2 <- prior * likelihoodAGE3[n,]
    # Likelihood 2
    n2 <- mat[i,7]
    Post[i,] <- prior2 * likelihoodAGE3[n2,]
    # Posterior
    Sum <- sum(Post[i,])
    Post[i,] <- Post[i,] / Sum
    i <- i + 1
  }

  column <- 0.0
  for (i in 1:ncol(Post)){
    Post[,i] <- Post[,i]*column
    column <- column + 0.1
    i <- i + 1
  }


  for (i in 1:nrow(Post)){
    PredictionM3a[i,ii] <- cbind(sum(Post[i,]))
    i <- i + 1
  }

  ii <- ii + 1
```

```
}

for (i in 1:length(mydata)){
  mydata[[i]] <- cbind(mydata[[i]], PredictionM3a[,i])
  i <- i + 1
}

# ---- BMII AGE-Action ----

for (ii in 1:length(mydata)){

  mat <- matrix(mydata[[ii]][,c("respid", "Iden_1", "Iden_2",
"Iden_3", "Age", "AgeT2", "AgeT3")], nrow = nrow(mydata[[ii]]),
ncol = 7)

  Post <- matrix(NA, ncol = 41, nrow = nrow(mat))
  colnames(Post) <- c("0.0", "0.1", "0.2", "0.3", "0.4", "0.5",
"0.6", "0.7", "0.8", "0.9", "1.0", "1.1", "1.2", "1.3", "1.4",
"1.5", "1.6", "1.7", "1.8", "1.9", "2.0", "2.1", "2.2", "2.3",
"2.4", "2.5", "2.6", "2.7", "2.8", "2.9", "3.0", "3.1", "3.2",
"3.3", "3.4", "3.5", "3.6", "3.7", "3.8", "3.9", "4.0")
  for (i in 1:nrow(mat)){
    # Prior
    mean <- mean(mat[i,c(2,3,4)])
    mean <- ifelse(is.na(mean) > 0, 0, mean)
    sd <- sd(mat[i,c(2,3,4)])
    sd <- sd + sdprior
    y <- seq(0,4,0.1)
    prior <- dnorm(y, mean, sd, log = FALSE)
    # Likelihood 1
    n <- mat[i,6]
    prior2 <- prior * likelihoodAGE4[n,]
    # Likelihood 2
    n2 <- mat[i,7]
    Post[i,] <- prior2 * likelihoodAGE4[n2,]
    # Posterior
    Sum <- sum(Post[i,])
    Post[i,] <- Post[i,] / Sum
    i <- i + 1
  }

  column <- 0.0
  for (i in 1:ncol(Post)){
    Post[,i] <- Post[,i]*column
    column <- column + 0.1
    i <- i + 1
  }


  for (i in 1:nrow(Post)){
    PredictionM4a[i,ii] <- cbind(sum(Post[i,]))
```

```
    i <- i + 1
  }

  ii <- ii + 1

}

# ---- Combination of prediction ----

for (i in 1:length(mydata)){
  mydata[[i]] <- cbind(mydata[[i]], PredictionM4a[,i])
  i <- i + 1
}


for (i in 1:length(mydata)){
  colnames(mydata[[i]]) <- c("respid",
                              "Int_2", "IntT2_2", "IntT3_2",
                              "Int_3", "IntT2_3", "IntT3_3",
                              "Int_4", "IntT2_4", "IntT3_4",
                              "GInt_2", "GIntT2_2", "GIntT3_2",
                              "GInt_3", "GIntT2_3", "GIntT3_3",
                              "GInt_4", "GIntT2_4", "GIntT3_4",
                              "Iden_1", "IdenT2_1", "IdenT3_1",
                              "Iden_2", "IdenT2_2", "IdenT3_2",
                              "Iden_3", "IdenT2_3", "IdenT3_3",
                              "CatT1", "CatT2", "CatT3",
                              "CompT1_1", "CompT2_1", "CompT3_1",
                              "CompT1_2", "CompT2_2", "CompT3_2",
                              "GCatT1", "GCatT2", "GCatT3",
                              "GCompT1_1", "GCompT2_1",
"GCompT3_1",
                              "GCompT1_2", "GCompT2_2",
"GCompT3_2",
                              "GFrequency", "GFrequencyT2",
"GFrequencyT3",
                              "Valence", "ValenceT2", "ValenceT3",
                              "Safety_1", "SafetyT2_1",
"SafetyT3_1",
                              "Safety_2", "SafetyT2_2",
"SafetyT3_2",
                              "Safety_3", "SafetyT2_3",
"SafetyT3_3",
                              "SuiviPot", "SuiviPotT2",
"SuiviPotT3",
                              "IntT3", "GIntT3", "IdenT3",
"GCompT3",
                              "Age", "AgeT2", "AgeT3",
                              "SafetyT2", "SafetyT3",
                              "PredictionM1", "PredictionM2",
"PredictionM3", "PredictionM4",
```

```
                             "PredictionM1a", "PredictionM2a",
"PredictionM3a", "PredictionM4a")

  i <- i + 1
}

# ---- Results ----

# Conversion of a list object into a mice object.
a.mids <- miceadds::datlist2mids(mydata)

fitM1 <- with(data = a.mids, exp = lm(scale(IdenT3) ~
scale(PredictionM1)))
MeanM1 <- summary(pool(fitM1))$estimate[2] # Mean SD
SDM1 <- summary(pool(fitM1))$std.error[2] # Pooled SD

fitM2 <- with(data = a.mids, exp = lm(scale(IdenT3) ~
scale(PredictionM2)))
MeanM2 <- summary(pool(fitM2))$estimate[2] # Mean SD
SDM2 <- summary(pool(fitM2))$std.error[2] # Pooled SD

fitM3 <- with(data = a.mids, exp = lm(scale(IdenT3) ~
scale(PredictionM3)))
MeanM3 <- summary(pool(fitM3))$estimate[2] # Mean SD
SDM3 <- summary(pool(fitM3))$std.error[2] # Pooled SD

fitM4 <- with(data = a.mids, exp = lm(scale(IdenT3) ~
scale(PredictionM4)))
MeanM4 <- summary(pool(fitM4))$estimate[2] # Mean SD
SDM4 <- summary(pool(fitM4))$std.error[2] # Pooled SD

fitM5 <- with(data = a.mids, exp = lm(scale(IdenT3) ~
scale(PredictionM1a)))
MeanM5 <- summary(pool(fitM5))$estimate[2] # Mean SD
SDM5 <- summary(pool(fitM5))$std.error[2] # Pooled SD

fitM6 <- with(data = a.mids, exp = lm(scale(IdenT3) ~
scale(PredictionM2a)))
MeanM6 <- summary(pool(fitM6))$estimate[2] # Mean SD
SDM6 <- summary(pool(fitM6))$std.error[2] # Pooled SD

fitM7 <- with(data = a.mids, exp = lm(scale(IdenT3) ~
scale(PredictionM3a)))
MeanM7 <- summary(pool(fitM7))$estimate[2] # Mean SD
SDM7 <- summary(pool(fitM7))$std.error[2] # Pooled SD

fitM8 <- with(data = a.mids, exp = lm(scale(IdenT3) ~
scale(PredictionM4a)))
MeanM8 <- summary(pool(fitM8))$estimate[2] # Mean SD
SDM8 <- summary(pool(fitM8))$std.error[2] # Pooled SD
```

```
fit2 <- with(data = a.mids, exp = lm(scale(IdenT3) ~
scale(Cannabis$IdenT1)))
Mean <- summary(pool(fit2))$estimate[2] # Mean SD
SD <- summary(pool(fit2))$std.error[2] # Pooled SD

