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L'analyse appliquée du comportement en autisme et ses enjeux : Une évaluation du potentiel de la technologie pour améliorer la pratique et la recherche

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Résumé

Le trouble du spectre de l'autisme (TSA) est un trouble neurodéveloppemental caractérisé par des déficits importants de la communication sociale et des interactions sociales ainsi que par la présence de comportements ou d'intérêts restreints et répétitifs. Les données empiriques suggèrent que les interventions découlant de l'analyse appliquée du comportement (AAC) sont les plus efficaces pour intervenir auprès des personnes ayant un TSA. Néanmoins, certaines lacunes en lien avec les interventions découlant de l'analyse du comportement existent. Notamment, le manque d'accessibilité aux services, le manque de connaissances quant aux facteurs sous-jacents à l'efficacité des interventions et les perceptions divergentes de l'AAC freinent son adoption à plus grande échelle. Cette thèse comprend trois études qui mettent à profit la technologie pour mieux comprendre ou améliorer ces enjeux entourant l'AAC.

Dans le cadre ma première étude, les effets d'une formation interactive en ligne qui vise à enseigner aux parents des stratégies découlant de l'AAC pour réduire les comportements problématiques de leur enfant ont été évalués à l'aide d'un devis randomisé contrôlé avec liste d'attente. Les résultats de cette étude soutiennent le potentiel et l'efficacité de la formation pour augmenter la fréquence d'utilisation de stratégies d'intervention découlant de l'AAC par les parents ainsi que pour réduire l'occurrence et la sévérité des comportements problématiques de leur enfant. En revanche, aucune différence significative n'a été observée pour la mesure des pratiques parentales. Certains enjeux éthiques et pratiques entourant la dissémination de la formation en ligne complètement auto-guidées sont discutés.

La deuxième étude de ma thèse doctorale visait donc à montrer comment utiliser des algorithmes d'apprentissage automatique pour identifier les personnes qui sont plus enclines à observer des améliorations suivant une intervention. Plus spécifiquement, l'utilisation de quatre algorithmes d'apprentissage automatique pour prédire les participants ayant pris part à la première étude de cette thèse qui étaient les plus propices à rapporter une diminution des comportements problématiques de leur enfant est démontrée. Cette étude soutient que des algorithmes d'apprentissage automatique peuvent être utilisés avec de petits échantillons pour soutenir la prise de décision des cliniciens et des chercheurs.

La troisième étude cette thèse visait à quantifier l'information sur l'AAC publiée dans quatre sous-forums d'un forum internet, une ressource en ligne souvent utilisée par les familles pour identifier des interventions à utiliser après de leur enfant. Pour atteindre cet objectif, une procédure de forage de données a été réalisée. Les analyses de cette étude appuient que les parents qui fréquentent le forum sont exposés à une proportion importante de messages présentant une désapprobation de l'AAC pour intervenir auprès des personnes ayant un TSA ou bien une description inexacte des principes, méthodes, procédures ou interventions qui en découlent.

Ensemble, les études effectuées dans le cadre de ma thèse doctorale mettent en évidence les bienfaits de la technologie pour l'intervention psychosociale, tant au niveau de l'évaluation que de l'intervention et du transfert de connaissances. Comme souligné dans les trois études de cette thèse, chacun des outils utilisés présente des limites et doit donc être utilisé pour soutenir les cliniciens et les chercheurs, et non pour remplacer leurs interventions et leur jugement clinique. Les études futures doivent continuer à s'intéresser à l'efficacité des outils technologiques, mais également aux facteurs sous-jacents qui favoriseront leur utilisation et aux considérations éthiques liées à leur emploi.
Mots-clés : Autisme, comportements problématiques, formation en ligne pour parents, forage de données, algorithmes d'apprentissage automatique, analyse appliquée du comportement.

Abstract

Autism Spectrum Disorder (ASD) is a neurodevelopmental disorder characterized by significant deficits in social communication and social interactions and by the presence of restricted and repetitive behaviors or interests. Empirical evidence suggests that interventions based on applied behavior analysis (ABA) are the most effective for treating individuals with ASD. Nevertheless, interventions based on behavior analysis present some issues. In particular, intervention services are hard to access, knowledge about the underlying factors of the effectiveness of interventions is lacking and divergent perceptions about of ABA hamper the adoption of the science. This dissertation includes three studies in which technology is used to better understand or improve these issues regarding ABA.

As part of my first study, the effects of a fully self-guided interactive web training (IWT) developed for teaching parents of children with ASD ABA-derived strategies to reduce their child's challenging behaviors were evaluated using a randomized waitlist trial. The results of this study support the effectiveness of the IWT for increasing the frequency of parents' use of behavioral interventions as well as for reducing the frequency and severity of their child's challenging behaviors. In contrast, no significant difference was observed for the measurement of parenting practices. Ethical and practical consideration regarding the dissemination of fully self-guided online trainings are discussed.

The second study of my doctoral thesis aimed to show how to use machine learning algorithms to predict individuals who were most likely to improve following an intervention. Specifically, a demonstration of how to implement four machine learning algorithms to predict the participants from my first study who were the most likely to report a decrease in their child's challenging behaviors. This study argues that machine learning algorithms can be used with small samples to support clinicians' and researchers' decision making.

The third study of my dissertation aimed to quantify the information about ABA published on four subforums of an internet forum; an online resource often used by families to identify potential interventions for their child. This goal was achieved through the use of a data mining procedure. The analyses showed that parents who visited the forum were exposed to a significant proportion of messages that disapproved of ABA for individuals with ASD or that inaccurately described its underlying principles, methods, procedures, or interventions.

Together, the studies carried out as part of my doctoral dissertation highlight the benefits of technology to support assessments, interventions, and knowledge gains or transfer within psychosocial practices. As highlighted in the three studies of this dissertation, each of the tools used presents limitations and should therefore be used to support clinicians and researchers, and should not replace their interventions and clinical judgment. Future studies should continue to focus on the effectiveness of technological tools and on the underlying factors that will promote their use. Finally, researchers must reflect on the ethical considerations related to use of technology when working with humans.

Keywords: Autism, challenging behavior, online parenting training, data mining, machine learning algorithms, applied behavior analysis.

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Liste des sigles et des abréviations

AAC : Analyse appliquée du comportement

ABA : Applied behavior analysis

ABAS-II : Adaptive Behavior Assessment System – Second Edition

ANCOVA : Analysis of covariance

ANESM : Agence Nationale de l'Évaluation et de la Qualité des Établissements et Services Sociaux et Médico-Sociaux

APQ-SF : Alabama Parenting Questionnaire – Short Form

BPI-01 : Behavior Problem Inventory

BST : Behavioral Skill Training

CONSORT : Consolidated Standards of Reporting Trials

csv : Comma-separated values

df : Degrees of freedom

d_{ppc} : Effect size based on the pooled pretest standard deviation

HAS : Haute Autorité de Santé

ID : Identity document

IRA : Interrater agreement

IWT : Interactive Web Training

K : Nearest number of neighbors

OPPQ : Ordre des Psychoéducateurs et Psychoéducatrices du Québec

PAD : Potentiel adaptatif

PEX : Potentiel expérientiel

TARF-R-VF : Treatment Acceptability Rating Form - Revised -Version française

TSA : Trouble du spectre de l’autisme

URL : Uniform Resource Locator

À Malik. Always remember that
« When you wish upon a star
Makes no difference who you are
Anything your heart desires
Will come to you
If your heart is in your dream
No request is too extreme
[…]
When you wish upon a star
Your dreams come true.»
(Leigh Harline and Ned Washington, 1940)

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Je tiens tout d'abord à remercier toutes les personnes qui présentent une DI ou un TSA que j'ai côtoyées et leurs familles. Tout au long de mes études, vous m'avez permis de comprendre ce que sont les petits bonheurs de la vie. Si je retiens une chose, c'est que vous avez tellement à nous apprendre et que votre diagnostic ne vous définit pas. Merci!

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Mes 10.35

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Contribution des auteurs aux articles

J'affirme avoir apporté une contribution majeure aux trois articles qui composent ma thèse doctorale. Spécifiquement, dans le cadre de mon premier article, j'ai participé à la conception du protocole de l'étude, à l'adaptation de la formation en ligne, au recrutement des participants, à la collecte et à l'analyse des données puis à la rédaction de l'article scientifique. Marc J. Lanovaz a supervisé toutes les étapes de la recherche et Marie-Michèle Dufour a participé à la conception du protocole de recherche et à la préparation de la formation en ligne. En ce qui a trait au deuxième article, j'ai contribué à la conception du protocole de l'étude, à la vérification et l'adaptation du code Python ainsi qu'à la rédaction de l'article scientifique. De plus, j'ai collecté les données utilisées pour ce tutoriel dans le cadre de mon premier article. Marc J. Lanovaz a supervisé toutes les étapes de la recherche et a rédigé le code Python pour le tutoriel. Enfin, pour mon troisième article, j'ai contribué à la conception du protocole de recherche de l'étude, à l'extraction, la classification et l'analyse des données secondaires et à la rédaction de l'article scientifique. Marc J. Lanovaz a supervisé chacune des étapes de cette étude.

Présentation de la thèse

Ma thèse doctorale comprend cinq chapitres. Le premier chapitre présente le contexte théorique entourant ce projet de thèse. Les trois chapitres qui suivent présentent chacun des trois articles scientifiques effectués dans le cadre de ma thèse. Enfin, le dernier chapitre présente la discussion et la conclusion de la thèse.

Dans le premier chapitre, les thèmes introduits et mis en contextes entourent le trouble du spectre de l'autisme (TSA), les comportements problématiques, l'analyse appliquée du comportement (AAC), les parents comme agent d'intervention et les formations interactives en ligne. Ce chapitre est clos par la présentation des objectifs généraux de ma thèse : (a) évaluer les effets d'une formation interactive en ligne basée sur les principes de l'AAC sur les comportements des parents et sur les comportements problématiques de leur enfant, (b) présenter comment des algorithmes d'apprentissage automatiques peuvent être utilisés pour prédire si une intervention produira ou non des effets chez une personne et (c) mesurer la perception de l'AAC dans un forum internet français.

Les trois chapitres qui suivent présentent chacun des trois articles scientifiques effectués dans le cadre de ma thèse, chacune faisant l'utilisation d'un outil technologique pour contribuer à la recherche en AAC. Le chapitre deux présente l'article intitulé « *Effects of an interactive web training to support parents in the management of challenging behaviors in children with Autism* » publié dans la revue *Behavior Modification* (Turgeon et al., 2020). Cette étude fait suite à celle de Marleau et al. (2018) dans laquelle les auteurs ont évalué les effets d'une formation en ligne sur le savoir des parents entourant l'AAC. Concrètement, l'objectif de ma première étude était de mesurer les effets de la formation en ligne sur les comportements problématiques des enfants et le savoir-faire des parents. Ensemble, l'étude de Marleau et al. (2018) et l'étude

Turgeon et al. (2020) visaient à évaluer l'efficacité de la formation en ligne pour répondre à une problématique d'actualité, soit l'accessibilité aux services d'intervention pour les personnes ayant un TSA.

Le chapitre trois présente le deuxième article de ma thèse doctorale « *Tutorial: Applying machine learning in behavioral research* » publié dans la revue *Perspective on Behavior Science* (Turgeon et Lanovaz, 2020). Cet article a été motivé par la méconnaissance et la sous-exploitation des algorithmes d'apprentissage automatique par les analystes du comportement. Ainsi, l'objectif était de faire la démonstration séquentielle de l'utilisation de quatre algorithmes d'intelligence artificielle pour prédire les effets d'une intervention (c.-à-d., la formation présentée dans le chapitre deux).

Le quatrième chapitre de ma thèse doctorale présente l'article « *Perceptions of behavior analysis in la Francophonie: Accuracy and tone of posts in online forums on autism* » a été soumis au numéro spécial *International Perspectives on Cultural and Social Issues* de la revue *Behavior and Social Issues*. Le haut taux d'attrition observé lors de la première étude de ma thèse, combiné avec des difficultés importantes liées au recrutement de participants par l'entremise des réseaux sociaux ont servi de point de départ pour la dernière étude de ma thèse. Alors, l'objectif de mon troisième article était de mesurer l'information sur l'AAC à laquelle sont exposés les parents qui se tournent vers des forums internet pour identifier des interventions à utiliser pour leur enfant (Green et al., 2006; Pham et al., 2019; Shepherd et al., 2020).

Le cinquième chapitre présente la discussion et la conclusion de ma thèse doctorale. Spécifiquement, dans cette section, je présente les contributions de ma thèse pour la recherche et pour la pratique psychoéducative ainsi que les limites rattachées aux objectifs et aux études présentées.

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Chapitre I : Introduction générale

Contexte théorique

Le trouble du spectre de l'autisme (TSA) est un trouble neurodéveloppemental généralement diagnostiqué avant l'âge de cinq ans (Lyall et al., 2017). Selon l'American Psychiatric Association (2013), le TSA est caractérisé par des déficits importants de la communication et des interactions sociales ainsi que par la présence de comportements ou d'intérêts restreints et répétitifs. L'étiologie du TSA est encore mal comprise. Au cours des dernières décennies, une augmentation progressive de la prévalence du TSA a été observée, avec une hausse plus importante des cas présentant des symptômes moins sévères et sans comorbidité de déficience intellectuelle (DI; Fombonne, 2018). Il est suggéré que certains facteurs dont la sensibilisation au TSA, les changements des critères diagnostiques ou encore la méthodologie utilisée pour mesurer la prévalence dans diverses études jouent un rôle dans cette croissance (Hansan et al. 2015; Neggers, 2014). Au Québec, Diallo et al. (2018) ont récemment estimé à 1,2 % la prévalence du TSA chez les individus de moins de 18 ans. Des chercheurs ont identifié certains facteurs génétiques et environnementaux contribuant au développement d'un TSA, mais l'hétérogénéité des résultats et la force des associations limitent les conclusions causales (Lyall et al., 2017; Newschaffer et al., 2007).

Les personnes ayant un TSA présentent souvent d'autres troubles ou conditions concomitantes. Selon des études récentes, la DI et le trouble du déficit de l'attention avec ou sans hyperactivité seraient présents chez environ 30% à 50% des personnes ayant un TSA (Christensen et al., 2016; Matson & Cervantes, 2014; Matson & Goldin, 2013). D'autres conditions, dont des particularités sensorielles, des problèmes gastro-intestinaux, des difficultés de sommeil et des comportements problématiques, sont associées au TSA. Les comportements problématiques seraient parmi les symptômes associés les plus souvent observés (p.ex. : Baghdadli et al., 2003; M. L. Matson et al., 2009; McTiernan et al., 2011).

Comportements problématiques et TSA

Définition et classification

Les comportements problématiques sont généralement définis comme des comportements socialement inacceptables pouvant physiquement blesser un individu ou son entourage, entraver ses apprentissages ou nuire à son fonctionnement dans les différentes sphères de sa vie (Mahan, 2012; Matson et al., 2010; Myrbakk & Tetzchner, 2008). Dans la littérature scientifique, plusieurs expressions sont employées pour faire référence aux comportements problématiques, dont comportements problématiques [*problem behaviors*], comportements inadaptés [*maladaptive behaviors*], comportements aberrants [*aberrant behaviors*], comportements difficiles [*challenging behaviors*] et comportements destructeurs [*destructive behaviors*]. Les chercheurs utilisent également des classifications de comportements problématiques différentes. Par exemple, certains classent les comportements selon leurs traits, soit internalisés ou externalisés (Bauminger et al., 2010; Matson et al., 2008), tandis que d'autres chercheurs privilégient une classification qui prend uniquement en considération la forme spécifique des comportements extériorisés (p.ex. : destruction de biens matériaux, agressivité verbale et comportements stéréotypés; Horner et al., 2002; Matson & Nebel-Schwalm, 2007; Rojahn et al., 2001).

Tout comme pour la classification, le nombre de topographies (c.-à-d., la forme) de comportements problématiques pour les personnes ayant un TSA varie selon les études (p.ex.: l'agression, la destruction, les crises et les comportements sociaux et verbaux inappropriés; Achenbach & Rescorla, 2000; J. L. Matson et al., 2009; Swender et al., 2006). Didden et al.

(1997) ont identifié 34 topographies de comportements problématiques dans leur méta-analyse comprenant 482 études empiriques qui évaluaient le traitement des comportements problématiques chez des personnes ayant une DI, un retard de développement ou un TSA. Quelques années plus tard, Horner et al., (2002) ont publié une synthèse de la littérature dans laquelle ils ont noté les topographies les plus étudiées chez la population ayant un TSA, soit la stéréotypie, l'agression envers des personnes et des objets et l'automutilation. D'autres études récentes ont adopté cette catégorisation de topographies (Ritter et al., 2018; Rojahn et al., 2001).

Prévalence et facteurs de risque

Au cours des 20 dernières années, les chercheurs ont rapporté des prévalences de comportements problématiques chez les personnes présentant un TSA variant entre 21,9 % et 97,5 % (Baghdadli et al., 2003; Bodfish et al., 2000; Farmer & Aman, 2010; Holden & Gitlesen, 2006; Jang et al., 2011; J. L. Matson et al., 2009; McTiernan et al., 2011; Melo et al., 2019; Murphy et al., 2009; Severini et al., 2018). Des différences importantes quant aux mesures utilisées, à la taille d'échantillons et aux caractéristiques des populations étudiées (p.ex. : la comorbidité d'une DI, l'âge et la sévérité des symptômes liés au TSA) peuvent expliquer les variations d'une étude à l'autre. Il est également important de noter que la prévalence des comportements problématiques varie en fonction de la topographie : les comportements stéréotypés étant généralement les plus fréquemment observés (J. L. Matson et al., 2009; McTiernan et al., 2001; Melo et al., 2020; Rojahn et al., 2001; Chebli et al., 2016). La sévérité des symptômes liés au TSA, ainsi que la présence et la sévérité d'une DI sont les facteurs les plus souvent rapportés comme prédicteur des comportements problématiques (Jang et al., 2011; McTiernan et al., 2011; Williams et al., 2017). Les données sur l'âge sont moins homogènes. Certains chercheurs ont identifié une relation inversement proportionnelle entre l'âge et la fréquence des comportements problématiques (Baghdadli et al., 2003; Mazurek et al. 2013; Shattuck et al., 2007) tandis que l'absence d'une association significative a été rapportée par d'autres (Murphy et al., 2009; McTiernan et al., 2011). Des limites méthodologiques importantes dont l'utilisation de petits échantillons dans les études épidémiologiques (moins de 250 participants), le recours à des devis transversaux et l'absence de critères d'exclusion ou de contrôle pour la prestation d'intervention (p.ex. : chimique ou comportementale) peuvent expliquer en partie les résultats divergents. Malgré certaines disparités dans la catégorisation, la prévalence et les facteurs de risque des comportements problématiques, les chercheurs s'entendent sur l'importance d'intervenir tôt pour augmenter les chances de favorablement influencer la trajectoire développementale des personnes ayant un TSA (Eldevik et al., 2009; Maurice et al., 2001; Virués-Ortega, 2010; Wong et al., 2015).

Comportements problématiques et analyse appliquée du comportement

Les interventions basées sur la fonction d'un comportement, une caractéristique de l'analyse appliquée du comportement (AAC), seraient plus efficaces que les interventions qui ne prennent pas en considération la fonction du comportement pour intervenir auprès des personnes ayant un TSA (Beavers et al., 2013; Hanley, et al., 2003; Ingram et al., 2005). L'AAC est fondée sur les principes du conditionnement opérant de Skinner (1953). Le conditionnement opérant, inspiré par la loi de l'effet (*Law of effect*) the Thorndike, est fondé sur la prémisse qu'une réponse souhaitée à un comportement (p.ex. : renforcement positif ou négatif) augmente la probabilité qu'il se reproduise (Skinner, 1963). Par exemple, le dessert que reçoit un enfant lorsqu'il mange tous les légumes dans son assiette augmente la probabilité qu'il consomme tous ses légumes pendant les prochains repas. Son utilisation pour intervenir auprès des personnes ayant un TSA est étudiée depuis plus de 70 ans (Ayllon & Micheal, 1959; Williams, 1959) et l'AAC a maintenant une place centrale dans l'intervention auprès de cette population. Quoique la majorité des programmes de formation sont offerts aux États-Unis (638/844), soit son pays d'origine, il est maintenant possible de trouver un programme de certification dans 45 pays à travers le monde. De plus, on retrouve des politiques qui soutiennent l'ABA et qui visent à augmenter son accessibilité (p.ex. : États-Unis, Suisse, Belgique, Canada; Keenan et al., 2015; Richelle et al., 2017; Ministère de la Santé et des Services Sociaux, 2003). Enfin, une récente revue de la littérature qui visait à identifier les interventions jugées probantes pour intervenir auprès des personnes ayant un TSA suggère que la majorité d'entre elles implique l'utilisation de principes de l'analyse du comportement (p.ex. : le renforcement différentiel, les interventions basées sur la modification des antécédents, l'extinction; Wong et al., 2015). Aujourd'hui, l'efficacité des interventions découlant de l'AAC est reconnue, entre autres, pour enseigner des comportements adaptatifs et réduire les comportements problématiques des personnes ayant un TSA (Wong et al., 2015; Roth et al., 2014). Néanmoins, certaines lacunes en lien avec les interventions découlant de l'analyse du comportement existent, soit le manque d'accessibilité aux services, le manque de connaissances quant aux facteurs sous-jacents à l'efficacité des interventions et les perceptions divergentes de l'AAC.

L'accessibilité

Plusieurs familles éprouvent des défis quant à l'accessibilité aux des interventions basées sur l'AAC pour leur enfant. Notamment, les longues listes d'attente des services publics, les coûts associés aux services privés et habiter dans un milieu rural ou éloigné peuvent agir comme barrière à l'accès à des interventions pour réduire les comportements problématiques (Csanady, 2015; Kogan et al., 2008; Protecteur du citoyen, 2015). Néanmoins, les parents peuvent pallier l'absence de service en agissant comme agent d'intervention auprès de leur enfant.

Les parents comme agent d'intervention

En plus d'être « l'expert » de leur enfant, les parents passent généralement beaucoup de temps avec leur enfant dans divers contextes naturels, ce qui offre des opportunités riches d'apprentissages et d'intervention. Ainsi, enseigner aux parents à intervenir efficacement auprès de leur enfant peut limiter les conséquences sociales, développementales et physiques que peuvent engendrer les comportements problématiques, en plus de favoriser la généralisation des acquis (Postorino et al., 2017; Prata et al., 2018). Rendre accessible les formations pour les parents est d'autant plus important considérant que plusieurs chercheurs ont noté que l'implication des parents est un critère d'efficacité important des interventions visant à réduire les comportements problématiques de leur enfant avec un TSA (Cooper et al., 2007; Lanovaz et al., 2013; M. L. Matson et al., 2009; Reichow & Barton, 2014; Rogers et al., 2012; Roth, et al., 2014).

Un nombre croissant de données appuient l'efficacité des formations pour parents visant la gestion des comportements problématiques des enfants ayant un TSA. Des chercheurs ont trouvé que participer à une formation structurée en personne ou à distance (p.ex. : formation en ligne ou par télésanté) permet aux parents d'acquérir des connaissances théoriques et pratiques basées sur l'AAC, d'augmenter leur utilisation des principes de l'analyse du comportement et d'améliorer les comportements problématiques de leur enfant (p. ex. : Antonsson et al., 2016; Bearss et al., 2013; Bearss et al., 2015; Heitzman-Powell et al., 2014; Jang et al., 2012; Marleau et al., 2018; McGarry et al., 2019; Pennefather et al., 2020; Sivaraman & Fahmie, 2020; Sourander et al., 2016; Suess et al., 2016). Malgré le soutien empirique grandissant de l'efficacité des formations en personnes et par télésanté pour soutenir les familles, elle nécessite une personne pour les implanter. Étant donné le manque de ressources humaines pour intervenir auprès des personnes ayant un TSA, l'accessibilité de ces types de formations reste limitée.

Les formations interactives en ligne

Contrairement aux interventions en personne et par télésanté, les formations interactives en ligne comportent plusieurs avantages. D'une part, lorsque la formation est prête à être diffusée, aucune ressource humaine n'est requise pour son animation. D'autre part, elles sont peu coûteuses à implanter et permettent une utilisation flexible et continue répondant aux horaires des familles utilisatrices (Souranders et al., 2016). Il est également possible d'y inclure plusieurs des modalités recommandées pour favoriser les apprentissages des parents (p. ex.: modalités de transmission écrites, verbales et visuelles, du modelage à l'aide d'exemples vidéo et une modalité de la rétroaction via des questionnaires formatifs et sommatifs; Dogan et al., 2017; Miles & Wilder, 2009; McNeil & Hembree-Kigin, 2010; Stewart et al., 2007). Selon une enquête menée par Statistique Canada (2019), 94% des Canadiens habitent un foyer avec une connexion internet, ce qui rend cette modalité de formation pour parents accessible pour la majorité des familles nonobstant leur localisation géographique. En revanche, les formations interactives en ligne n'impliquent pas nécessairement l'accès à du soutien ni à de la rétroaction humaine sur la fidélité d'implantation, deux autres modalités liées à l'efficacité des formations pour les parents (Matthews & Hudson, 2001; Nosik, et al., 2013). Alors, les formations interactives en ligne sont des outils qui devraient viser à pallier aux besoins de familles durant la période d'attente pour des services spécialisés et non à remplacer les interventions spécialisées traditionnelles. Pour qu'une intervention soit qualifiée d'interactive, elle doit inclure une action bidirectionnelle entre la formation et la personne qui la suit. Par exemple, il pourrait s'agir d'une composante de rétroaction verbale ou écrite intégrée à la formation.

Pour favoriser le développement du savoir et du savoir-faire des parents, les formations interactives en ligne doivent inclure diverses méthodes didactiques, dont des modalités de transmission écrites, verbales et visuelles, du modelage à l'aide d'exemples vidéo et une modalité de la rétroaction via des questionnaires formatifs et sommatifs. L'utilisation de diverses stratégies d'enseignement s'avère non seulement plus efficace que l'utilisation d'une seule méthode, mais permet aussi de répondre aux caractéristiques d'un plus grand nombre de personnes (Sitzmann et al., 2006). Les modalités d'apprentissage fondées sur les principes du Behavioral Skill Training (BST) comprennent habituellement des instructions verbales et/ou écrites, du modelage, des opportunités pour mettre en pratique les apprentissages et de la rétroaction (Dib & Sturmey, 2012). Le Behavioral Skill Training (BST) est une procédure d'apprentissage multimodale qui peut comprendre diverses modalités didactiques, donc les principales sont des instructions verbales et/ou écrites, du modelage, des opportunités pour mettre en pratique les apprentissages faits (p.ex. : des activités de jeu de rôle) et de la rétroaction (Dib et Sturmey, 2012; Miltenberger, 2013). Par exemple, Parson et al., 2012 décrit une procédure qui comprend une séquence de cinq étapes : 1) décrire habiletés qui seront travaillées dans le cadre de l'intervention, 2) remettre une description écrite des habiletés à la personne, 3) enseigner les habiletés à l'aide de modelage (c.-à-d., faire une démonstration de l'habileté), 4) effectuer un jeu de rôles pour pratiquer les habiletés apprises et 5) offrir de la rétroaction verbale sur le déroulement de l'étape 4. Plusieurs études appuient l'efficacité du BST pour l'enseignement de diverses habiletés, incluant l'enseignement des techniques d'intervention pour des intervenants et des parents (p.ex. : Dogan et al., 2017; McNeil et Hembree-Kigin, 2010; Miles et Wilder, 2009 Stewart, Carr et LeBlanc, 2007).