# Matrix for the Figure
boxLabels = c("Frequence", "Valence", "Safety", "Action",
              "Age-Frequency", "Age-Valence", "Age-Safety", "Age-
Action",
              "Identification time 1")
allo <- data.frame(yAxis = length(boxLabels):1,
                   boxOdds = c(MeanM1,
                               MeanM2,
                               MeanM3,
                               MeanM4,
                               MeanM5,
                               MeanM6,
                               MeanM7,
                               MeanM8,
                               Mean),
                   boxCILow = c(MeanM1 - (2.01 * SDM1),
                                MeanM2 - (2.01 * SDM2),
                                MeanM3 - (2.01 * SDM3),
                                MeanM4 - (2.01 * SDM4),
                                MeanM5 - (2.01 * SDM5),
                                MeanM6 - (2.01 * SDM6),
                                MeanM7 - (2.01 * SDM7),
                                MeanM8 - (2.01 * SDM8),
                                Mean - (2.01 * SD)),
                   boxCIHigh = c(MeanM1 + (2.01 * SDM1),
                                 MeanM2 + (2.01 * SDM2),
                                 MeanM3 + (2.01 * SDM3),
                                 MeanM4 + (2.01 * SDM4),
                                 MeanM5 + (2.01 * SDM5),
                                 MeanM6 + (2.01 * SDM6),
                                 MeanM7 + (2.01 * SDM7),
                                 MeanM8 + (2.01 * SDM8),
                                 Mean + (2.01 * SD))
)
# Figure
ggplot(allo, aes(x = boxOdds, y = reorder(boxLabels, yAxis))) +
    geom_errorbarh(aes(xmax = boxCIHigh, xmin = boxCILow), size =
.2, height =
                     .1, color = "black") +
    geom_point(size = 3.5, color = "black") +
    scale_x_continuous(limits = c(min(allo$boxCILow) - .20,
max(allo$boxCIHigh) + .20)) +
    theme_bw()+
    theme(panel.grid.minor = element_blank(),
          text = element_text(size = 25)) +
    ylab("") +
    xlab("Standardized regression values")
```

# Annexe C : Script R pour les états d'intégrations identitaires et la fréquence de consommations par les autres membres du groupe (article 2)

```
# ----  Packages ----

library(haven)
library(Amelia)
library(reshape2)
library(dplyr)
library(ggplot2)
library(na.tools)
library(psych)
library(mice)

# ---- Data ----

df <- read_sav("D:/Cannabis/R/CannabisNew/CannabisMergedAll.sav")

set.seed(10802020)

# ---- Matrix of Variables ----

Cannabis <- df[ ,c("respid", "Int_2", "Int_3", "Int_4",
                   "IntT2_2", "IntT2_3", "IntT2_4",
                   "IntT3_2", "IntT3_3", "IntT3_4",
                   "GInt_2", "GInt_3", "GInt_4",
                   "GIntT2_2", "GIntT2_3", "GIntT2_4",
                   "GIntT3_2", "GIntT3_3", "GIntT3_4",
                   "IdentifyPot", "CommonPot", "ImpPot",
                   "IdentifyPotT2", "CommonPotT2", "ImpPotT2",
                   "IdentifyPotT3", "CommonPotT3", "ImpPotT3",
                   "GFrequency", "GFrequencyT2", "GFrequencyT3",
                   "Cat", "CatT2", "CatT3",
                   "Comp_1", "CompT2_1", "CompT3_1",
                   "Comp_2", "CompT2_2", "CompT3_2",
                   "GCat", "GCatT2", "GCatT3",
                   "GComp_1", "GCompT2_1", "GCompT3_1",
                   "GComp_2", "GCompT2_2", "GCOmpT3_2",
                   "Neg_Pos", "Neg_PosT2", "Neg_PosT3",
                   "Safety_1", "SafetyT2_1", "SafetyT3_1",
                   "Safety_2", "SafetyT2_2", "SafetyT3_2",
                   "Safety_3", "SafetyT2_3", "SafetyT3_3",
                   "SuiviPot", "SuiviPotT2", "SuiviPotT3",
                   "Age", "Gender", "Diploma", "Situation",
"life_cond")]

Cannabis$GintT1 <- rowMeans(Cannabis[,c("GInt_2", "GInt_3",
"GInt_4")])
```

```
Cannabis$IdenT1 <- rowMeans(Cannabis[,c("IdentifyPot",
"CommonPot", "ImpPot")])
Cannabis$SafetyT1 <- rowMeans(Cannabis[,c("Safety_1", "Safety_2",
"Safety_3")])
Cannabis$GCompT1 <- rowMeans(Cannabis[,c("GComp_1", "GComp_2")])

Cannabis[,"AgeT2"] <- Cannabis[,"Age"]
Cannabis[,"AgeT3"] <- Cannabis[,"Age"]
Cannabis[,"GenderT2"] <- Cannabis[,"Gender"]
Cannabis[,"GenderT3"] <- Cannabis[,"Gender"]
Cannabis[,"DiplomaT2"] <- Cannabis[,"Diploma"]
Cannabis[,"DiplomaT3"] <- Cannabis[,"Diploma"]
Cannabis[,"SituationT2"] <- Cannabis[,"Situation"]
Cannabis[,"SituationT3"] <- Cannabis[,"Situation"]
Cannabis[,"life_condT2"] <- Cannabis[,"life_cond"]
Cannabis[,"life_condT3"] <- Cannabis[,"life_cond"]

Int_2 <- melt(Cannabis,  id.vars = "respid", measure.vars =
c("Int_2", "IntT2_2", "IntT3_2"))
Int_2 <- Int_2[order(Int_2$respid),]
Int_3 <- melt(Cannabis,  id.vars = "respid", measure.vars =
c("Int_3", "IntT2_3", "IntT3_3"))
Int_3 <- Int_3[order(Int_3$respid),]
Int_4 <- melt(Cannabis,  id.vars = "respid", measure.vars =
c("Int_4", "IntT2_4", "IntT3_4"))
Int_4 <- Int_4[order(Int_4$respid),]

Cat <- melt(Cannabis,  id.vars = "respid", measure.vars =
c("Cat", "CatT2", "CatT3"))
Cat <- Cat[order(Cat$respid),]

Comp_1 <- melt(Cannabis,  id.vars = "respid", measure.vars =
c("Comp_1", "CompT2_1", "CompT3_1"))
Comp_1 <- Comp_1[order(Comp_1$respid),]
Comp_2 <- melt(Cannabis,  id.vars = "respid", measure.vars =
c("Comp_2", "CompT2_2", "CompT3_2"))
Comp_2 <- Comp_2[order(Comp_2$respid),]

GCat <- melt(Cannabis,  id.vars = "respid", measure.vars =
c("GCat", "GCatT2", "GCatT3"))
GCat <- GCat[order(GCat$respid),]

GComp_1 <- melt(Cannabis,  id.vars = "respid", measure.vars =
c("GComp_1", "GCompT2_1", "GCompT3_1"))
GComp_1 <- GComp_1[order(GComp_1$respid),]
GComp_2 <- melt(Cannabis,  id.vars = "respid", measure.vars =
c("GComp_2", "GCompT2_2", "GCOmpT3_2"))
GComp_2 <- GComp_2[order(GComp_2$respid),]

GInt_2 <- melt(Cannabis,  id.vars = "respid", measure.vars =
c("GInt_2", "GIntT2_2", "GIntT3_2"))
GInt_2 <- GInt_2[order(GInt_2$respid),]
```

```
GInt_3 <- melt(Cannabis,  id.vars = "respid", measure.vars =
c("GInt_3", "GIntT2_3", "GIntT3_3"))
GInt_3 <- GInt_3[order(GInt_3$respid),]
GInt_4 <- melt(Cannabis,  id.vars = "respid", measure.vars =
c("GInt_4", "GIntT2_4", "GIntT3_4"))
GInt_4 <- GInt_4[order(GInt_4$respid),]

Iden_1 <- melt(Cannabis,  id.vars = "respid", measure.vars =
c("IdentifyPot", "IdentifyPotT2", "IdentifyPotT3"))
Iden_1 <- Iden_1[order(Iden_1$respid),]
Iden_2 <- melt(Cannabis,  id.vars = "respid", measure.vars =
c("CommonPot", "CommonPotT2", "CommonPotT3"))
Iden_2 <- Iden_2[order(Iden_2$respid),]
Iden_3 <- melt(Cannabis,  id.vars = "respid", measure.vars =
c("ImpPot", "ImpPotT2", "ImpPotT3"))
Iden_3 <- Iden_3[order(Iden_3$respid),]

GFrequency <- melt(Cannabis,  id.vars = "respid", measure.vars =
c("GFrequency", "GFrequencyT2", "GFrequencyT3"))
GFrequency <- GFrequency[order(GFrequency$respid),]