L'état des connaissances sur l'efficacité des formations en ligne pour parents basées sur l'AAC visant la gestion des comportements problématiques des personnes ayant un TSA n'est qu'à un stade préliminaire. Concrètement, six études portant sur ce sujet ont été publiées à ce jour (Blackman et al., 2020; Kolb, 2007; Heitzman-Powelle & al., 2013; Jang et al., 2012; Marleau et al., 2018; Sourander et al., 2016). De ces études, seulement trois ont porté sur des formations complètement auto-guidées (c.-à-d., aucun de soutien d'un intervenant ou d'un chercheur; Blackman et al., 2020; Jang, et al., 2012; Marleau et al., 2018). De plus, les principales variables étudiées étaient liées aux connaissances des parents. Dans leur étude, Jang et al. (2012) ont noté des améliorations significatives des scores des parents au questionnaire portant sur les composantes importantes d'intervention de l'AAC. Marleau et al. (2018), quant à eux, ont rapporté des améliorations au niveau de l'identification de la fonction de comportements problématiques et la sélection d'intervention fonctionnelle suivant la formation suivant la complétion leur formation *Interactive Web Training*. Enfin, Blackman et al. (2020) ont relevé des améliorations significatives de leur formation en ligne sur les connaissances des parents sur le contenu enseigné dans la formation, les interactions positives et négatives avec leur enfant et le stress parental. En sus, ils ont trouvé que l'efficacité de version en personne de la formation ne différait pas significativement de celle offerte exclusivement en ligne. Bien que ces résultats soient encourageants, l'efficacité des formations en ligne basées sur l'AAC complètement auto-guidées pour augmenter l'utilisation des interventions comportementales par les parents et pour réduire les comportements problématiques des enfants ayant un TSA reste inconnue.

Les facteurs sous-jacents à l'efficacité

Une autre limite de l'AAC est que les chercheurs comprennent encore très peu les facteurs personnels et environnementaux prédisent les effets d'une intervention qui découlent de cette science (Tiura et al., 2020). Une façon de remédier à cette situation est d'utiliser des algorithmes d'apprentissage automatique [*machine learning algorithms*]. L'apprentissage automatique est une facette de l'intelligence artificielle dans laquelle des données sont utilisées pour identifier et utiliser des patrons dans les données. Depuis près de 10 ans, des chercheurs utilisent des algorithmes d'apprentissage automatique pour améliorer la prise de décision entourant le TSA (Thabtah, 2019). Les études qui découlent de l'AAC sont généralement réalisées à l'aide de petits échantillons (p.ex. : Rodgers et al., 2021; Yu et al., 2020) et des devis à cas unique (Fisher & Piazza, 2014), ce qui peut amener certaines personnes à penser que cette branche de l'intelligence artificielle n'est pas adaptée à la recherche et à la pratique clinique en analyse du comportement. Bien que certains algorithmes nécessitent de grandes bases de données pour fonctionner efficacement (p.ex. : *artificial neural network*), un nombre croissant d'études soutiennent que des algorithmes peuvent offrir des prédictions adéquates avec des échantillons de plus petite taille (p.ex. : Xhang et Ling, 2018; Vabalas et al., 2019).

Lorsqu'ils sont utilisés rigoureusement, les algorithmes d'apprentissage automatique ont le potentiel de soutenir les cliniciens et les chercheurs dans de multiples tâches de prise de décision, dont la sélection d'interventions efficaces pour les familles (Thabtah, 2019) ou encore la réalisation d'analyses sémantiques (Mandala et al., 2021), et peuvent soutenir la démarche d'évaluation diagnostique (Bone et al., 2015). Un des principaux avantages des algorithmes d'apprentissage automatique est leur capacité à détecter des patrons [*pattern*] inconnus et non-linéaires pour augmenter la certitude d'une prédiction (Rebala, et al., 2019). De plus, une fois les modèles développés et validés, les résultats sont généralement simples à interpréter. Le champ de recherche portant sur l'intelligence artificielle a progressé rapidement dans plusieurs domaines et champs de recherche, mais l'état actuel des connaissances, de la recherche et de l'utilisation des algorithmes d'apprentissages automatique entourant l'AAC n'est qu'à ses balbutiements. Par conséquent, son fonctionnement, ses outils et son potentiel restent inconnus par la majorité des cliniciens et chercheurs formés dans l'analyse du comportement.

La perception

La science de l'AAC détient une réputation polarisée à travers le monde, ce qui peut être attribué à différents enjeux. D'une part, l'information qui circule au sujet de l'AAC (p.ex. : dans les journaux et les médias sociaux) n'est pas toujours exacte (Amouroux, 2017; Freedman, 2016; Krapfl, 2016) ou facile à comprendre (Rivière, 2015), ce qui peut conduire certaines personnes à rejeter les interventions qui en découlent. D'autre part, certaines instances gouvernementales ne reconnaissent pas à ce jour l'efficacité des interventions qui découlent de l'AAC. Une explication possible est que la majorité des études utilisent des devis à cas unique et non des devis de groupes avec groupes contrôles. Certains événements publics (p.ex. : des procès juridiques contre l'ABA; Keenan and Dillenburger, n.d.; NeuroClasitc, 2019) peuvent également avoir négativement teinté la réputation de la science.

Bien qu'il soit reconnu que les principes de l'AAC et les interventions qui en découlent ne font pas l'unanimité, aucune étude à ce jour ne semble avoir quantifié l'information sur l'AAC. Considérant que 1) l'information et les témoignages auxquels les parents sont exposés semble influencer leur décision d'adhérer ou de sélectionner des interventions (Call et al., 2015; Grant et al., 2016) et que 2) les familles font souvent appel aux réseaux sociaux pour soutenir leurs pratiques parentales et identifier des interventions pour leur enfant (Clifford and Minnes, 2013; Shepherd et al., 2020), il devient important d'évaluer le contenu publié sur ces plateformes.

Le forage de données est une pratique qui permet d'extraire des connaissances d'une grande base de données (Kantardzic, 2011). À l'aide d'algorithmes, il est maintenant possible d'extraire les données de différentes plateformes de réseaux sociaux pour effectuer une analyse qualitative ou quantitative. Quelques études portant sur le TSA ont utilisé des stratégies de forage de données pour effectuer des analyses sémantiques de différents réseaux sociaux (p.ex. : twitter; Beykikhoshk et al., 2014; 2015; Hswen et al., 2019), mais aucune à ce jour ne s'est intéressée à l'extraction et l'analyse des données portant sur l'AAC.

Objectifs de la thèse

La présente thèse doctorale vise donc à utiliser la technologie pour présenter des solutions potentielles ou mieux comprendre les enjeux d'accessibilité, de connaissance et de perception entourant l'AAC en (a) évaluant les effets d'une formation interactive en ligne basée sur les principes de l'AAC sur les comportements des parents et sur les comportements problématiques de leur enfant, (b) présentant comment des algorithmes d'apprentissage automatiques peuvent être utilisés pour prédire si une intervention produira ou non des effets chez une personne et (c) mesurant la perception de l'AAC dans un forum internet français

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Chapitre II - Article 1: Effects of an interactive web training to support parents in the management of challenging behaviors in children with Autism

Effects of an interactive web training to support parents in the management of challenging behaviors in children with Autism

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Abstract

Many children with autism spectrum disorder (ASD) engage in challenging behaviors, which may interfere with their daily functioning, development, and well-being. To address this issue, we conducted a four-week randomized waitlist control trial to examine the effects of a fully self-guided interactive web training (IWT) on (a) child engagement in challenging behaviors and (b) parental intervention. After four weeks, parents in the treatment group reported lower levels of challenging behaviors in their children and more frequent use of behavioral interventions than those in the waitlist groups. Furthermore, within-group analyses suggest that these changes persisted up to 12 weeks following completion of the IWT. Our results highlight the potential utility of web training, but our high attrition rate and potential side effects prevent us from recommending the training as a standalone treatment.

Keywords: autism, behavioral interventions, challenging behavior, parent training, web training.

Effects of an Interactive Web Training to Support Parents in Reducing Challenging Behaviors in Children with Autism

Children with autism spectrum disorder (ASD) frequently display challenging behaviors such as aggression, destruction, self-injury, tantrums, and stereotypy (Medeiros et al., 2014; Ritter et al., 2018). Specifically, researchers have found that 50% to 90% of children with ASD display at least one of these topographies of challenging behavior (J. F. Lee et al., 2015; McTiernanet al., 2011; Soke et al., 2018; Stevens et al., 2017). Challenging behaviors may interfere with the development, well-being, and health of children with ASD and others around them (Minshawi et al., 2015; Stevens et al., 2017; Walsh et al., 2013). If left untreated, challenging behaviors tend to persist, or even increase in severity, continuously exposing the child to potentially detrimental developmental and functional consequences (G. T. Lee et al., 2018; McTiernan et al., 2011).

Interventions based on behavior analytic principles have the most evidence for decreasing challenging behaviors and teaching adaptive behaviors to children with ASD (Roth et al., 2014; Wong et al., 2015). In brief, these interventions involve operationally defining the challenging behavior, identifying its function, and selecting a function-based intervention to reduce its occurrence and intensity (Hanley et al., 2003; Iwata & Dozier, 2008; Shayne & Miltenberger, 2013). Researchers also consider parental involvement as an important component for short- and long-term effectiveness of behavioral interventions (Postorino et al., 2017; Rogers & Vismara, 2008; Williams et al., 2016). As parents are often the primary caretakers of their child, training them to manage challenging behaviors is essential. Training parents may increase the intensity of intervention a child receives, enhance opportunities for generalization by intervening in a broad array of contexts (e.g., at home, in the community), and prevent challenging behaviors from worsening over time (Postorino et al., 2017; Prata et al., 2018).

Practitioners traditionally offer training to parents of children with ASD in the form of an in-person intervention (Postorino et al., 2017; Prata et al., 2018), which involves group or one-on-one sessions. Researchers have associated in-person training with positive parent and child outcomes (e.g., Argumedes et al., 2018; Bearss et al., 2013; Bearss et al., 2015; Shayne & Miltenberger, 2013). Recent reviews have highlighted that in-person training for the management of challenging behaviors can increase parental knowledge of empirically-supported assessment and intervention procedures for reducing challenging behaviors (Postorino et al., 2017; Prata et al., 2018). For example, Shayne and Miltenberger (2013) found that, after completing a 3-hr training, parents of children with ASD could effectively identify the function of challenging behavior and select function-based treatments. Moreover, further studies have found that gains in knowledge may translate to significant reductions in the frequency and severity of challenging behaviors (e.g., Bearss et al., 2013; Bearss et al., 2015; Ginn et al., 2017; Ilg et al., 2017).

Although traditional parent training has been consistently associated with positive parent and child outcomes, in-person interventions comprise many barriers that limit their accessibility. On one hand, public services are not meeting the intervention demands as parents can be placed on waiting lists for several years (Csanady, 2015; Kogan et al., 2008; Rivard et al., 2017). On the other hand, private sector services can be unaffordable for some families, especially those with lower socioeconomic status or without insurance coverage (Kogan et al., 2005; Kogan et al., 2008; Young et al., 2009). Other barriers to in-person parent training can include a lack of transportation, geographical isolation, and conflicting schedules (e.g., public services are often offered during standard business hours; Meadan et al., 2013; Murphy & Ruble, 2012). Finally, some parents may be reluctant to seek professional help regarding parenting practices due to cultural, socioeconomic and psychological barriers (e.g., feeling of incompetence; Keller & McDade, 2000; Morawska & Sultan, 2016). Thus, improving accessibility to parent trainings that teach empirically-supported interventions appears important.

Recent studies have found that parents of children with ASD (a) primarily use the internet to seek information on ASD and interventions to utilize, (b) do not consider evidence of effectiveness when selecting an intervention, and (c) usually use a "trial and error" approach for intervention selection and implementation with their children (Grant et al., 2016; Hall et al., 2016). To support parents aquire knowledge on validated intervention principles, several researchers have developed and tested technology-based parent training programs for the management of challenging behaviors in children with ASD (Dai et al., 2018; Marleau et al., 2019; Pannefather et al., 2018; Sourander et al., 2016; Suess et al., 2016). These technology-based trainings typically involve either a telehealth intervention or a web-based training.

According to the World Health Organization (2019), telehealth intervention "involves the use of telecommunications and virtual technology to deliver health care outside of traditional health-care facilities". This type of parent training requires real-time interaction with a practitioner or research professional (J. F. Lee et al., 2015). Recent studies have found positive parent and child outcomes following telehealth interventions (Heitzman-Powell et al., 2014; Pannefather et al.. 2018; Suess et al., 2016; Wacker, Lee, Padilla Dalmau, Kopelman, Lindgren, Kuhle, Pelzel, & Waldron, 2013; Wacker, Lee, Padilla Dalmau, Kopelman, Lindgren, Kuhle, Pelzel, Dyson et al., 2013). Altogether, telehealth interventions can support parents of children with ASD to correctly identify the function of a targeted challenging behavior, select an appropriate functionally-based intervention, and reduce challenging behaviors. Telehealth interventions have advantages such as not requiring the parent or practitioner to travel and giving parents access to real-time feedback regarding parenting practices. However, telehealth interventions comprise some barriers such as requiring specialized equipment (i.e., a webcam and a microphone) and high-speed internet (J. F. Lee et al., 2015). The most important barrier, however, is the requirement of real-time access to a trained professional, which may be limited due to increasing demand for services and the shortage of trained professionals (Csanady, 2015; Kogan et al., 2008; Rivard et al., 2017).

Technology-based parent training can also take the form of a web-based training. Web-based training has benefits such as being low cost, easily disseminated, and highly accessible (Dai et al., 2018; Nieuwboer et al., 2013). Most importantly, the presence of a trained professional is not required for its implementation once the web-based training has been developed (Dai et al., 2018; Nieuwboer et al., 2013). Given the above-mentioned features, this form of parent training is especially interesting to increase program reach to parents who do not have access to support of a trained professional (Piotrowska et al., 2019). In a meta-analysis comprising 12 studies, researchers found that web-based parent training of children with variable profiles (e.g., health issues, developmental disability, attention-deficit/hyperactivity disorder) produced improvements in knowledge, attitudinal and behavioral outcomes for parents as well as in behavioral and attitudinal outcomes for children (Nieuwboer et al., 2013). Specifically, Nieuwboer et al. (2013) found small-to-medium effect sizes for parent (e.g., positive parenting) and child (e.g., adherence to family rules, social competency) behavioral outcomes. That said, few web-based parent training programs specifically targeted challenging behavior in children with ASD.