Valence <- melt(Cannabis,  id.vars = "respid", measure.vars =
c("Neg_Pos", "Neg_PosT2", "Neg_PosT3"))
Valence <- Valence[order(Valence$respid),]

Safety_1 <- melt(Cannabis,  id.vars = "respid", measure.vars =
c("Safety_1", "SafetyT2_1", "SafetyT3_1"))
Safety_1 <- Safety_1[order(Safety_1$respid),]
Safety_2 <- melt(Cannabis,  id.vars = "respid", measure.vars =
c("Safety_2", "SafetyT2_2", "SafetyT3_2"))
Safety_2 <- Safety_2[order(Safety_2$respid),]
Safety_3 <- melt(Cannabis,  id.vars = "respid", measure.vars =
c("Safety_3", "SafetyT2_3", "SafetyT3_3"))
Safety_3 <- Safety_3[order(Safety_3$respid),]

SuiviPot <- melt(Cannabis,  id.vars = "respid", measure.vars =
c("SuiviPot", "SuiviPotT2", "SuiviPotT3"))
SuiviPot <- SuiviPot[order(SuiviPot$respid),]

Gender <- melt(Cannabis,  id.vars = "respid", measure.vars =
c("Gender", "GenderT2", "GenderT3"))
Gender <- Gender[order(Gender$respid),]

Diploma <- melt(Cannabis,  id.vars = "respid", measure.vars =
c("Diploma", "DiplomaT2", "DiplomaT3"))
Diploma <- Diploma[order(Diploma$respid),]

life_cond <- melt(Cannabis,  id.vars = "respid", measure.vars =
c("life_cond", "life_condT2", "life_condT3"))
life_cond <- life_cond[order(life_cond$respid),]
```

```
Age <- melt(Cannabis,  id.vars = "respid", measure.vars =
c("Age", "AgeT2", "AgeT3"))
Age <- Age[order(Age$respid),]

Long <- cbind(Int_2[,1], Int_2[,2], Int_2[,3], Int_3[,3],
Int_4[,3],
              GInt_2[,3], GInt_3[,3], GInt_4[,3],
              Iden_1[,3], Iden_2[,3], Iden_3[,3],
              Cat[,3], Comp_1[,3], Comp_2[,3],
              GCat[,3], GComp_1[,3], GComp_2[,3],
              GFrequency[,3], Valence[,3],
              Safety_1[,3], Safety_2[,3], Safety_3[,3],
SuiviPot[,3],
              Gender[,3], Diploma[,3], life_cond[,3], Age[,3])

colnames(Long) <- c("respid", "Temps",
                    "Int_2", "Int_3", "Int_4",
                    "GInt_2", "GInt_3", "GInt_4",
                    "Iden_1", "Iden_2", "Iden_3",
                    "Cat", "Comp_1", "Comp_2",
                    "GCat", "GComp_1", "GComp_2",
                    "GFrequency", "Valence",
                    "Safety_1", "Safety_2", "Safety_3",
"SuiviPot",
                    "Gender", "Diploma", "life_cond", "Age")


# ---- Imputation ----

x <- matrix(1, nrow = 21, ncol = 3)
x[,1] <- c(3:23)
x[,2] <- 0
x[,3] <- 4


amelia_fit <- amelia(Long, m = 50,
                     idvars = "respid", ts = "Temps", polytime =
2,
                     noms = c("Gender", "Diploma", "life_cond"),
                     ords = c("Int_2", "Int_3", "Int_4",
                              "GInt_2", "GInt_3", "GInt_4",
                              "Iden_1", "Iden_2", "Iden_3",
                              "Cat", "Comp_1", "Comp_2",
                              "GCat", "GComp_1", "GComp_2",
                              "GFrequency", "Valence",
                              "Safety_1", "Safety_2", "Safety_3",
"SuiviPot"),
                     incheck = TRUE,
                     bounds = x)

# ---- ** Multiple datasets ----
```

```
a <- amelia_fit$imputations
a <- a[-which_na(amelia_fit$imputations)]

mydata <- list()
for (i in 1:length(a)){

  Int_2I <- matrix(a[[i]][,3], nrow = nrow(Cannabis), ncol = 3,
byrow = TRUE)
  Int_3I <- matrix(a[[i]][,4], nrow = nrow(Cannabis), ncol = 3,
byrow = TRUE)
  Int_4I <- matrix(a[[i]][,5], nrow = nrow(Cannabis), ncol = 3,
byrow = TRUE)

  GInt_2I <- matrix(a[[i]][,6], nrow = nrow(Cannabis), ncol = 3,
byrow = TRUE)
  GInt_3I <- matrix(a[[i]][,7], nrow = nrow(Cannabis), ncol = 3,
byrow = TRUE)
  GInt_4I <- matrix(a[[i]][,8], nrow = nrow(Cannabis), ncol = 3,
byrow = TRUE)

  Iden_1I <- matrix(a[[i]][,9], nrow = nrow(Cannabis), ncol = 3,
byrow = TRUE)
  Iden_2I <- matrix(a[[i]][,10], nrow = nrow(Cannabis), ncol = 3,
byrow = TRUE)
  Iden_3I <- matrix(a[[i]][,11], nrow = nrow(Cannabis), ncol = 3,
byrow = TRUE)

  Cat <- matrix(a[[i]][,12], nrow = nrow(Cannabis), ncol = 3,
byrow = TRUE)
  Comp_1 <- matrix(a[[i]][,13], nrow = nrow(Cannabis), ncol = 3,
byrow = TRUE)
  Comp_2 <- matrix(a[[i]][,14], nrow = nrow(Cannabis), ncol = 3,
byrow = TRUE)

  GCat <- matrix(a[[i]][,15], nrow = nrow(Cannabis), ncol = 3,
byrow = TRUE)
  GComp_1 <- matrix(a[[i]][,16], nrow = nrow(Cannabis), ncol = 3,
byrow = TRUE)
  GComp_2 <- matrix(a[[i]][,17], nrow = nrow(Cannabis), ncol = 3,
byrow = TRUE)

  GFrequencyI <- matrix(a[[i]][,18], nrow = nrow(Cannabis), ncol
= 3, byrow = TRUE)
  ValenceI <- matrix(a[[i]][,19], nrow = nrow(Cannabis), ncol =
3, byrow = TRUE)

  Safety_1I <- matrix(a[[i]][,20], nrow = nrow(Cannabis), ncol =
3, byrow = TRUE)
  Safety_2I <- matrix(a[[i]][,21], nrow = nrow(Cannabis), ncol =
3, byrow = TRUE)
  Safety_3I <- matrix(a[[i]][,22], nrow = nrow(Cannabis), ncol =
3, byrow = TRUE)
```

```
  SuiviPotI <- matrix(a[[i]][,23], nrow = nrow(Cannabis), ncol =
3, byrow = TRUE)

  mydata[[i]] <- cbind(Cannabis$respid, Int_2I, Int_3I, Int_4I,
                       GInt_2I, GInt_3I, GInt_4I,
                       Iden_1I, Iden_2I, Iden_3I,
                       Cat, Comp_1, Comp_2 , GCat, GComp_1,
GComp_2,
                       GFrequencyI, ValenceI,
                       Safety_1I, Safety_2I, Safety_3I,
SuiviPotI)

  colnames(mydata[[i]]) <- c("respid",
                             "Int_2", "IntT2_2", "IntT3_2",
                             "Int_3", "IntT2_3", "IntT3_3",
                             "Int_4", "IntT2_4", "IntT3_4",
                             "GInt_2", "GIntT2_2", "GIntT3_2",
                             "GInt_3", "GIntT2_3", "GIntT3_3",
                             "GInt_4", "GIntT2_4", "GIntT3_4",
                             "Iden_1", "IdenT2_1", "IdenT3_1",
                             "Iden_2", "IdenT2_2", "IdenT3_2",
                             "Iden_3", "IdenT2_3", "IdenT3_3",
                             "CatT1", "CatT2", "CatT3",
                             "CompT1_1", "CompT2_1", "CompT3_1",
                             "CompT1_2", "CompT2_2", "CompT3_2",
                             "GCatT1", "GCatT2", "GCatT3",
                             "GCompT1_1", "GCompT2_1",
"GCompT3_1",
                             "GCompT1_2", "GCompT2_2",
"GCompT3_2",
                             "GFrequency", "GFrequencyT2",
"GFrequencyT3",
                             "Valence", "ValenceT2", "ValenceT3",
                             "Safety_1", "SafetyT2_1",
"SafetyT3_1",
                             "Safety_2", "SafetyT2_2",
"SafetyT3_2",
                             "Safety_3", "SafetyT2_3",
"SafetyT3_3",
                             "SuiviPot", "SuiviPotT2",
"SuiviPotT3")

  i <- i + 1

}

# ---- Compute ----

for (i in 1:length(mydata)){
  mydata[[i]] <- cbind(mydata[[i]], rowMeans(mydata[[i]][,
c("IntT3_2", "IntT3_3", "IntT3_4")]),
```

```
                       rowMeans(mydata[[i]][, c("GIntT3_2",
"GIntT3_3", "GIntT3_4")]),
                       rowMeans(mydata[[i]][, c("IdenT3_1",
"IdenT3_2", "IdenT3_3")]),
                       rowMeans(mydata[[i]][, c("GCompT3_1",
"GCompT3_2")]),
                       rowMeans(mydata[[i]][, c("SafetyT2_1",
"SafetyT2_2", "SafetyT2_2")]),
                       rowMeans(mydata[[i]][, c("SafetyT3_1",
"SafetyT3_2", "SafetyT3_2")]),
                       Cannabis$Age, Cannabis$Age, Cannabis$Age +
1)

  colnames(mydata[[i]]) <- c("respid",
                             "Int_2", "IntT2_2", "IntT3_2",
                             "Int_3", "IntT2_3", "IntT3_3",
                             "Int_4", "IntT2_4", "IntT3_4",
                             "GInt_2", "GIntT2_2", "GIntT3_2",
                             "GInt_3", "GIntT2_3", "GIntT3_3",
                             "GInt_4", "GIntT2_4", "GIntT3_4",
                             "Iden_1", "IdenT2_1", "IdenT3_1",
                             "Iden_2", "IdenT2_2", "IdenT3_2",
                             "Iden_3", "IdenT2_3", "IdenT3_3",
                             "CatT1", "CatT2", "CatT3",
                             "CompT1_1", "CompT2_1", "CompT3_1",
                             "CompT1_2", "CompT2_2", "CompT3_2",
                             "GCatT1", "GCatT2", "GCatT3",
                             "GCompT1_1", "GCompT2_1",
"GCompT3_1",
                             "GCompT1_2", "GCompT2_2",
"GCompT3_2",
                             "GFrequency", "GFrequencyT2",
"GFrequencyT3",
                             "Valence", "ValenceT2", "ValenceT3",
                             "Safety_1", "SafetyT2_1",
"SafetyT3_1",
                             "Safety_2", "SafetyT2_2",
"SafetyT3_2",
                             "Safety_3", "SafetyT2_3",
"SafetyT3_3",
                             "SuiviPot", "SuiviPotT2",
"SuiviPotT3",
                             "IntT3", "GIntT3", "IdenT3",
"GCompT3",
                             "SafetyT2", "SafetyT3",
                             "Age", "AgeT2", "AgeT3")

  i <- i + 1
}

# ---- Codes ----
```

```
PredictionCat <- matrix(NA, nrow = nrow(Cannabis), ncol =
length(mydata))
PredictionComp <- matrix(NA, nrow = nrow(Cannabis), ncol =
length(mydata))
PredictionInt <- matrix(NA, nrow = nrow(Cannabis), ncol =
length(mydata))

# ---- CrÃ©ation matrice likelihood ----

MLike <- matrix(NA, ncol = 3, nrow = 41)
for (i in 1:nrow(MLike)){
  MLike[i,1] = cor(Cannabis[, c("Cat", "GFrequency")])[2,1] * (i
/ 10 - .1)
  i <- i + 1
}
MLike[,1] <- abs(rev(MLike[,1]))

for (i in 1:nrow(MLike)){
  MLike[i,2] = cor(Cannabis[, c("GCompT1", "GFrequency")])[2,1] *
(i / 10 - .1)
  i <- i + 1
}
MLike[,2] <- abs(rev(MLike[,2]))

for (i in 1:nrow(MLike)){
  MLike[i,3] = cor(Cannabis[, c("GintT1", "GFrequency")])[2,1] *
(i / 10 - .1)
  i <- i + 1
}


MLike[41,1] <- MLike[39,1]/4 # Donner des probabilitÃ©s aux
valeurs de 0.00
MLike[41,2] <- MLike[39,2]/4
MLike[1,3] <- MLike[2,3]/4

MLike <- MLike/sum(MLike) # Transformer la matrice en
probabilitÃ©s jointes

MLike[,1] <- MLike[,1]/colSums(MLike)[1] # Transformer la matrice
en probabilitÃ©s conditionnelles
MLike[,2] <- MLike[,2]/colSums(MLike)[2]
MLike[,3] <- MLike[,3]/colSums(MLike)[3]

# ---- BMII ----

for (ii in 1:length(mydata)){

  mat <- matrix(mydata[[ii]][,c("respid", "GInt_2", "GInt_3",
"GInt_4", "GFrequency", "GFrequencyT2", "GFrequencyT3")], nrow =
nrow(mydata[[ii]]), ncol = 7)
```

```
  Post <- matrix(NA, ncol = 3, nrow = nrow(mat))
  colnames(Post) <- c("cat", "comp", "int")
  for (i in 1:nrow(mat)){
    # Prior
    Post[i,] <- cbind(Cannabis$GCat[i], Cannabis$GCompT1[i],
Cannabis$GintT1[i])
    Post[i,] <- Post[i,]/sum(Cannabis$GCat[i],
Cannabis$GCompT1[i], Cannabis$GintT1[i])
    # Likelihood 1
    n <- mat[i,6] * 10 + 1
    Post[i,] <- Post[i,] * MLike[n,]
    # Likelihood 2
    n2 <- mat[i,7] * 10 + 1
    Post[i,] <- Post[i,] * MLike[n,]
    # Posterior
    Sum <- sum(Post[i,])
    Post[i,] <- Post[i,] / Sum
    i <- i + 1
  }

  for (i in 1:nrow(Post)){
    PredictionCat[i,ii] <- cbind(sum(Post[i,1]))
    i <- i + 1
  }
  for (i in 1:nrow(Post)){
    PredictionComp[i,ii] <- cbind(sum(Post[i,2]))
    i <- i + 1
  }
  for (i in 1:nrow(Post)){
    PredictionInt[i,ii] <- cbind(sum(Post[i,3]))
    i <- i + 1
  }

  ii <- ii + 1

}

for (i in 1:length(mydata)){
  mydata[[i]] <- cbind(mydata[[i]], PredictionCat[,i],
PredictionComp[,i], PredictionInt[,i])
  i <- i + 1
}

for (i in 1:length(mydata)){
  colnames(mydata[[i]]) <- c("respid",
                             "Int_2", "IntT2_2", "IntT3_2",
                             "Int_3", "IntT2_3", "IntT3_3",
                             "Int_4", "IntT2_4", "IntT3_4",
                             "GInt_2", "GIntT2_2", "GIntT3_2",
                             "GInt_3", "GIntT2_3", "GIntT3_3",
                             "GInt_4", "GIntT2_4", "GIntT3_4",
                             "Iden_1", "IdenT2_1", "IdenT3_1",
```