To our knowledge, only four studies have specifically evaluated the effects of a web-based training to teach parents of children with ASD theoretical or practical concepts to manage challenging behaviors (Heitzman-Powell et al., 2014; Kolb, 2007; Marleau et al., 2019; Sourander et al., 2016). These studies suggest that web-based training is a promising tool to increase parental knowledge and implementation of behavioral principles, and possibly decrease challenging behaviors. Of these four studies, Marleau et al. (2019) is the only one that did not include a feedback component from a practitioner or a researcher. In a pre-experimental pre-test/post-test design, Marleau et al. (2019) found that 26 parents of children with a diagnosis of ASD or intellectual disability performed significantly better on a behavior function identification task as well as on a function-based intervention selection task following the completion of an interactive web training (IWT). This study suggests that IWT as a standalone intervention can lead to positive knowledge development outcomes in the absence of a trained professional. The main limitation of Marleau et al. was that the researchers did not examine whether the knowledge acquired through a fully self-guided IWT translated to changes in child and parent behavior (i.e., knowledge acquisition was measured using written case examples only).

Thus, the purpose of our study was to extend Marleau et al.'s (2019) findings by evaluating the effects of a modified version of the fully self-guided IWT on child behavioral outcomes and parental intervention. The primary objectives of our study were to examine the effects of the IWT alone on the frequency and severity of challenging behaviors, reported use of behavioral interventions by parents, and parenting practices. We hypothesized that following the completion of the IWT, parents would report lower frequency, lower severity of challenging behavior, more frequent use of behavioral interventions, and improved parental practices. We also measured social validity and quantified intervention usage (i.e., completion time, numbers of attempts until successful completion of each module, and score on quizzes) as secondary outcomes.

Method

Participants

To recruit participants, we posted a message in 7 Facebook® groups for parents of children with ASD as well as on our research lab's public Facebook® page. The message included a brief description of the purpose of the project, the target population, and the first author's contact information. We encouraged parents, professionals, and groups who contacted us to share the post. Our post resulted in 32,401 views and 292 shares over the span of 11 months. Individuals were eligible to participate in the study if (a) they were the parent or primary caretaker of a child 12 years of age or younger with a formal diagnosis of ASD[1], (b) their child presented challenging behaviors as confirmed by a frequency score of at least three and a severity score of at least two on one or more items of the Behavior Problems Inventory-01 (BPI-01; Rojahn et al., 2001), (c) they lived in the province of Québec, Canada, and (d) they understood French. We excluded parents from the study if they had formal training in psychosocial interventions (e.g., behavior analysis, education, psychology, social work).

In total, 50 parents contacted the first author to participate in the study. Forty-seven parent/child dyads met all the inclusion and exclusion criteria with the parent providing informed consent to participate. Parents were predominantly female (n = 39; 83%) and children were mostly male (n = 42; 89%). On average, children were 7 years old (*SD* = 2.40) and their mean

[1] Parents were asked to provide information found on their diagnostic report (i.e., diagnosis, date of the report, and name and profession of the specialist that signed the report)

general adaptive composite score ranged between 40 and 108 on the Adaptive Behavior Assessment System – Second Edition (ABAS-II; Harrison & Oakland, 2011a; M= 66.30; SD = 15.52). Our sample did not include households with more than one dyad. Parent and child demographic characteristics are presented in Table 1 (see initial sample column). Of the 47 parent/child dyads, only 26 completed their participation in the study. We ran our analyses with this sample of 26 parents (see non-attrition column in Table 1 for sample characteristics).

Measures

Characteristics of the participants

The parents completed a sociodemographic questionnaire to collect information on their gender, education, language spoken at home and household income as well as on the age, gender and any comorbid diagnosis of their child. The interviewer also administered the ABAS-II (Harrison & Oakland, 2011a) to document adaptive functioning. Each item of the ABAS-II measures the frequency of a behavior with a four-point Likert scale (0 = unable to 3 = always when necessary). The psychometric properties of the questionnaire include high internal consistency values (e.g., alpha coefficients for each of the domains of competence of .91 to .98) and an inter-rater fidelity score between .60 and .79. The ABAS-II has a good concurrent validity as supported by correlations obtained with other adaptive behaviors scales (Harrison & Oakland, 2011b).

Challenging behavior

The parents reported the frequency and severity of their child's challenging behaviors using the French translation of the BPI-01 (Rojahn et al., 2001). The BPI-01 comprises 52 items that are divided into three subscales: stereotyped behaviors, self-injurious behaviors, and aggressive/destructive behaviors. The BPI-01 has a good test-retest reliability of .76 and a

Cronbach alpha of .83. Parents assessed the frequency (0 = never to 4 = every hour) and the severity (1 = low to 3 = severe) of their child's challenging behaviors during the last four weeks, rather than during the last two months, as indicated by Rojahn et al. (2001). We selected a four-week data collection interval as our study aimed to monitor behavior every four weeks.

Use of behavioral intervention

We created an eight-item ad hoc questionnaire to measure the use of behavioral interventions by parents (see Appendix for the detailed questionnaire). The items represented strategies that parents were taught to use as part of the IWT. Parents scored each item using a four-point Likert scale (0 = never to 3 = always). A higher overall score corresponded to a more frequent use of appropriate behavioral interventions by parents.

Parenting practices

The Alabama Parenting Questionnaire-Short Form (APQ-SF) is a brief assessment tool for self-reported parenting practices (Elgar et al., 2007; Shelton et al., 1996). The APQ-SF includes nine items that are divided into three subdomains: positive parenting, inconsistent discipline, and poor supervision (Elgar et al., 2007). The parents scored all items using a five-point Likert scale (1 = almost never to 5 = always). The APQ-SF has internal consistency values ranging from .59 to .84. A three-factor confirmatory factor analysis with a sample of 1,296 mothers and a sample of 745 fathers suggested a good fit (see Elgar et al., 2007 for the model fit indices).

Social validity

The parents assessed the social validity of the IWT using the Treatment Acceptability Rating Form – Revised (TARF-R; Carter, 2007). This 20-item questionnaire measures parental perception of acceptability, effectiveness, and ease of use of the IWT. Parents scored all items using a five-point Likert scale, where a value of one represented a lower social validity score for an item and a value of five presented a higher social validity score. The TARF-R has a good internal consistency with a Cronbach's alpha value of .92 and is considered as a suitable measurement for clinical subpopulations (Carter, 2007). We translated the TARF-R to French (TARF-R-VF) using a similar procedure to the one proposed by Sousa and Rojjanasrirat (2011).

Web training usage

The server automatically recorded parental use of the IWT. For each participant, the server saved completion time, number of attempts to pass each module, and scores obtained for all end-of-module quizzes.

Interactive Web Training

As part of the current study, parents completed a modified version of the IWT described in Marleau et al. (2019), which was designed as a fully self-guided training to reduce challenging behavior in children with developmental disabilities. The teaching procedures included a written user guide, slide-supported video-based presentations, video models of the correct implementation of the behavioral interventions, and questions to promote active participation (Gerencser et al., 2017; Pollard et al., 2014). The original IWT involved four modules. Module 1 taught parents how to define a challenging behavior and identify its function, while emphasizing the importance of excluding potential medical and physiological causes (e.g., change in medication, tiredness). Modules 2 and 3 demonstrated how to change the antecedents and consequences of a challenging behavior. Finally, module 4 explained how to implement strategies to teach appropriate alternative behaviors. Each module ended with a quiz containing 10 multiple-choice questions. The parent had to obtain a score of 80% or more on the end-of-module quiz to move on to the next module. If not, the training prompted the parent to restart the current module.

To improve the training based on the results of Marleau et al. (2019), we added and changed some video examples, and inserted a fifth module. Thus, the new version of the IWT included five modules: the first four teaching the same content as the original IWT, and the fifth module discussing practical and ethical considerations for the management of challenging behaviors. We also updated the user guide to ensure consistency with the content of the new IWT (see Table 2 for summary of the content).

Procedures

Upon approval by the research ethics board of our university, we assessed the effects of the IWT using a four-week randomized waitlist control trial. This type of design has a good internal validity and allows all participants to receive the tested intervention (Marchand et al., 2011; Ronaldson et al., 2014). Moreover, within-group post-test measures were collected for all participants at four-week intervals for 12 weeks after completing the IWT. Using block randomization, a spreadsheet automatically assigned the participants to the experimental group or waitlist group (Beller et al., 2002). We remained blind to group assignment until the first data collection was completed. Parents assigned to the experimental group completed interviews to respond to the questionnaires at baseline (T1), four (T2), eight (T3), and twelve (T4) weeks after the IWT. Parents assigned to the waitlist group completed interviews at five time points: two baseline measures (i.e., T1 and T2) administered four weeks apart and then three post-test measures at four (T3), eight (T4), and twelve (T5) weeks after the IWT (see Figure 1 for the study procedure by group). We administered the questionnaires to assess the characteristics of the participants at T1 only and the social validity measure at the 4-week post-test (T2 for experimental group and T3 for waitlist group). The parents responded to all other questionnaires (i.e., challenging behaviors, behavioral intervention use, and parenting practices) at all time points.

We administered all questionnaires over the phone. During these calls, the first author or a research assistant read each item to the parents while recording their responses on the questionnaires. Upon request, the parents received an electronic version of each questionnaire via email for visual support. At the end of the first interview, we informed parents whether they would have access to the IWT immediately or had to complete a second interview in four weeks before getting access. Immediately following the first baseline measure (experimental group) or second baseline measure (waitlist group), the parents received a link, a unique username, and a password by email to access the training. We informed the parents that the IWT lasted approximately 3 hr that they could complete it intermittently, that she would not respond to any of their questions involving the content of the training, and that the training should be completed within the next two weeks.

Analysis

Given the high attrition rate observed, we first conducted preliminary analyses to test whether the participants that withdrew from the study differed significantly from those that did not. Second, analyses of covariance (ANCOVA) examined between-group differences for each dependent variable (i.e., challenging behavior, use of behavioral interventions, and parenting practices). In these analyses, group assignment (experimental or waitlist) was the fixed factor, the four-week post-test score was the dependent variable, and the pre-test score of the variable of interest was the covariate (to control for baseline levels of challenging behavior). We also calculated an effect size based on the pooled pretest standard deviation (d_{ppc2}; see Morris, 2008).

Third, our within-group analyses involved assessing changes four, eight and twelve weeks after completing the IWT for each dependent variable using a repeated measures analysis of variance (ANOVA). For these analyses, we combined the data (i.e., pre-test[2] and three post-tests) of the participants for both groups and applied a Bonferroni correction for our post hoc pairwise comparisons. Finally, we calculated descriptive statistics for our social validity and web training usage data.

Results

Preliminary Analyses

Of the initial 47 participants, 20 (43%) did not complete the IWT and 1 completed a single post-test measure (see Figure 1 for the CONSORT flow diagram). Of the 20 participants who did not complete the training, eight never started the modules, two did not complete module 1, six did not complete module 2, and five did not complete module 4. Table 1 shows the differences between the initial sample and the dyads who completed their participation in the study. Participants who completed their participation in the study differed significantly from participants who withdrew on family income, $t(41) = 2.70$, $p = .01$, as well as on child adaptive functioning based on the ABAS-II, $t(45) = 2.68$, $p = .01$. That is, parents in the attrition group had a lower mean revenue and children with lower adaptive functioning scores. Because the attrition rate was high (> 5%) and that 20 participants did not complete any post-test measures, we could not use imputation techniques (Schlomer et al., 2010). Hence, we conducted our analyses using the data of the 26 participants who completed their participation in the study. For

[2] Pre-test 2 scores were used as the pre-test score of participants in the waitlist group for the within-group analyses to ensure that the time between pre-test and post-test data was four weeks for all participants.

these 26 participants, the sociodemographic variables and pre-test measures did not significantly differ between those in the experimental group (n = 14) versus those in the waitlist group (n = 12).

Between-Group Effects

For child outcomes measured using the BPI-01, we found a significant main effect of group on the frequency of challenging behaviors after controlling for pre-test scores, $F(1,23)=5.501$, $p = .028$, $d_{ppc2}= .555$ [0.088, 1.705]. Descriptive statistics suggest that parents in the experimental group reported lower frequency scores during the four weeks following the pre-test. A significant difference was also observed for the severity of challenging behaviors after controlling for pre-test scores, $F(1,23)=4.720$, $p = .040$, $d_{ppc2}= .553$, 95% CI [.031, 1.641]. Parents reported lower severity of challenging behaviors four weeks after completing the IWT.

For parent outcomes, the IWT produced a significant main effect on behavioral intervention use (measured by the ad hoc questionnaire), after controlling for pre-test scores, $F(1,23) = 5.478$, $p = .025$, $d_{ppc2} = .892$, 95% CI [.160, 1.791]. Mean comparisons suggest that the parents in the experimental group reported using more appropriate behavioral interventions to manage challenging behaviors during four weeks after completing the IWT than the parents still on the waiting list. Finally, parenting practices as measured by the APQ-SF did not differ significantly across groups, $F(1,23) = .126$, $p > .05$, $d_{ppc2} = .08$, 95% CI [-.847, .696].

Within-Group Effects

Figure 2 presents mean changes in the frequency and severity of challenging behaviors over time (data of both groups combined). We found a significant main within-group effect of time for the frequency of challenging behaviors, $F(3, 72) = 12.413$, $p < .001$, $\eta p^2 = .341$. Post-hoc pairwise comparisons reveal significant differences in frequency means between the pre-test score and the four- (M = -9.429, p = .017), eight- (M = -11.619, p = .002) and twelve-week (M = -14.006, $p < .001$) post-test scores, but no differences between the post-test scores themselves. For severity, the main within-group effect for time was also statistically significant, $F(3, 72) = 15.344$, $p < .001$, $\eta p^2 = .390$. Post-hoc pairwise comparisons identified significant differences between the pre-test score and the four- (M = -6.732, p = .021), eight- (M = -8.935, p = .002) and twelve-week (M = -12.077, $p < .001$) post-tests, and between the four- and twelve-week post-tests scores (M = -5.345, $p < .022$).