```
                              "Iden_2", "IdenT2_2", "IdenT3_2",
                              "Iden_3", "IdenT2_3", "IdenT3_3",
                              "CatT1", "CatT2", "CatT3",
                              "CompT1_1", "CompT2_1", "CompT3_1",
                              "CompT1_2", "CompT2_2", "CompT3_2",
                              "GCatT1", "GCatT2", "GCatT3",
                              "GCompT1_1", "GCompT2_1",
"GCompT3_1",
                              "GCompT1_2", "GCompT2_2",
"GCompT3_2",
                              "GFrequency", "GFrequencyT2",
"GFrequencyT3",
                              "Valence", "ValenceT2", "ValenceT3",
                              "Safety_1", "SafetyT2_1",
"SafetyT3_1",
                              "Safety_2", "SafetyT2_2",
"SafetyT3_2",
                              "Safety_3", "SafetyT2_3",
"SafetyT3_3",
                              "SuiviPot", "SuiviPotT2",
"SuiviPotT3",
                              "IntT3", "GIntT3", "IdenT3",
"GCompT3",
                              "SafetyT2", "SafetyT3",
                              "Age", "AgeT2", "AgeT3",
                              "PredictionCat", "PredictionComp",
"PredictionInt")

  i <- i + 1
}

for (ii in 1:length(mydata)){
  for (i in 1: nrow(mydata[[ii]])){
    mydata[[ii]][i,"PredictionCat"] <-
ifelse(is.na(mydata[[ii]][i,"PredictionCat"]), 1/3,
mydata[[ii]][i,"PredictionCat"])
    i <- i + 1
  }
  ii <- ii + 1
}

for (ii in 1:length(mydata)){
  for (i in 1: nrow(mydata[[ii]])){
    mydata[[ii]][i,"PredictionComp"] <-
ifelse(is.na(mydata[[ii]][i,"PredictionComp"]), 1/3,
mydata[[ii]][i,"PredictionComp"])
    i <- i + 1
  }
  ii <- ii + 1
}

for (ii in 1:length(mydata)){
```

```
  for (i in 1: nrow(mydata[[ii]])){
    mydata[[ii]][i,"PredictionInt"] <-
ifelse(is.na(mydata[[ii]][i,"PredictionInt"]), 1/3,
mydata[[ii]][i,"PredictionInt"])
    i <- i + 1
  }
  ii <- ii + 1
}

a.mids <- miceadds::datlist2mids(mydata)

fitCatPF <- with(data = a.mids, exp = lm(scale(GCatT3) ~
scale(PredictionCat)))
MeanCatPF <- summary(pool(fitCatPF))$estimate[2] # Mean SD
SDCatPF <- summary(pool(fitCatPF))$std.error[2] # Pooled SD

fitCompPF <- with(data = a.mids, exp = lm(scale(GCompT3) ~
scale(PredictionComp)))
MeanCompPF <- summary(pool(fitCompPF))$estimate[2] # Mean SD
SDCompPF <- summary(pool(fitCompPF))$std.error[2] # Pooled SD

fitIntPF <- with(data = a.mids, exp = lm(scale(GIntT3) ~
scale(PredictionInt)))
MeanIntPF <- summary(pool(fitIntPF))$estimate[2] # Mean SD
SDIntPF <- summary(pool(fitIntPF))$std.error[2] # Pooled SD



fitCat <- with(data = a.mids, exp = lm(scale(GCatT3) ~
scale(GCatT1)))
MeanCat <- summary(pool(fitCat))$estimate[2] # Mean SD
SDCat <- summary(pool(fitCat))$std.error[2] # Pooled SD

fitComp <- with(data = a.mids, exp = lm(scale(GCompT3) ~
scale(Cannabis$GCompT1)))
MeanComp <- summary(pool(fitComp))$estimate[2] # Mean SD
SDComp <- summary(pool(fitComp))$std.error[2] # Pooled SD

fitInt <- with(data = a.mids, exp = lm(scale(GIntT3) ~
scale(Cannabis$GintT1)))
MeanInt <- summary(pool(fitInt))$estimate[2] # Mean SD
SDInt <- summary(pool(fitInt))$std.error[2] # Pooled SD

# ---- Results ----

boxLabels = c("Predicted Categorisation and Categorisation T3",
              "Categorisation T1 and Categorisation T3",
              "Predicted Compartmentation and Compartmentation
T3",
              "Compartmentation T1 and Compartmentation T3",
              "Predicted Integration and Integration T3",
```

```
              "Integration T1 and Integration T3")
allo <- data.frame(yAxis = length(boxLabels),
                   boxOdds = c(MeanCatPF,
                               MeanCat,
                               MeanCompPF,
                               MeanComp,
                               MeanIntPF,
                               MeanInt),
                   boxCILow = c(MeanCatPF - (2.01 * SDCatPF),
                                MeanCat - (2.01 * SDCat),
                                MeanCompPF - (2.01 * SDCompPF),
                                MeanComp - (2.01 * SDComp),
                                MeanIntPF - (2.01 * SDIntPF),
                                MeanInt - (2.01 * SDInt)),
                   boxCIHigh = c(MeanCatPF + (2.01 * SDCatPF),
                                 MeanCat + (2.01 * SDCat),
                                 MeanCompPF + (2.01 * SDCompPF),
                                 MeanComp + (2.01 * SDComp),
                                 MeanIntPF + (2.01 * SDIntPF),
                                 MeanInt + (2.01 * SDInt))

)