For parent outcomes, the within-group analysis on the use of behavioral interventions indicated a significant difference across time, $F(3, 72) = 15.344$, $p < .001$, $\eta p^2 = .390$. Post-hoc pairwise comparisons revealed significant differences in means for reported use of behavioral interventions between the pre-test score and the four- (M = 2.077, p = .011), eight- (M = 1.935, p = .003) and twelve-week (M = 2.244, $p < .001$) post-test scores while no differences were observed across post-test scores. Finally, we found no significant within-group effect of time on parenting practices, $F(3, 72) = .835$, $p > .05$, $\eta p^2 = .034$.

IWT usage measure and social validity

Table 3 shows the descriptive statistics of the IWT. The median time for parents to complete the IWT was 3.9 hr. In general, parents completed each module once. However, 9 of the 26 parents had to restart one or more modules before obtaining a passing score of 80% or more to move on to a subsequent module. Table 4 presents the item-level descriptive statistics of the social validity measure. On average, parents scored the TARF-R-VF items 4.0 out of a possible score of 5.0. The highest-rated items were related to the affordability of the IWT, the cost to carry out the intervention, and the comprehension of the interventions taught through the IWT. Parents rated the following items as lowest on the TARF-R-VF: " "How much discomfort is your child likely to experience during the course of this treatment?", "To what extent are undesirable side-effects likely to result from this treatment?", "How much time will be needed each day for you to carry out this treatment?", and "How disruptive will it be to the family (in general) to carry out this treatment". Mean scores on these items were 3.00, 2.92, 2.65, and 2.46, respectively. These results suggest that parents concerns regarding these items were generally neutral to mild.

Discussion

The purpose of our study was to extend a study conducted by Marleau et al. (2019) by assessing the effects of a modified version of the IWT on child and parent outcomes within a randomized waitlist control trial. Our results indicate that parents in the experimental group reported using more behavioral interventions and observed lower frequency and severity of challenging behaviors in their child than parents on the waiting list for four weeks after completing the IWT. These changes persisted up to 12 weeks after the training. Surprisingly, the medium-to-large effect sizes observed for our fully self-administered short-duration IWT were comparable to previous research evaluating in-person, personalized parent trainings (Postorino et al., 2017). On the other hand, we did not find the IWT to significantly improve parenting practices as measured by the APQ-SF. Parents rated the social acceptability of the training highly.

Consistent with Marleau et al. (2019), one of the main concerns reported by parents related to their child experiencing discomfort or side-effects during the implementation of the behavioral interventions. Through the IWT, parents learned about the possible short-term side-effects of some interventions such as extinction, which probably explains these results. As we did not measure the side-effects or discomfort directly, we do not know whether these concerns materialized when the parents implemented some of the interventions. The results indicate that it would be essential to implement a side-effect monitoring system in the future and to provide on demand support from a practitioner when the intervention produces undesirable consequences. Parents also reported that implementing the treatment may be time consuming and effortful, underlying the need to integrate strategies to support and encourage parents during implementation.

Despite the low response effort associated with completing the IWT, the observed attrition rate remained high (i.e., 45%; n = 21), but comparable to the 51% dropout rate found by Chacko et al. (2016) in their review of engagement in behavioral parent training comprising 262 studies with parents of children with disruptive behavior disorders (e.g., attention-deficit/hyperactivity disorder, conduct disorder). This issue significantly reduced our statistical power by forcing us to rely on only a subsample (i.e., parents who completed the study) to conduct our analyses. When parents informed the first author that they wanted to withdraw their participation, the predominant reason they provided was the lack of time (n = 19), which is consistent with prior research (Dadds et al., 2019). These results suggest that a standalone web training may be insufficient to maintain parental participation. Having active support and encouragements from a trained professional may potentially increase completion rate. Alternatively, implementing a reinforcement contingency for the parents may decrease attrition while potentially also addressing issues related to the high response effort associated with carrying out the interventions.

Consistent with our results, other researchers have found that a lower socioeconomic status is related to higher attrition rates in parent trainings (Chen & Fortson, 2015; Gross et al., 2018; Lavigne et al., 2010). Furthermore, we also observed that attrition was skewed towards parents with children with lower adaptive functioning scores, possibly highlighting the challenges of finding time when caring for a child with more substantial needs. Despite this difference, readers should note that mean and median adaptive behavior functioning score remained extremely low for children in both groups. Further, attrition was not related to pre-test frequency or severity of challenging behaviors. Because attrition results in parents not receiving the intervention, researchers should investigate components that may increase parent training completion rates, such as the presence of a parent support component and the type of teaching modality used. Researchers should also conduct interviews with participants who withdraw from studies to better understand the reasons of non-completion of the online training.

The initial purpose of our study was to develop and test a fully self-guided web training to reduce engagement in challenging behavior. Unfortunately, our high attrition rate and the concerns reported by the parents in the social validity questionnaire prevent us from recommending the web training as a standalone treatment at this point. The IWT does not include a direct feedback component for treatment implementation fidelity, which may alo raise some ethical issues. More specifically, parents may implement the learned intervention inadequately without realizing it (Meade et al., 2014; Neely et al., 2017). As shown by prior research, these errors in integrity may unknowingly increase engagement in challenging behavior (St. Peter et al., 2016; St. Peter Pipkin et al., 2010; Wilder et al., 2006). Therefore, we recommend that a practitioner be available to provide encouragement and support on a as needed basis to complete training and to monitor the side-effects of implementation. Professionals may provide this support by phone or by email. In doing so, the web training may still have potential benefits over other forms of training (e.g., reducing costs and wait times, providing services to those in remote areas) as the practitioner would not need to provide the actual training in person or live online.

Nevertheless, many parents primarily rely on the internet to identify potential interventions to use (Grant et al., 2016; Hall et al., 2016). Consequently, some parents have reported using unvalidated interventions that have been associated with negative health-related consequences (e.g., Arnold et al., 2003; Heiger et al., 2008) and even death (Brown et al., 2006). When parents do not have access to services, we would argue that teaching parents basic empirically-supported interventions outweighs the risks of parents acessing other unvalidated interventions found on the internet (Green et al., 2006; Smith et al., 2014). We thus need more research on the benefits and drawbacks of fully self-guided approaches.

Our study is the first to test the effects of a fully self-administered IWT on child challenging behavior within a randomized waitlist control trial. Another contribution of our study is the diversity of our sample. Most research on parent training of children with ASD has emphasized younger children (e.g., < 8 years of age) with higher levels of functioning (i.e., Ilg et al., 2017; Postorino et al., 2017; Suess et al., 2016; Wacker, Lee, Padilla Dalmau, Kopelman, Lindgren, Kuhle, Pelzel, & Waldron, 2013; Wacker, Lee, Padilla Dalmau, Kopelman, Lindgren, Kuhle, Pelzel, Dyson et al., 2013). In our study, adaptive scores for the ABAS-II varied from the 1st percentile (extremely low) to the 70th percentile (average) and the age of children ranged from 3.5 to 12.0 years. Parents followed the IWT and carried out the interventions in a real-life setting, which is also a strength of the study. From a practical standpoint, the training only lasted a median of 4 hr and parents rated its social acceptability and validity highly, which are two further benefits of using the IWT.

Although the IWT is promising, our study has limitations that should be noted. First, the parents reported all the measures collected as part of the current study. By relying solely on the parent, we can only conclude that parents perceived improvements in challenging behaviors following the IWT. Second, our measure of behavioral intervention use was an ad hoc questionnaire created by the second author, which focused on only one dimension of parent implementation. In the future, researchers should also measure other dimensions such as quality of implementation (Sanetti & Kratochwill, 2009). Third, our four-week randomized waitlist control trial does not allow us to experimentally assess the effect of the IWT at the eight- and twelve-week post-tests (Marchand et al., 2011; Ronaldson et al., 2014). Our within-group analyses only indicate that outcomes changed or persisted favorably over time.

Future research should replicate our study with a larger sample and should include other sources of data such as direct observation measurements or data collected from a third party (e.g., the other parent). Researchers should also study the effects of the IWT on specific behavior topographies. For example, Bearss et al. (2015) found that their parent training had an almost null effect size on stereotypic and social withdrawal behaviors, but a medium-to-large effect size for other disruptive behaviors. Since our effect sizes were comparable to other practitioner-supported parent trainings, comparing the effects of IWT with and without the support of a practitioner to identify the most effective training package seems important. Finally, researchers should assess the long-term effects of the IWT on parent and child outcomes as well as distal outcomes such as changes in adaptive behaviors of children, parental stress, and family quality of life. Despite the need for additional research, our results underline the potential utility of using web-based training as a short, low cost, and easily accessible option to supplement services provided to parents of children with ASD.

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Table 1

Parent and Child Characteristics

Variable	Initial sample (*N* = 47) Frequency	%	Non-attrition sample (*N* = 26) Frequency	%
Child characteristics				
Sex				
Male	42	89.4	23	88.5
Female	5	10.6	3	11.5
ABAS-II GAC score				
>130 (very superior)	0	0	0	0
120-129 (superior)	0	0	0	0
110-119 (above average)	1	2.1	1	3.8
90-109 (average)	3	6.4	3	11.5
80-89 (below average)	2	4.3	2	7.7
71-79 (borderline)	12	25.5	7	26.9
<70 (extremely low)	29	61.7	13	50.0
Comorbid diagnostic				
Yes	22	46.8	10	38.5
No	25	53.2	16	61.5
Parent characteristics				
Family income ($)				
Less then 10 000	1	2.1	0	0
10,000-29,999	7	14.9	2	7.7
30,000-49,999	4	8.5	1	3.8
50,000-69,999	9	19.1	6	23.1
70,000-89,999	7	14.9	5	19.2
90,000 or more	15	31.9	11	42.3
Prefer not to answer	4	8.5	1	3.8
Sex				
Female	39	83	22	15.4
Male	8	17	4	84.6
Spoken language at home				
French	43	91.5	25	96.2
English	0	0	0	0
Other	4	8.5	1	3.8
Education				
Uncompleted high school	1	2.1	0	0
High school	9	19.2	3	11.5
College	15	31.9	8	30.8
Undergraduate	16	34.0	10	38.5

Graduate	6	12.8	5	19.2

Notes: ABAS-II = Adaptive Behavior Assessment System – Second Edition; GAC = General adaptive composite

Table 2

Content of the Interactive Web Training

Module	Content
1: Understanding challenging behaviors	Part 1: What is a challenging behavior? Part 2: Why does my child engage in challenging behaviors (antecedents-behavior-consequence)? Part 3: What is the function of the behavior and how do I identify it?
2: Modify the antecedents	Part 1: Why modify the antecedents? Part 2: Modify the antecedents, regardless of behavioral function Part 3: Modify the antecedents based on the function of the behavior
3: Changing the consequences	Part 1: Why is my child engaging in challenging behavior? (review) Part 2: What are the consequence-based interventions? Part 3: Extinction Part 4: How to succeed with implementing extinction? Part 5: Response interruption and redirection
4: Teaching an appropriate behavior	Part 1: What is an appropriate behavior? Part 2: How can I teach an appropriate behavior? Part 3: Alternative intervention for self-stimulatory behavior
5: Practical considerations	Part 1: Combining interventions Part 2: Important considerations: (a) prioritizing safety, (b) choosing the number of behaviors to target, and (c) possible short-term effects of extinction. Part 3: What to do if the intervention is ineffective?

Table 3

Duration of Modules, End-of-Module Scores, and Number of Times Each Module Was Attempted

Module	Mean duration (min)	Median duration (min)	Mean score on end-of-module quiz (%)	Number of Attempts	
				Median	Maximum
1	77	55	90	1	3
2	104	45	96	1	1
3	59	48	83	1	7
4	69	48	97	1	10
5	18	16	95	1	4

Table 4

TARF-R-VF Mean Scores per Item from Highest to Lowest

Item	Mean	*SD*
How affordable is this treatment for your family?	4.65	0.75
How costly will it be to carry out this treatment?	4.62	0.85
How clear is your understanding of this treatment?	4.58	0.50
How willing are you to carry out this treatment?	4.42	0.95
How confident are you that the treatment will be effective?	4.42	0.76
How willing would you be to change your family routine to carry out this treatment?	4.38	0.70
How acceptable do you find the treatment to be regarding your concerns about your child?	4.35	0.80
How likely is this treatment to make permanent improvements in your child's behavior?	4.35	0.80
Given your child's behavioral problems, how reasonable do you find the treatment to be?	4.31	0.79
How much do you like the procedures used in the proposed treatment?	4.31	0.79
To what extent do you think there might be disadvantages in following this treatment?	4.15	0.92
How effective is this treatment likely to be for your child?	4.15	0.78
How well will carrying out this treatment fit into the family routine?	4.04	0.82
How willing will other family members be to help carry out this treatment?	3.46	1.24
How disruptive will it be to the family (in general) to carry out this treatment?	3.00	1.20
To what extent are undesirable side-effects likely to result from this treatment?	2.92	1.60
How much time will be needed each day for you to carry out this treatment?	2.65	1.47
How much discomfort is your child likely to experience during the course of this treatment?	2.46	1.48

Note. TARF-R-VF = Treatment Acceptability Rating Form-Version Française

Figure 1.

CONSORT Flow Diagram of our Randomized Controlled Trial With Waitlist Control.

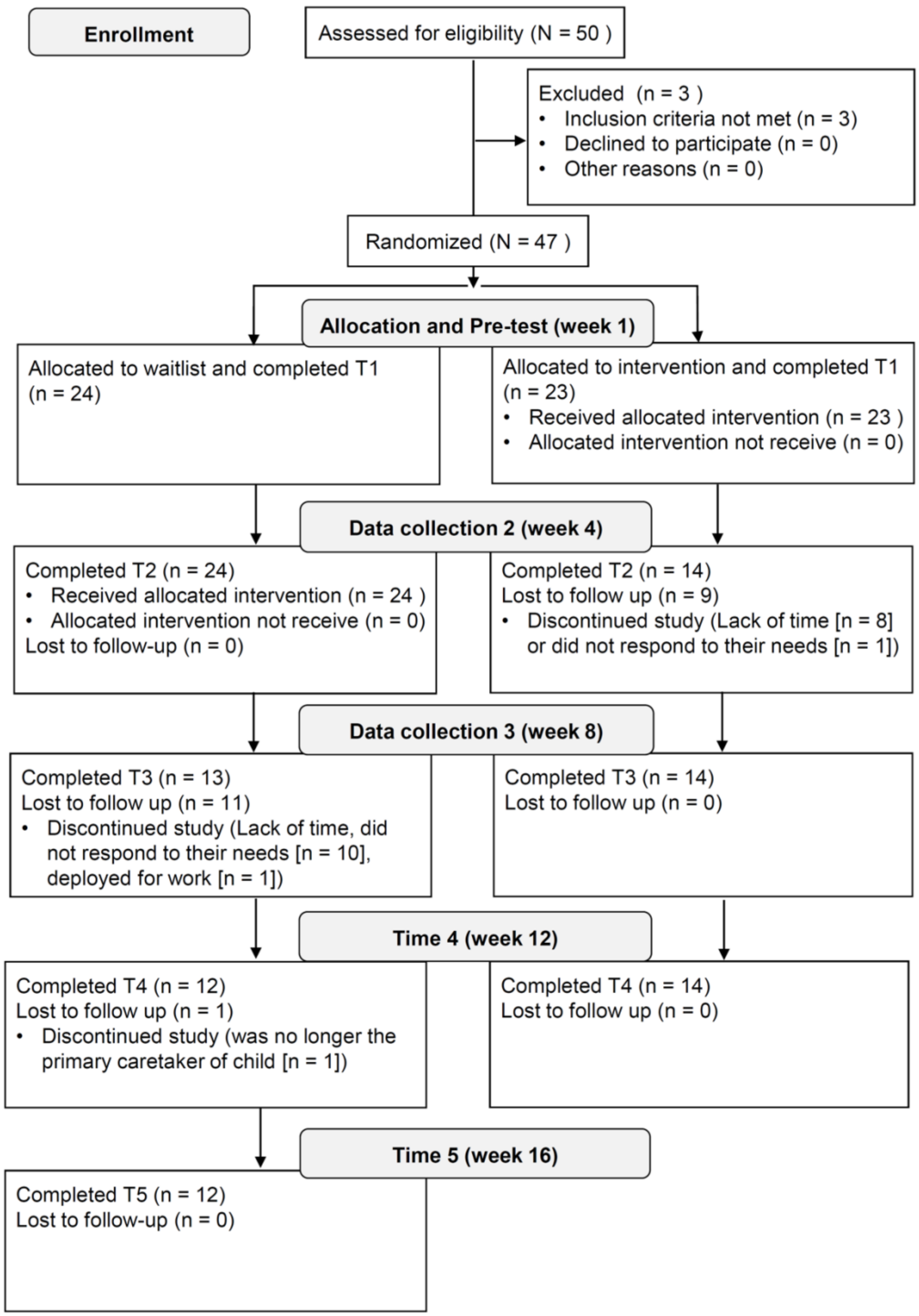
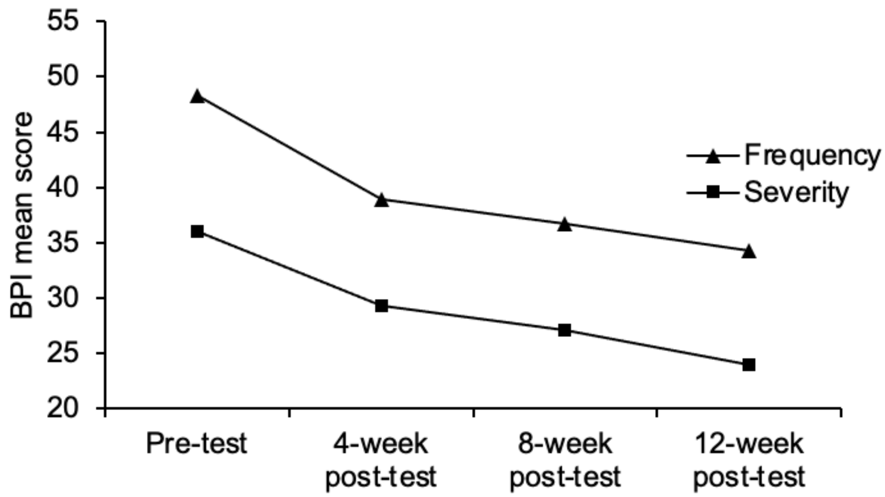


Figure 2.

Mean Frequency and Severity Scores on the Behavior Problem Inventory (BPI) at Pre- and Post-Tests.



Appendix

Behavioral Intervention Use Questionnaire

1) I give my child what he wants regularly throughout the day.

0 Never	1 Sometimes	2 Often	3 Always

2) I modify or remove the triggers associated with challenging behavior to prevent my child from engaging in them.

0 Never	1 Sometimes	2 Often	3 Always

3) When my child engages in challenging behavior, I immediately give him what he wants (e.g., attention, object, break). *

3 Never	2 Sometimes	1 Often	0 Always

4) I teach my child behaviors that allow him to keep himself busy in an acceptable manner and/or to express his needs.

0 Never	1 Sometimes	2 Often	3 Always

5) When my child engages in good behavior, I congratulate him or give him something to acknowledge it.

0 Never	1 Sometimes	2 Often	3 Always

6) I clearly explain to my child what he must do, how and where to get what he wants.**

0 Never	1 Sometimes	2 Often	3 Always

7) Prior to tasks or requests, I provide advanced notice to my child. **

0 Never	1 Sometimes	2 Often	3 Always

8) When I present a demand to my child, it is brief, direct, clear and specific. **

0 Never	1 Sometimes	2 Often	3 Always

* Reversed scoring
**These items may involve the use of nonverbal communication (if necessary), such as pictograms, images, or gestures.

Transition entre les chapitres

Le Chapitre II présente l'évaluation d'une formation interactive en ligne pour parents visant la gestion des comportements problématiques de leur enfant ayant un trouble du spectre de l'autisme. Les effets de groupe suggèrent que la formation en ligne a des effets positifs. Toutefois, pas tous les parents dans l'étude ont rapporté des effets positifs sur leur utilisation d'intervention basées sur l'AAC ou sur les comportements problématiques de leur enfant. Dans le Chapitre III, un outil pouvant soutenir les professionnels dans leurs prises de décisions cliniques est présenté. Plus précisément, une démonstration sur la façon d'utiliser des algorithmes d'apprentissage automatique pour prédire les effets d'une intervention est proposée. Un exemple détaillé avec les données de l'étude présentée au Chapitre II est utilisé pour la démonstration.

Chapitre III - Article 2: Tutorial: Applying machine learning in behavioral research

Tutorial: Applying machine learning in behavioral research

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Abstract

Machine learning algorithms hold promise in revolutionizing how educators and clinicians make decisions. However, researchers in behavior analysis have been slow to adopt this methodology to further develop their understanding of human behavior and improve the application of the science to problems of applied significance. One potential explanation for the scarcity of research is that machine learning is not typically taught as part of training programs in behavior analysis. This tutorial aims to address this barrier by promoting increased research using machine learning in behavior analysis. We present how to apply the random forest, support vector machine, stochastic gradient descent, and k-nearest neighbors algorithms on a small dataset to better identify parents who would benefit from a behavior analytic interactive web training. These step-by-step applications should allow researchers to implement machine learning algorithms with novel research questions and datasets.

Keywords: artificial intelligence, behavior analysis, machine learning, tutorial

Tutorial: Applying Machine Learning in Behavioral Research

Machine learning is a subfield of artificial intelligence that specializes in using data to make predictions or support decision-making (Raschka & Mirjalili, 2019). One specific use of machine learning is solving classification problems. A classification problem occurs when trying to predict a categorical outcome (Bishop, 2006). Examples in behavior analysis includes what is the function of a behavior (attention, escape, non-social, or tangible), whether a behavior is occurring at a given moment, whether an independent variable is changing a behavior or whether a treatment is likely to be effective for a given individual. Supervised machine learning is well suited to provide solutions to these types of classification problems and support decision-making.

In supervised machine learning, an algorithm (i.e., computerized instructions) trains a model using past observations to predict outcomes on new samples. In recent years, supervised machine learning algorithms have been studied as useful aids to support decision-making in multiple fields such as medicine, pharmacology, education, and health care (Coelho & Silveira, 2017; Miotto et al., 2018). Some examples include identifying breast cancer (Rajaguru & Chakravarthy, 2019), diagnosing autism (Sadiq et al., 2019), predicting school dropout (Chung et al., 2019), and detecting unsafe workplace behavior (Ding et al., 2018).

In behavior analysis, both researchers and practitioners rely on data to make decisions on a regular basis. These decisions may involve determining whether an independent variable produced an effect on a behavior, selecting an assessment, identifying the function of behavior, or predicting whether an intervention will produce meaningful behavior changes in a specific individual. However, researchers and practitioners may make unreliable decisions, especially when using their professional judgment (Ninci et al., 2015; Slocum et al., 2014). Consequently, relying on subjectivity for decision-making may result in differences from one behavior analyst to another. One potential solution to this issue is to increase the use of machine learning in behavior analysis (Lanovaz et al., 2020).

Machine learning also has direct applications for the experimental analysis of behavior and translational research. For example, researchers could use machine learning to develop new models that aim to predict engagement in multiple competing responses (akin to the matching law) under varying experimental conditions. Furthermore, some algorithms may facilitate the identification of variables associated with certain behaviors that may be difficult to isolate experimentally (e.g., suicidal behavior, risky sexual behavior). Machine learning may even simulate responding to test hypotheses that may be difficult to assess with living organisms (see Burgos, 2003, 2007 for examples).

Despite the growing number of studies on the topic in the fields of healthcare and education, applications of machine learning in behavior analysis remain limited (Burgos, 2003, 2007; Lanovaz et al., 2020; Linstead et al., 2015, 2017). In experimental work, Burgos (2003, 2007) used machine learning to simulate latent inhibition, automaintenance and autoshaping. The results indicated that it may be possible to simulate behavioral phenomena using artificial neural networks (i.e., a type of machine learning algorithm). In an applied example, Linstead et al. (2015, 2017) developed a machine learning model to identify predictors of learning progress in children with autism spectrum disorder from behavior analytic services. Their results indicated that treatment intensity positively predicted children's progress, but most interestingly that machine learning explained almost twice as much variance of this relationship than linear regression. Recently, Lanovaz et al. (2020) showed that machine learning algorithms outperformed a structured visual aid to analyze simulated data from single-case AB graphs. Their study indicated that machine learning produced smaller Type I error rates and larger power than the dual-criteria method.

One potential explanation for the scarcity of research is that machine learning is not taught as part of training programs in behavior analysis. This lack of knowledge on machine learning and the absence of training for its application may result in researchers overlooking this tool to contribute to the development of the science. This tutorial aims to address this barrier by applying machine learning to a problem involving decision-making in behavior analysis.

Machine Learning Procedures and Algorithms

One of the hallmarks of behavior analysis is the pervasive use of single-case designs, which require a small sample size. Given that machine learning is typically applied to large datasets (Raschka & Mirjalili, 2019), some researchers may believe that behavior analytic data are unsuitable for this type of analysis. As will be shown in the current tutorial, datasets with as few as 25 participants or 25 sessions may produce meaningful results using machine learning. With the growing use of consecutive case series designs in behavior analysis (e.g., Hagopian, 2020; Jessel, et al. 2019; Lomas Mevers et al., 2018; Rooker et al., 2013), several researchers and practitioners may already have sufficiently large datasets to apply such algorithms. Moreover, experimental researchers studying human and nonhuman organisms often use automated apparatus to monitor behavior, which provides sufficiently large datasets to potentially uncover novel relationships between variables. In the following sections, we present a step-by-step application of machine learning using data from a behavioral study published by Turgeon et al. (2020). As relevant, our paper also includes instructions on how to apply the algorithms to other datasets. A repository containing our datasets and code is freely available on the Open Science Framework at: https://osf.io/yhk2p/.

On Terms

Table 1 draws a parallel between behavioral terms and supervised machine learning. In supervised machine learning, an algorithm trains a model using samples, which is similar to using a specific teaching method when training a learner using exemplars. Thus, the algorithm, the model and the samples represent the teaching method, the learner and the exemplars, respectively. Each algorithm has its own specific hyperparameters, which are functions or values provided to the algorithm that can be modified by the experimenter prior to training. These hyperparameters are equivalent to the teaching parameters for a teaching method (e.g., number of trials in discrete trial instruction, prompting procedure in direct instruction).

In the application of machine learning in behavior analysis, a sample would typically involve the data from one participant or from one session. Supervised machine learning further divides samples into two components: features and class labels. The features involve the input data that are used by the algorithms. Features in machine learning are akin to discriminative stimuli in behavior analysis. The class labels represent the responses provided and predicted by the algorithm (i.e., the output variables). In sum, machine learning algorithms use features from samples to train models to predict class labels in a similar manner that teaching methods focus on using discriminative stimuli from exemplars to train learners to provide correct responses.

Our Dataset

To illustrate the application of machine learning, we used a previously published dataset involving behavior analytic procedures (Turgeon et al., 2020). Turgeon et al. (2020) assessed the effects of an interactive web training to teach parents behavior analytic procedures to reduce challenging behaviors in children with autism spectrum disorders. The results of the study showed that, on average, parents who completed the training reported larger reductions in child challenging behaviors than those who did not. However, eight children showed no improvement in challenging behaviors even though their parent had completed the training. As the behavior of individuals is central to research and practice in behavior analysis, one important question is "How can we predict which parent-child dyad are unlikely to benefit from the interactive web training?". Hence, a behavior analyst could recommend alternatives (e.g., in-person training) to families unlikely to benefit from web training.