# Figure
ggplot(allo, aes(x = boxOdds, y = reorder(boxLabels, yAxis))) +
  geom_errorbarh(aes(xmax = boxCIHigh, xmin = boxCILow), size =
.2, height =
                   .1, color = "black") +
  geom_point(size = 3.5, color = "black") +
  scale_x_continuous(limits = c(min(allo$boxCILow) - .20,
max(allo$boxCIHigh) + .20)) +
  theme_bw()+
  theme(panel.grid.minor = element_blank(),
        text = element_text(size = 25)) +
  ylab("") +
  xlab("Standardized regression values")
```

# Annexe D : Formulaire de consentement (article 2)

**FORMULAIRE D'INFORMATION ET DE CONSENTEMENT**

**Chercheure :**

Roxane de la Sablonnière, professeure titulaire, Département de psychologie, Université de Montréal;

**Vous êtes invités à participer à un projet de recherche. Avant d'accepter, veuillez prendre le temps de lire ce document présentant les conditions de participation au projet. N'hésitez pas à poser toutes les questions que vous jugerez utiles.**

**A) RENSEIGNEMENTS AUX PARTICIPANTS**

**1. Objectifs de la recherche**
Ce projet de recherche vise à mieux comprendre l'impact de la légalisation du cannabis sur les schémas identitaires des Canadiens. Il vise également une meilleure compréhension des processus en jeu dans l'adaptation de cette population dans un contexte de changement social spécifique, soit la légalisation du cannabis au Canada.

**2. Participation à la recherche**
Votre participation consiste à remplir un questionnaire qui prendra 10 minutes à compléter, et ce, à au moins 3 reprises. Vous serez avisés par courriel quand le moment sera venu de remplir le questionnaire à nouveau.

**3. Risques et inconvénients**
Il n'y a pas de risques particuliers, connus ou anticipés, à participer à ce projet.

**4. Avantages et bénéfices**
Il n'y a pas d'avantage particulier à participer à ce projet. Vous contribuerez cependant à l'avancement des connaissances en psychologie sociale.

**5. Confidentialité**
Les renseignements personnels que vous nous donnerez demeureront confidentiels. Aucune information permettant de vous identifier d'une façon ou d'une autre ne sera publiée. De plus, chaque participant à la recherche se verra attribuer un code et seuls les chercheurs et leur équipe pourront connaître son identité. Les données seront conservées dans un lieu sûr. Les enregistrements seront transcrits et seront détruits, ainsi que toute information personnelle, 7 ans après la fin du projet. Seules les données ne permettant pas de vous identifier seront conservées après cette période.

**6. Compensation**

Une invitation par courriel sera envoyée par AskingCanadians aux membres de leur communauté de recherche. Dans celle-ci sera décrite une opportunité de recherche et les récompenses pour la participation à la recherche si les membres répondent aux critères d'inclusion pour celle-ci. Les participants devront cliquer sur un lien menant à un questionnaire préliminaire afin de déterminer s'il répond aux critères d'inclusion pour participer à la recherche. Les questions ont été créées par l'Université de Montréal et programmées par AskingCanadians. Si un participant ne peut participer à l'étude, basé sur ses réponses au questionnaire préliminaire, il sera remercié pour son temps et recevra un incitatif nominal. Le coût de cette incitation est inclus dans le coût du projet de l'Université de Montréal. Si un participant répond aux critères d'inclusion déterminés dans le questionnaire préliminaire, il recevra le formulaire de consentement provenant de l'Université de Montréal dans lequel sera décrit la portée de la recherche.

**7. Droit de retrait**
Votre participation à ce projet est entièrement volontaire et vous pouvez à tout moment vous retirer de la recherche sur simple avis verbal et sans devoir justifier votre décision, sans conséquence pour vous. Si vous décidez de vous retirer de la recherche, veuillez communiquer avec le chercheur au numéro de téléphone indiqué ci-dessous.

À votre demande, tous les renseignements qui vous concernent pourront aussi être détruits. Cependant, après le déclenchement du processus de publication, il sera impossible de détruire les analyses et les résultats portant sur vos données.

**B) CONSENTEMENT**

**Déclaration du participant**

- Je comprends que je peux prendre mon temps pour réfléchir avant de donner mon accord ou non à participer à la recherche.
- Je peux poser des questions à l'équipe de recherche et exiger des réponses satisfaisantes.
- Je comprends qu'en participant à ce projet de recherche, je ne renonce à aucun de mes droits ni ne dégage les chercheurs de leurs responsabilités.
- J'ai pris connaissance du présent formulaire d'information et de consentement et j'accepte de participer au projet de recherche.

**Pour toute question relative à l'étude ou pour vous retirer de la recherche**, veuillez communiquer avec Roxane de la Sablonnière au numéro de téléphone 514 343-6732 ou à l'adresse courriel roxane.de.la.sablonniere@umontreal.ca.

Pour toute préoccupation sur vos droits ou sur les responsabilités des chercheurs concernant votre participation à ce projet, vous pouvez contacter le Comité d'éthique de la recherche en arts et en sciences par courriel à l'adresse ceras@umontreal.ca ou par téléphone au 514 343-7338 ou encore consulter le site Web http://recherche.umontreal.ca/participants.

Toute plainte relative à votre participation à cette recherche peut être adressée à l'ombudsman de l'Université de Montréal en appelant au numéro de téléphone 514 343-2100 ou en communiquant par courriel à l'adresse ombudsman@umontreal.ca **(l'ombudsman accepte les appels à frais virés).**

**En répondant au questionnaire suivant**, je déclare avoir pris connaissance des informations ci-dessus, savoir que je peux obtenir les réponses à mes questions sur ma participation à la recherche auprès du chercheur et comprendre le but, la nature, les avantages, les risques et les inconvénients de cette recherche. Je consens librement à prendre part à cette recherche. Je sais que je peux retirer ma participation en tout temps sans préjudice et sans devoir justifier ma décision.

J'accepte de participer à cette recherche

Oui

Non

# Annexe E : Questionnaire (article 2)

**<u>Informations démographiques</u>**

1. À quel genre vous identifiez-vous ?
1- Homme
2- Femme
3- Autre

2. Quel est votre âge ?
Je préfère ne pas répondre
3. Quel est votre pays natal ?
Je préfère ne pas répondre
3.2 Quel est le pays natal de votre mère ?
Je préfère ne pas répondre
3.3. Quel est le pays natal de votre père ?
Je préfère ne pas répondre
3.4. Dans quel pays habitez-vous ?
1- Canada
2- États-Unis
3- Autre

3.5. Dans quelle province habitez-vous ?
1- Alberta
2- Colombie-Britannique
3- Île du Prince-Édouard
4- Manitoba
5- Nouveau-Brunswick
6- Nouvelle-Écosse
9- Nunavut
8- Ontario
9- Québec
10- Saskatchewan
11- Terre-Neuve et Labrador
12- Territoires du Nord-Ouest
13- Yukon

4. Dans quelle ville habitez-vous actuellement ?
Je préfère ne pas répondre

5. Quelle est votre langue maternelle ? ____________________
Je préfère ne pas répondre

6. Choisissez le chiffre qui correspond le mieux à votre degré de connaissance de la langue française :

| 0 | 1 | 2 | 3 | 4 |
|---|---|---|---|---|
| Très faible | | | | Très bonne |

7. Choisissez le chiffre qui correspond le mieux à votre degré de connaissance de la langue anglaise :

| 0 | 1 | 2 | 3 | 4 |
|---|---|---|---|---|
| Très faible | | | | Très bonne |

8. Quelle est votre nationalité ?
   1. Canadienne
   2. Canadienne et autre. Précisez : ______________________________
   3. Autre. Précisez : ______________________________

9. Parmi les groupes suivants, à quel groupe vous identifiez-vous le plus ? Le but de cette question est simplement de réduire la longueur du questionnaire.
   1. Les Canadiens
   2. Les Québécois
   3. Autant aux Canadiens qu'aux Québécois (Canadiens/Québécois)

10. Quel est le plus haut diplôme que vous avez obtenu?
    1. Sans diplôme
    2. Diplôme d'études primaires
    3. Diplôme d'études secondaires
    4. Diplôme d'études professionnelles