Preparing the Data

Our dataset includes 26 samples, four features and one class label. Table 2 presents the characteristics of our dataset. The samples involved 26 parents of children with autism spectrum disorders who completed the interactive web training. We provided four features to our machine learning algorithms: household income, most advanced degree of the parent, the child's social functioning, and the baseline scores on parental use of behavioral interventions at home (prior to training). Parents initially rated their household income and most advanced degree on an ordinal scale. Because data were highly skewed and our sample was small, data for these features were dichotomized to create more balanced categories (i.e., categories with similar sample sizes)[3]. It should be noted that dichotomizing data entails many limitations when analyzing large datasets (e.g., loss of power, decreased effect size, and limited generalisation of findings). You should avoid using this procedure with continuous and ordinal variables containing a large number of samples (see Dawson & Weiss, 2012; MacCallum et al., 2002; Irwin & McClelland, 2003; Sankey & Weissfeld, 1998). We chose the four features because three of them (i.e., most

[3] These data are available at https://osf.io/yhk2p/

advanced degree, social functioning, and parental use of behavioral interventions) had the highest correlation with our class label values and the fourth feature (i.e., household income) had been previously shown to predict challenging behaviors (Leijenet et al., 2013; Shelleby & Shaw, 2014). Furthermore, our variables did not show multicollinearity[4]. Our class label was whether the frequency of the child's challenging behavior decreased from baseline to the four-week post-test (i.e., 0 = no improvement and 1 = improvement) based on the Behavior Problem Inventory-01 (Rojahn et al., 2001). Table 3 contains our complete dataset, which is also available as a comma-separated values (.csv) file in the repository (see TurgeonetalData.csv).

We arranged the data of our dataset into five columns in our .csv file (i.e., four features and one class label). The first row of each column contains the name of the variable while subsequent rows contain the data from one sample. As such, the number of lines for each column should equal the number of samples plus one. In our tutorial, we used 26 samples to train our machine learning models, which produced a total of 27 rows (including the header). You should save this file in your working directory (see below). If you want to organize your own data for analysis with machine learning, you may enter them in a spreadsheet in a .csv compatible program (e.g., Microsoft Excel, Google Sheets, Apple Numbers) and save your file as a .csv. Each row should include a single sample and each column a feature or class label (keep the class label in the rightmost column). To use the code in the current tutorial, your class label should remain a binary variable (see Alternatives to Single Binary Classification for other options).

The Basics

---

[4] No significant linear association between the features

Installing Software and Packages

To train our models, we used Python as it is free, offers many open access algorithms, functions the same across operating systems, and has a large network of community support (see Python tutorials in Appendix). The first step to training a machine learning model is downloading a Python distribution. We strongly recommend that you download and install the Anaconda distribution of Python. This distribution facilitates package management and installation, and ensures that you have the same environment as ours to replicate the procedures presented in this tutorial. You may download and install Anaconda from https://www.anaconda.com. Once Anaconda has been installed, you should create a new virtual environment by opening Anaconda Prompt (in Windows) or Terminal (in macOS or Linux) and running the following commands in a sequential order:

```
conda create -n myenv python=3.7
conda activate myenv
```

From now on, make sure you run "conda activate myenv" whenever you close and open Anaconda Prompt or Terminal[5]. If not, your code may be unable to locate the packages to run the algorithms. Next, we must download and install three packages in this virtual environment: spyder, pandas and scikit-learn. Spyder is an easy to use integrated development environment, pandas facilitates the loading of data in Python, and scikit-learn contains the machine learning algorithms. To install the packages, run the following commands sequentially (one at a time) in myenv of Anaconda prompt (in Windows) or Terminal (in macOS or Linux):

```
conda install spyder
conda install pandas
```

[5] The last line of your Anaconda Prompt or Terminal screen should begin with (myenv). If it begins with (base), you have not activated your environment correctly.

```
conda install scikit-learn
```

Whenever you receive a prompt, choose “y” to install the packages and their dependencies.

Initializing the Integrated Development Environment

Once you have downloaded and installed the necessary programs and packages, open the spyder integrated development environment that you will use to write and run your code. To open spyder, run the following command in Anaconda Prompt or Terminal:

```
spyder
```

Figure 1 presents a screenshot of the integrated development environment. The integrated development environment is separated in three main work areas: the editor, the iPython console, and the variable explorer. You should write all your code in the editor (box on the left of your screen). To run a block of code from the editor, select the code by highlighting it with your cursor and press F9 (or click on “run selection” in the menu bar). When you run your code, any warnings, errors, or results that you print will appear in the iPython console (box on the lower right of your screen). If you assign a variable or load data, you can view it by clicking on the variable explorer tab of the upper right box.

The first lines of code involve setting the working directory. That is, you need to instruct your environment where to find the path to access the folder in which you saved the TurgeonetalData.csv data file. To do so, write the following lines in your editor and run the selection[6]:

```
import os
```

[6] Do not copy the line numbers (on the left). These numbers are meant to guide the reader through each code block. A line with no number indicates that the line is a continuation of the line above. It should also be noted that Python code is *case sensitive*.

```
os.chdir("PATH")
```

In the above command, you should replace PATH by your working directory[7] where the .csv file is located. You should select these lines of code and press F9 to run the selection (or click on run selection in the menu bar above the editor).

Loading and Preparing the Data

Next, the lines of code below import the packages that include the functions that we need to load and organize the data:

```
import numpy as np
import pandas as pd
```

Once both packages have been imported, load the .csv data file into the environment with the following code:

```
data = pd.read_csv("TurgeonetalData.csv")
data_matrix = data.values
```

The first line loads our dataset and names it "data" whereas the second line transforms this data to a matrix, thus facilitating the manipulation of the data. When loading your own data, you should replace TurgeonetalData.csv by the filename of your own .csv file.

Prior to conducting machine learning, you must standardize the data of all non-normally distributed continuous features. Non-standardized data may render the machine learning model unable to correctly use the features to predict the class labels (Raschka & Mirjalili, 2019). Therefore, we transformed the social functioning scores and the parental use of behavioral

[7] For example: C:/Users/Bob/Documents/ . If you copy the file location from the property menu of Windows Explorer, you need to replace the backslashes with forward slashes.

interventions scores to *z* scores. A *z* score is a standardized score that is obtained by subtracting the raw score from the mean score then dividing this value by the standard deviation. To transform the raw scores to *z* scores, we need to write and run the following instructions in the editor:

```
1 from sklearn import preprocessing
2 standard_scaler = preprocessing.StandardScaler()
3 data_matrix[:,2:4] =
      standard_scaler.fit_transform(data_matrix[:,2:4])
```

The first and second lines of code import a function to rapidly transform the raw scores to a *z* score. The third line instructs the program to apply this standardization only to columns that include the social functioning and parental use of behavioral interventions scores[8]. If you are using your own data, you should apply the standardization to all continuous variables that have large ranges or that are non-normally distributed. The final step to preparing the data is separating the features from the class labels:

```
x = data_matrix[:,0:4]
y = data_matrix[:,4]
```

Matrix “x” now contains the four features whereas vector “y” contains the true class labels. When using your own data, you should replace number 4 in the code block by the number of features in your dataset.

---

[8] For those unfamiliar with matrices, we can call and manipulate specific locations in the matrix using a bracket [*i*, *j*], where *i* is the row number and *j* the column number. Python begins indexing (numbering of rows and columns) at 0 and the last value is excluded from ranges. Therefore, data_matrix[0, 1] refers to the first row (index = 0) and second column (i.e., index = 1). In the current example, data_matrix[:, 2:4] refers to all rows for the third and fourth columns of the .csv file (indices = 2 and 3).

Outcome Measures

The most common outcome measure for binary classifications is accuracy. Accuracy involves dividing the number of agreements between the true class label values and the predictions of the models by the total number of predictions (Lee, 2019). One drawback of accuracy is that it does not consider that some values may be correct as a result of chance, which may skew the results in favor of correct predictions. Kappa is a more stringent measure of performance than accuracy as it takes into consideration correct classifications due to chance (we refer the reader to McHugh [2012] for a demonstration on how to compute the Kappa statistic). The following lines import the functions to calculate these values for you:

```
from sklearn.metrics import accuracy_score, cohen_kappa_score
```

For kappa, any value above .20 indicates that the model reliably predicts some of the class label values in the dataset, regardless of chance (McHugh, 2012). In contrast, benchmarks for accuracy do not exist as the measure is dependent on the distribution of the data.

Comparison Measures

Given that there is no fixed criterion to determine whether an accuracy value is adequate, we must compute comparison measures for accuracy. One potential measure represents the accuracy if predictions were randomly selected. The following lines of code use a Monte Carlo method to determine this accuracy value:

```
np.random.seed(48151)
y_random = []
for i in range(100000):
     y_random_values = np.random.choice(data_matrix[:,4], 26,
            replace = False)
     y_random.append(accuracy_score(y, y_random_values))
```

The first line sets the random seed for numpy at 48151. Although not necessary in practice, we recommend that you implement this line of code so that your environment produces the same results as the ones reported in the tutorial. The next line (i.e., 2) creates an empty list in which the accuracy values are stored for each iteration. The third line is a loop instructing Python to repeat the procedures 100,000 times[9] (Monte Carlo simulations). During each loop, the program first randomly permutates the values for the 26 samples, which produces a vector named random_values (line 4). The fifth line of code computes the accuracy score for these random_values and appends it to the list. Finally, to compute the accuracy of a random selection measure, we take the mean of these 100,000 iterations by running the following code:

```
1 print(np.mean(y_random))
```

The print function displays the value in the iPython console. In our example, the iPython console should show that random selection produced an accuracy of .574 (i.e., it correctly guessed the class labels 57.4% of the time).

A second more stringent comparison measure involves reporting the class value with the highest probability response. That is, what is the best accuracy we could produce if we always guessed the same value? In our case, the most frequently observed class label value is improvement (n = 18), which would lead to an accuracy of .692 (18 divided by 26) if we simply predicted that all class label values were the same.

A third candidate for comparison is the logistic regression. Although sometimes categorized as a machine learning algorithm, logistic regression is a traditional statistical

[9] Lines that are part of a loop (i.e., indented lines of code) must be preceded by a tab.

approach (i.e., a generalized linear model) that uses a linear boundary to separate data into classes (Stefanski et al., 1986). In a systematic review, Christodoulou et al. (2019) reported that machine learning does not systematically outperform logistic regression, which makes it a good comparison measure. It should be noted that the purpose of the tutorial is not to show that machine learning is always superior to the logistic regression, but how to apply machine learning in order to determine which provides the best predictions based on your data's distribution. Presenting how to perform logistic regression using Python goes beyond the scope of this article. We have made the code accessible as a supplement document and invite the reader to consult Lee (2019) for more information on logistic regression and on how to apply this algorithm. The logistic regression yielded an accuracy of .731 and a kappa value of .428 when applied to our dataset.

Leave-One Out Cross-Validation

Prior to training our machine learning models, we need to specify how to test them. One issue with machine learning is that using the same data to train and test a model may lead to overfitting. Overfitting carries the risk of fitting "the noise in the data by memorizing various peculiarities of the training data rather than finding a general predictive rule" (Dietterich, 1995, p. 327). In behavior analytic terms, the model would fail to generalize responding to novel, untrained exemplars. To address this issue, researchers use cross-validation methodology to assess their models. In cross-validation, the researcher removes part of the data during training. This removed data is then used to test for the generalization of the model. Therefore, researchers do not report the outcome for the training data, but rather for the test data, which were removed and not used during the development of the model.

For small datasets, researchers recommend the leave-one out cross-validation methodology (Wong, 2015). The leave-one out cross-validation methodology separates the dataset into two sets of data. The first set, the training set, contains the data of all samples except for one (hence the name leave-one out). The machine learning model uses the features and true class labels of the training set to learn how to predict the class label values. The second dataset, the test set, contains the remaining sample (i.e., a single sample). The latter tests the model's generalization to a novel, untrained sample. As such, the sample of the test set is not used during training. The leave-one out cross-validation methodology is repeated *N* times (i.e., number of samples in the dataset) so that each sample is used as the test set once. In our tutorial, the leave-one out cross-validation methodology was repeated 26 times as our dataset contained 26 samples. To import the leave-one out cross-validation methodology, you should run the following code from the scikit-learn package:

```
1 from sklearn.model_selection import LeaveOneOut
2 loo = LeaveOneOut()
```

The first line imports the function whereas the second line defines the parameters of the function. In the example above, we kept the default parameters.

Some Algorithms

Many machine learning algorithms exist. In this tutorial, we selected four algorithms useful for classification problems with small datasets: random forest, support vector, stochastic gradient descent, and k-nearest neighbors classifiers. We targeted these four algorithms because they have been widely used and apply different underlying mathematical approaches (i.e., use the features differently to create a machine learning model; Lee, 2019; Raschka & Mirjalili, 2019)[10]. The purpose of the subsequent section is not to compare the machine learning algorithms together, which would require a large number of datasets from other studies, but to show how to apply them.

Random Forests

Random forests are machine learning algorithms that use an ensemble of decision trees (called a forest) to predict an outcome (Breiman, 2001). These decision trees are a collection of nodes that describe conditions that can be true or false for a given dataset (see Figure 2). The algorithm follows different paths in the tree depending on whether the value of each condition in the tree is true or false. In brief, the algorithm creates individual decision trees by (a) randomly selecting a subset of the training set, (b) randomly selecting a subset of features at each split (i.e., node), and (c) keeping the feature that decreases entropy (or uncertainty of the decision) the most to create each decision node. The algorithm then repeats this process several times (100 by default with scikit-learn) to create a forest with many different trees. For classification problems, the predictions of all independent trees are aggregated and the most popular prediction is selected as the predicted class label. As an example, Figure 2 presents the first of the 100 trees in the random forest that we produced as part of the current tutorial. The algorithm used 16 samples to produce a tree with three features and four decision nodes. The model has 100 trees similar to the one depicted in Figure 2 that vote on the outcome. The most likely outcome becomes the prediction of the algorithm.

[10] We did not include artificial neural networks because they require larger datasets than our current sample size.