    5. Diplôme d'études collégiales (techniques, DEC, ou AEC)
    6. Diplôme universitaire de premier cycle
    7. Diplôme universitaire de deuxième ou troisième cycle

___________________

11. Actuellement, quelle est votre situation ?

1. Travailleur(se) indépendant(e), à votre compte
2. Salarié(e) du secteur public
3. Salarié(e) du secteur privé
4. En formation professionnelle (DEP)
5. Étudiant(e) au CÉGEP
6. Étudiant(e) universitaire
7. Chômeur(se)
8. Retraité(e) ou pré-retraité(e)
9. Homme ou femme au foyer
10. Malade ou handicapé(e) de manière permanente
11. Prestataire d'aide sociale
12. Bénévole
13. Autre

12. Pensez à cette échelle comme représentant l'endroit où les gens se positionnent dans notre société. Au **sommet** (4) de l'échelle sont les gens qui sont les mieux nantis, ceux qui ont le plus d'argent et de meilleurs emplois. Au **bas** (0) de l'échelle sont les gens qui sont les moins nantis, ceux qui ont le moins d'argent et les pires emplois ou aucun emploi. Indiquez le niveau de l'échelle qui représente le mieux l'endroit où **vous pensez vous retrouvez** (en termes d'argent et d'emploi) sur l'échelle.

| | | | | | | |
|---|---|---|---|---|---|---|
| Bas de l'échelle | 0 | 1 | 2 | 3 | 4 | Sommet de l'échelle |

13x1. En ce qui concerne la politique, les gens parlent souvent de «gauche» et de «droite». Vous, personnellement, où vous classeriez-vous sur l'échelle suivante ?

| | | | | |
|---|---|---|---|---|
| Gauche | Centre-gauche | Centre | Centre-droite | Droite |

13x2. Entre le changement social et le maintien des traditions, où vous situez-vous?

| 0 | 1 | 2 | 3 | 4 |
|---|---|---|---|---|
| Pour le changement social | | | | Pour le maintien des traditions |

13. Veuillez cocher le choix qui correspond le mieux à la fréquence de votre consommation de cannabis (toutes méthodes d'utilisation confondues) au cours d'un mois typique.
    a) Jamais
    b) Une fois par mois ou moins
    c) Deux à trois fois par mois
    d) Une fois par semaine ou plus

14. Comment qualifiez-vous votre statut de consommateur de cannabis ?
    a) Non-consommateur (je n'ai jamais consommé)
    b) Ex-consommateur (je consommais avant)
    c) Expérimentateur (j'ai consommé du cannabis, juste pour essayer, mais je ne pense pas nécessairement recommencer)
    d) Occasionnel (je consomme du cannabis parfois, à l'occasion)
    e) Régulier (je consomme fréquemment du cannabis)

**Veuillez indiquer votre degré d'accord ou de désaccord avec les affirmations suivantes en vous référant à l'échelle ci-dessous.**

| 0 | 1 | 2 | 3 | 4 |
|---|---|---|---|---|
| Fortement en désaccord | En désaccord | Ni en accord, ni en désaccord | En accord | Fortement en accord |

| | | | | | |
|---|---|---|---|---|---|
| 15. Lorsque le cannabis sera légal, je vais m'en procurer <u>de manière légale</u> (p. ex., à la Société Québécoise du Cannabis [SQDC]). | 0 | 1 | 2 | 3 | 4 |
| 16. Lorsque le cannabis sera légal, je vais m'en procurer <u>de manière illégale</u> (p. ex., par un revendeur, etc.). | 0 | 1 | 2 | 3 | 4 |

**Veuillez répondre aux affirmations suivantes en vous référant <u>à votre consommation actuelle de cannabis</u> selon l'échelle ci-dessous.**

| 0 | 1 | 2 | 3 | 4 |
|---|---|---|---|---|
| Diminuer | | Rester la même | | Augmenter |

| | | | | | |
|---|---|---|---|---|---|
| 17. Lorsque le cannabis sera légal, la **quantité** que je consomme va… | 0 | 1 | 2 | 3 | 4 |

| | | | | | |
|---|---|---|---|---|---|
| 18. Lorsque le cannabis sera légal, la **fréquence** à laquelle je consomme va… | 0 | 1 | 2 | 3 | 4 |

**Veuillez indiquer votre degré d'accord ou de désaccord avec les affirmations suivantes en vous référant à l'échelle ci-dessous.**

| 0 | 1 | 2 | 3 | 4 |
|---|---|---|---|---|
| Fortement en désaccord | En désaccord | Ni en accord, ni en désaccord | En accord | Fortement en accord |

| | | | | | |
|---|---|---|---|---|---|
| 19. Je n'aurais pas d'inconvénient à fonder une famille avec une personne qui consomme du cannabis ou à avoir un partenaire qui consomme du cannabis. | 0 | 1 | 2 | 3 | 4 |
| 20. Je n'aurais pas d'inconvénient à ce que mon enfant choisisse un partenaire qui consomme du cannabis. | 0 | 1 | 2 | 3 | 4 |
| 21. Je n'aurais pas d'inconvénient à avoir des amis qui consomment du cannabis. | 0 | 1 | 2 | 3 | 4 |
| 22. Je n'aurais pas d'inconvénient à avoir des relations avec des consommateurs de cannabis. | 0 | 1 | 2 | 3 | 4 |

**Veuillez répondre aux affirmations suivantes en vous référant à l'échelle ci-dessous.**

| 0 | 1 | 2 | 3 | 4 |
|---|---|---|---|---|
| Diminuer | | Rester la même | | Augmenter |

| | | | | | |
|---|---|---|---|---|---|
| 23. Selon moi, quand le cannabis sera légal, la **quantité** consommée **par les (group)** va… | 0 | 1 | 2 | 3 | 4 |
| 24. Selon moi, quand le cannabis sera légal, la **fréquence** de la consommation de cannabis **par les (group)** va… | 0 | 1 | 2 | 3 | 4 |

25. Croyez-vous que les changements portant sur la légalisation du cannabis soient ***négatifs ou positifs***?

| 0 | 1 | 2 | 3 | 4 |
|---|---|---|---|---|
| Très négatifs | Négatifs | Neutres | Positifs | Très positifs |

26. À quel point les changements portant sur la légalisation du cannabis ***vous affectent***?

| 0 | 1 | 2 | 3 | 4 |
|---|---|---|---|---|
| Ne m'affectent pas d tout | Ne m'affectent pas | M'affectent un peu | M'affectent | M'affectent beaucoup |

27. À quel point les changements portant sur la légalisation du cannabis ***affectent-ils les* (group)** ?

| 0 | 1 | 2 | 3 | 4 |
|---|---|---|---|---|
| Ne les affectent pas du tout | Ne les affecten pas | Les affectent un peı | Les affectent | Les affectent beaucoup |

28. Croyez-vous que les changements sur la légalisation du cannabis ont été ***rapides ou lents***?

| 0 | 1 | 2 | 3 | 4 |
|---|---|---|---|---|
| Très lents | Lents | Ni lents ni rapides | Rapides | Très rapides |

29. Croyez-vous que les changements concernant la légalisation du cannabis ont été ***nombreux ou peu nombreux***?

| 0 | 1 | 2 | 3 | 4 |
|---|---|---|---|---|
| Très peu | Peu | Ni peu ni nombreux | Nombreux | Très nombreux |

29. Croyez-vous que les changements concernant la légalisation du cannabis sont ***trop grands ou trop petits***?

| 0 | 1 | 2 | 3 | 4 |
|---|---|---|---|---|
| Trop petits | Petits | Ni grands ni petits | Grands | Trop grands |

**Identité personnelle et identité liée au cannabis**

Nous avons tous plusieurs identités qui nous définissent. Nous aimerions que vous considériez d'abord deux de vos identités, soit votre **identité personnelle** et votre **identité liée au cannabis**.

Dans cette étude, votre **identité personnelle** fait référence à votre concept de soi (par exemple, les valeurs auxquelles vous adhérez, vos choix, vos motivations, etc.).

Votre **identité liée au cannabis** fait référence à l'importance que vous accordez au cannabis.

Cette importance peut se refléter par: 1. Votre opinion positive ou négative par rapport à la consommation de cannabis (ex: si vous êtes fortement contre la consommation ou si vous accordez beaucoup d'importance à la consommation); 2. Votre opinion positive ou négative par rapport à la légalisation au Canada.

La perception de deux identités :
Dans la section suivante, nous souhaitons comprendre la relation entre deux identités : votre **identité personnelle** et votre **identité liée au cannabis**. Nous souhaitons comprendre comment vous percevez ces deux identités. Présentement…

| 0 | 1 | 2 | 3 | 4 |
|---|---|---|---|---|
| Fortement en désaccord | En désaccord | Ni en accord, ni en désaccord | En accord | Fortement en accord |

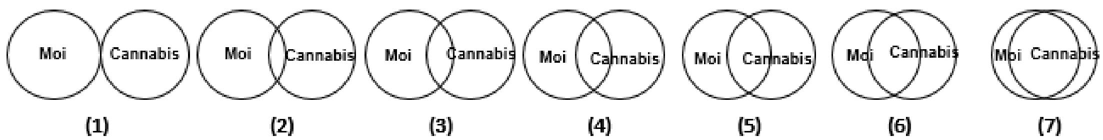
| | | | | | |
|---|---|---|---|---|---|
| 30. … mon **identité personnelle** et mon **identité liée au cannabis** représentent des parties séparées de qui je suis. | 0 | 1 | 2 | 3 | 4 |
| 31. … les différences entre mon **identité personnelle** et mon identité **liée au cannabis** ne peuvent pas être réconciliées. | 0 | 1 | 2 | 3 | 4 |
| 32. … je m'identifie exclusivement à mon **identité personnelle**. | 0 | 1 | 2 | 3 | 4 |
| 33. … mon **identité personnelle** et mon **identité liée au cannabis** sont intégrées dans une identité plus globale. | 0 | 1 | 2 | 3 | 4 |
| 34. … mon **identité personnelle** et mon **identité liée au cannabis** sont liées. | | | | | |
| 35. … mon **identité personnelle** inclut mon **identité liée au cannabis**. | 0 | 1 | 2 | 3 | 4 |
| 36. … je perçois des similarités entre mon **identité personnelle** et mon **identité liée au cannabis**. | 0 | 1 | 2 | 3 | 4 |

Dans les trois prochaines questions, nous nous intéressons à la façon dont vous vous voyez par rapport aux consommateurs de cannabis.

| | | | | | |
|---|---|---|---|---|---|
| 37. … je m'identifie aux consommateurs de cannabis. | 0 | 1 | 2 | 3 | 4 |
| 38. … j'ai beaucoup en commun avec les consommateurs de cannabis. | 0 | 1 | 2 | 3 | 4 |
| 39. … être un consommateur de cannabis est une partie importante de qui je suis. | 0 | 1 | 2 | 3 | 4 |

40. Mesure graphique à un seul item du lien avec la communauté (adaptée)

Dans chaque paire de cercles, le cercle de gauche (moi) représente votre **identité personnelle** (p. ex., vos valeurs, choix, motivations), alors que le cercle de droite (cannabis) représente, dans ce cas, votre **identité liée au cannabis** (p. ex., votre consommation, vos opinions par rapport au débat sur le cannabis et sur cette substance). Veuillez choisir la paire de cercles qui décrit le mieux votre lien avec le cannabis.




**<u>Identité canadienne/québécoise et identité liée au cannabis</u>**

Nous aimerions que vous considériez deux de vos identités, soit votre **identité (group)** et votre identité liée au cannabis.

Dans cette étude, votre **identité (group)** fait référence au fait que vous vous considérez comme **(group)** (p. ex. les valeurs auxquelles les **(group)** adhèrent, leurs attributs, leurs comportements, leurs normes, etc.).

Votre **identité liée au cannabis** fait référence à l'importance que vous accordez au cannabis. Cette importance peut se refléter par:

1. Votre opinion positive ou négative par rapport à la consommation de cannabis (ex: si vous êtes fortement contre la consommation ou si vous accordez beaucoup d'importance à la consommation);
2. Votre opinion positive ou négative par rapport à la légalisation au Canada.

<u>La perception de deux identités :</u>
Dans la section suivante, nous souhaitons comprendre la relation entre deux identités, **l'identité (group)** et votre **identité liée au cannabis**. Nous désirons comprendre comment vous percevez ces deux identités. Présentement…

| 0 | 1 | 2 | 3 | 4 |
|---|---|---|---|---|
| Fortement en désaccord | En désaccord | Ni en accord, ni en désaccord | En accord | Fortement en accord |

| | | | | | |
|---|---|---|---|---|---|
| 30. … mon **identité (group)** et mon **identité liée au cannabis** représentent des parties séparées de qui je suis. | 0 | 1 | 2 | 3 | 4 |
| 31. … mon **identité (group)** et mon **identité liée au cannabis** ne peuvent pas être réconciliées. | 0 | 1 | 2 | 3 | 4 |

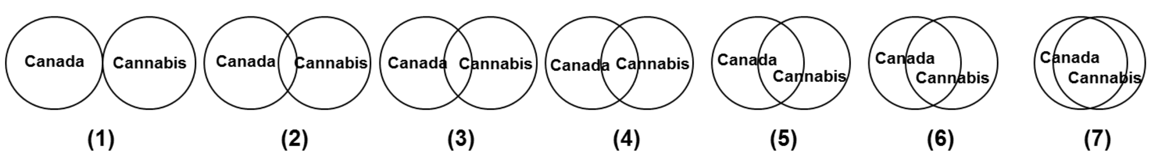
| | | | | | |
|---|---|---|---|---|---|
| 32. … je m'identifie exclusivement à mon **identité (group).** | 0 | 1 | 2 | 3 | 4 |
| 38. … mon **identité (group)** et mon **identité liée au cannabis** sont intégrées dans une identité plus globale. | 0 | 1 | 2 | 3 | 4 |
| …mon identité **(group)** et **identité liée au cannabis** sont liées | 0 | 1 | 2 | 3 | 4 |
| 39. … mon **identité (group)** inclut mon **identité liée au cannabis**. | 0 | 1 | 2 | 3 | 4 |
| 40. … je perçois des similarités entre mon **identité (group)** et mon **identité liée au cannabis**. | 0 | 1 | 2 | 3 | 4 |

Dans les trois prochaines questions, nous nous intéressons à la façon dont vous voyez les **(group)** par rapport aux consommateurs de cannabis.

| | | | | | |
|---|---|---|---|---|---|
| 41. … … les **(group)** s'identifient aux consommateurs de cannabis. | 0 | 1 | 2 | 3 | 4 |
| 42. … les **(group)** ont beaucoup en commun avec les consommateurs de cannabis. | 0 | 1 | 2 | 3 | 4 |
| 43. …en général, être un consommateur de cannabis est une part importante du fait d'être **(group).** | 0 | 1 | 2 | 3 | 4 |

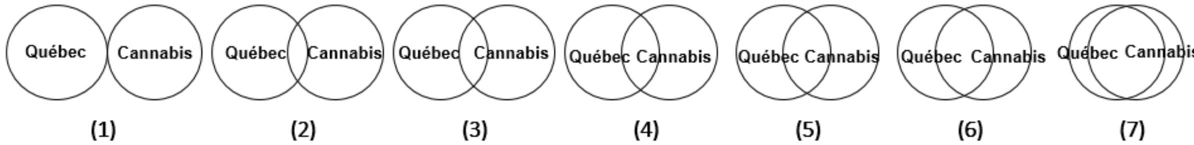
44. A SINGLE-ITEM PICTORIAL MEASURE OF COMMUNITY CONNECTEDNESS (adaptée)

Dans chaque paire de cercles, le cercle de gauche (Canada) représente votre **identité canadienne** (p.ex., les valeurs, attributs, façons d'agir et normes canadiennes), alors que le cercle de droite (cannabis) représente votre **identité liée au cannabis** (p.ex., votre consommation, vos opinions par rapport au débat sur le cannabis et sur cette substance). Veuillez choisir la paire de cercles qui décrit le mieux votre lien avec le cannabis.




44. Mesure graphique à un seul item du lien avec la communauté (adaptée)

Dans chaque paire de cercles, le cercle de gauche (Québec) représente votre **identité québécoise** (p. ex., les valeurs, attributs, façons d'agir et normes québécoises), alors que le cercle de droite (cannabis) représente votre **identité liée au cannabis** (p. ex., votre consommation, vos opinions par rapport au débat sur le cannabis et sur cette substance). Veuillez choisir la paire de cercles qui décrit le mieux votre lien avec le cannabis.




**Veuillez indiquer votre degré d'accord ou de désaccord avec les affirmations suivantes en vous référant à l'échelle ci-dessous.**

| 0 | 1 | 2 | 3 | 4 |
|---|---|---|---|---|
| Fortement en désaccord | En désaccord | Ni en accord, ni en désaccord | En accord | Fortement en accord |

| | | | | | |
|---|---|---|---|---|---|
| 45. J'ai suivi le débat politique (p.ex. dans les médias) portant sur la légalisation du cannabis. | 0 | 1 | 2 | 3 | 4 |
| 46. Quelque fois, je pense que je suis bien renseigné sur les propositions des gouvernements fédéral et provincial concernant la légalisation du cannabis et d'autres fois non. | 0 | 1 | 2 | 3 | 4 |
| 47. En général, j'ai une idée claire des propositions faites par les gouvernements fédéral et provincial concernant la légalisation du cannabis. | 0 | 1 | 2 | 3 | 4 |
| 48. À mon avis, les nombreuses propositions faites par les gouvernements fédéral et provincial sur la légalisation du cannabis sont claires. | 0 | 1 | 2 | 3 | 4 |
| 49. Les multiples propositions des gouvernements fédéral et provincial sur la légalisation du cannabis sont connectées entre elles. | 0 | 1 | 2 | 3 | 4 |
| 50. Les nombreuses propositions des gouvernements fédéral et provincial | 0 | 1 | 2 | 3 | 4 |

| | | | | | |
|---|---|---|---|---|---|
| sur le cannabis font partie d'une idéologie plus globale. | | | | | |
| 51. Les multiples propositions des gouvernements fédéral et provincial sur la légalisation du cannabis se complètent. | 0 | 1 | 2 | 3 | 4 |
| 52. Une seule idéologie regroupe toutes les propositions des gouvernements fédéral et provincial concernant la légalisation du cannabis. | 0 | 1 | 2 | 3 | 4 |

**Veuillez indiquer votre degré d'accord ou de désaccord avec les affirmations suivantes en vous référant à l'échelle ci-dessous.**

| 0 | 1 | 2 | 3 | 4 |
|---|---|---|---|---|
| Fortement en désaccord | En désaccord | Ni en accord, ni en désaccord | En accord | Fortement en accord |

| | | | | | |
|---|---|---|---|---|---|
| 53. Je partage mes joies et mes peines avec quelqu'un. | 0 | 1 | 2 | 3 | 4 |
| 54. Je sais que mes amis se soucient vraiment de moi. | 0 | 1 | 2 | 3 | 4 |
| 55. Je fais partie d'une famille (ou un autre groupe) qui se soucie de moi. | 0 | 1 | 2 | 3 | 4 |
| 56. Je fais des activités avec d'autres personnes plutôt que seul. | 0 | 1 | 2 | 3 | 4 |
| 57. Je vis dans une société ordonnée et pourvue de lois. | 0 | 1 | 2 | 3 | 4 |
| 58. Je me sens en sécurité dans mon quartier et ma maison. | 0 | 1 | 2 | 3 | 4 |
| 59. J'ai un mode de vie stable. Je sais ce qui m'attend à l'avance. | 0 | 1 | 2 | 3 | 4 |
| 60. Je me sens libre de toute anxiété et inquiétude. | 0 | 1 | 2 | 3 | 4 |

61N'hésitez pas à partager tout commentaire ou questionnement que vous pouvez avoir concernant le cannabis ou ce sondage.