To apply the random forest algorithm, we must first import the random forest classifier function:

```
1 from sklearn.ensemble import RandomForestClassifier
2 rf = RandomForestClassifier(class_weight = 'balanced', random_state
      = 48151)
```

The second line of the code above provides the hyperparameters for the algorithm. The random_state variable is optional in practice, but it guarantees the production of a consistent output. Because there is a random component to the algorithm, setting the random_state will ensure that you obtain the same results as the ones presented in this tutorial every time you run the code in Python. Setting the class_weight as balanced ensures that both values of our class label carry the same weight, which is necessary because the number of samples with the class label value improvement (*n* = 18) was much larger than that of the no improvement (n = 8) class label value. Hence, balancing the weights of the class label values prevents the model from overclassifying predictions in the class label value with the largest number of samples.

Now, we need to run the code to train and test our models:

```
1 rf_pred = []
2 for train_index, test_index in loo.split(data_matrix):
3     x_train, y_train, x_test, y_test = x[train_index, :],
         y[train_index], x[test_index, :], y[test_index]
4     rf.fit(x_train, y_train)
5     prediction = rf.predict(x_test)
6     rf_pred.append(prediction)
```

The first line of code creates an empty list to store the prediction made by the random forest model after each iteration. The second line instructs Python to use the leave-one out cross-validation methodology to train and test the random forest algorithm. The loop runs 26 iterations during which it trains and tests 26 models, which are each computed using a different sample as the test set. The code of the third line creates the training and test sets for the features (x) and the class labels (y) for each iteration. The next step (line 4) involves using the fit function to train the random forest machine learning model to solve your classification problem using the features (x_train) and class labels (y_train) of your training set. Finally, the fifth line predicts the class label of the test set using the test features (x_test) and the last line appends the results to the list.

Once Spyder has run the 26 iterations, we can write the following code to compute the accuracy and kappa scores:

```
print(accuracy_score(rf_pred, y))
print(cohen_kappa_score(rf_pred, y))
```

The rf_pred list contains the predictions whereas the y vector includes the true values. At this point, we remind the reader that these predictions were made on data not included in the set used to train the models (out-of-sample prediction) to prevent overfitting. In our example, the model trained using the random forest classifier produced an accuracy of .769. Put differently, using the models developed by the algorithms led to correctly predicting whether a child would benefit from their parent following the web training in 77% of the sample. The random forest algorithm outperforms all tree comparison measures for this classification task (see left side of Table 4 for comparisons). In addition, the model produced a kappa value of .458, which represents a moderate agreement of the models with the actual observations (McHugh, 2012). The main advantage of random forests over the other proposed algorithms is that we can visualize the individual trees (see Figure 2), which may lead to the development of novel hypotheses on the contribution of each feature. For example, a researcher could print all the trees and examine how each feature influences categorization to develop hypotheses about the underlying decision-making process.

Support Vector Classifier

Support vector classifiers separate opposing class labels (i.e., in our example improvement and no improvement) using decision boundaries (called hyperplanes). In support vector classifiers, only extreme data points (i.e., those that are closest to the opposing class label) contribute to the development of the prediction model. Maximizing the margin (i.e., the space between the decision boundary and the nearest samples for each class) increases the model's ability to correctly predict the class label of untrained data (Bishop, 2006). Support vector classifier relies on linearity (i.e., a directly proportional relationship between the feature and the class label) to classify data into class labels. When the relation between the features and the class labels are non-linear or use multiple features (i.e., more than two), a function is applied (called a kernel) to transform the data into a higher dimension (e.g., two-dimensions into three dimensions) so that data can be linearly separated with a hyperplane (Qian et al., 2015). Figure 3 presents an example of data that could not be separated linearly in a two-dimensional space, but that could be separated by a plane when a third dimension was added. The space (i.e., the area in the graph in relation to the plane or hyperplane) where a sample is located predicts the class label value.

To apply the support vector classified algorithm, we start by importing the function from the scikit-learn package:

```
from sklearn import svm
svc = svm.SVC(class_weight = 'balanced')
```

We only specified one hyperparameter for this machine learning algorithm: the class weight. As per random forest, we balanced the class weights. The remaining code is identical to the one we have developed for the random forest algorithm, except that we replaced rf by svc:

```
svc_pred = []
for train_index, test_index in loo.split(data_matrix):
    x_train, y_train, x_test, y_test = x[train_index, :],
      y[train_index],x[test_index, :], y[test_index]
    svc.fit(x_train, y_train)
    prediction = svc.predict(x_test)
    svc_pred.append(prediction)
print(accuracy_score(svc_pred, y))
print(cohen_kappa_score(svc_pred, y))
```

The output should show an accuracy of .654 and a kappa of .264, which is marginally better than the random selection but not as accurate as the highest probability response and logistic regression comparison measures. When compared to other algorithms, the support vector classifier has the benefit of being deterministic, which makes the results easier to replicate. In other words, the algorithm does not contain a random component: it will thus always produce the same results given the same features. The kernel function also makes is suitable for non-linear data.

Stochastic Gradient Descent

Stochastic gradient descent is an optimization algorithm designed to reduce the error produced by a function (Raschka and Mirjalili, 2019). As part of the tutorial, we focus on the logistic function as it is a common method to separate data into classes (Peng et al., 2002). The main difference with traditional logistic regression is that the response is optimized within an iterative process that produces a nonlinear transformation. During stochastic gradient descent, the features are multiplied by a matrix of weights and the algorithm calculates the prediction error using the logistic function. Based on this error, the algorithm applies a correction to adjust the weights decreasing the prediction error for each successive iteration, which are referred to as epochs. In other words, the process is akin to shaping in behavior analysis where the algorithm selects (reinforces) successively closer approximations (i.e., less error). That said, researchers must remain wary of running too many epochs as it may overfit the training data and fail to generalize to novel samples (faulty discriminative control). Compared to random forests that use multiple independent trees to make a prediction, stochastic gradient descent keeps a single model.

The first step to applying stochastic gradient descent is to import the function from scikit-learn and define the hyperparameters:

```
1 from sklearn.linear_model import SGDClassifier
2 sgd = SGDClassifier(class_weight = 'balanced', loss = "log",
      penalty="elasticnet", random_state = 48151)
```

In our example, we specified four hyperparameters: class weight, loss, penalty, and random state (see line 2). Given that the weight matrix is initialized using a random function, the random_state variable ensures that the results remain consistent. We balanced the class weights to prevent the model from always predicting the most probable response. The loss implements the logistic function. Finally, we added a penalty term to minimize overfitting. Elasticnet adds some variability when the algorithm updates the weights, which improves generalization to untrained samples. Once again, the code is the same as for the rf function except that we replace rf by sgd:

```
sgd_pred = []
for train_index, test_index in loo.split(data_matrix):
    x_train, y_train, x_test, y_test = x[train_index, :],
      y[train_index],x[test_index, :], y[test_index]
    sgd.fit(x_train, y_train)
    prediction = sgd.predict(x_test)
    sgd_pred.append(prediction)
print(accuracy_score(sgd_pred, y))
print(cohen_kappa_score(sgd_pred, y))
```

The iPython console shows that our stochastic gradient descent model produced an accuracy of .692 and a kappa of .325, outperforming the random selection comparison measure but not the highest probability response and the logistic regression. In the current study, we limited the application of the stochastic gradient descent to a logistic function. One of the advantages of the stochastic gradient descent is that its flexibility allows its application to other functions.

K-Nearest Neighbors

The k-nearest neighbors algorithm uses feature similarity between samples to predict a class label (Raschka and Mirjalili, 2019). In brief, the algorithm identifies samples that are most similar to a new sample (i.e., nearest neighbors). Using a predetermined number of nearest neighbors (i.e., k), the model makes a prediction based on the most popular class label. In the k-nearest neighbors algorithm, nearest neighbors are often identified by calculating the linear distance between two points. Selecting an appropriate k is essential because different numbers of nearest neighbors can result in different predictions (i.e., class labels).

As for the other algorithms, we must first import the k-nearest neighbors function and set its hyperparameters:

```
from sklearn.neighbors import KNeighborsClassifier
knn = KNeighborsClassifier()
```

In this example, the function uses the default hyperparameters, which involve the five closest neighbors (i.e., k = 5). Again, we then run the same code as for the random forest algorithm, replacing rf by knn:

```
knn_pred = []
for train_index, test_index in loo.split(data_matrix):
    x_train, y_train, x_test, y_test = x[train_index, :],
      y[train_index],x[test_index, :], y[test_index]
    knn.fit(x_train, y_train)
    prediction = knn.predict(x_test)
    knn_pred.append(prediction)
print(accuracy_score(knn_pred, y))
print(cohen_kappa_score(knn_pred, y))
```

The k-nearest neighbors algorithm produced the worst accuracy (i.e., .615) and kappa (i.e., -.048). This algorithm performed slightly better than the random selection comparison measure,but produced measures lower than those of the highest probability response and the logistic regression. Nonetheless, the k-nearest neighbors algorithm has the following advantages: it is deterministic, easy and fast to implement, and it can readily detect non-linear patterns.

Hyperparameter Tuning

Three of the four machine learning algorithms did not perform any better than the logistic regression. In all our applications, we generally used the default hyperparameters of the algorithms to train our models, which explains why the performance was not optimal. To improve accuracy, researchers should use a procedure referred to as hyperparameter tuning to set optimal values (Raschka and Mirjalili, 2019). In hyperparameter tuning, the experimenter (a) tests the accuracy (or error) of different combinations and values of hyperparameters, and (b) selects the one that produces the best outcome measure. This selection of the best outcome cannot rely on the test set as it may lead to overfitting and failures of the results to generalize to novel datasets. Therefore, we must create a new set, the validation set, on which to assess the outcome of hyperparameter tuning. The upper panel of Figure 4 shows how our code generated a validation set for the current dataset.

In most cases, researchers are unaware of the best hyperparameter settings for each of their algorithms as these values vary across datasets. Therefore, we strongly recommend the use of hyperparameter tuning if no prior values are available for similar datasets in the research literature. These hyperparameters to tune vary across algorithms. Examples of hyperparameters are the number of trees in the random forest, the number of epochs (loops) in stochastic gradient descent, and the number of neighbors in the k-nearest neighbors algorithm. Given that the hyperparameters vary considerably across algorithms, we cannot provide a comprehensive list here. When unsure which hyperparameters to manipulate, we strongly recommend that researchers examine prior studies using the same algorithm. Alternatively, researchers may use grid search or random search procedures to conduct comprehensive tuning (see Appendix for a link on instructions on how to proceed).

Because the k-nearest neighbors algorithm performed worst in our prior analyses, we use it as an example to explain how to implement hyperparameter tuning. To facilitate hyperparameter tuning using leave-one out cross-validation, we must program a function to conduct the tuning at each iteration. The first step is importing the joblib package, which allows us to save the best model:

```
1 import joblib
```

Then, we must write a function that keeps the best model (i.e., the highest accuracy on the validation set) following each iteration of the leave-one out cross-validation loop:

```
1 def knn_train(x_train, y_train, x_valid, y_valid):
2     k_values = np.arange(1, 11, 1)
3     best_acc = 0
4     for k in k_values:
5           knn = KNeighborsClassifier(k)
6           knn.fit(x_train, y_train)
7           prediction = knn.predict(x_valid)
8           current_acc = accuracy_score(prediction, y_valid)
9           if current_acc > best_acc:
10                best_acc = current_acc
11                filename = 'best_knn.sav'
12                joblib.dump(knn, filename)
13    best_knn = joblib.load('best_knn.sav')
14    return best_knn
```

The first line informs Python that the subsequent indented lines define a function that takes our training data (x_train, y_train) and our validation data (x_valid, y_valid) as input. The second line provides the range of k values to test (1 to 10 neighbors) whereas the third line initializes the best accuracy value at 0. The code runs in a loop wherein each loop tests a different value of k (see line 4). Lines 5 and 6 train the model using the training set with k neighbors. The seventh and eight lines assess accuracy on the validation data. Line 9 contains a conditional formula that runs lines 10 to 12 only if the accuracy computed for this value of k on the validation set is higher than for any previous k value. The instructions involve three steps: replacing the best accuracy value by the current accuracy value (line 10), providing a name of the file where to save the model (line 11), and saving this model. The last two lines return the model (i.e., the model with the number of k neighbors) that produced the best accuracy on the validation set.

The next step is to run this function with each loop of the leave-one out cross-validation to examine the effects of the model on the test set:

```
1 from sklearn.model_selection import train_test_split
2 best_knn_pred = []
3 for train_index, test_index in loo.split(data_matrix):
4     x_train, y_train, x_test, y_test = x[train_index, :],
           y[train_index],x[test_index, :], y[test_index]
5     x_train, x_valid,y_train, y_valid = train_test_split(x_train,
           y_train, test_size = 0.20, random_state = 48151)
6     best_knn = knn_train(x_train, y_train, x_valid, y_valid)
7     prediction = best_knn.predict(x_test)
8     best_knn_pred.append(prediction)
9 print(accuracy_score(best_knn_pred, y))
10print(cohen_kappa_score(best_knn_pred, y))
```

The reader should already be familiar with some of the code in the previous block because it is very similar to the code used during training with the default hyperparameters. We will focus on the lines that differ. The first line imports a function that splits the training set into two subsets: the training set and the validation set (see line 5). The test_size parameter indicates that 20% of the data should be moved to the validation set and 80% should remain in the training set. Thus, the validation set contains 5 samples and the training set 20 samples. In line 6, we replace the knn.fit formula by our new function, which returns the tuned model that produces the best accuracy on the validation set. The output clearly shows that the tuned model outperforms the model with the default hyperparameters. The accuracy on the test set increased from .615 to .808 whereas the kappa score increased from -.048 to .591.

In a similar manner, we could conduct hyperparameter tuning for the other machine learning algorithms, but we leave it up to the reader to try it out on their own. The code is available in the ML_step-by-step.py file of the repository starting on line 162. Table 4 compares the results obtained by each algorithm without and with hyperparameter tuning so that the readers can compare their results. Clearly, conducting hyperparameter tuning leads to more accurate models. Except for the stochastic gradient descent which produced similar results, all hypertuned models outperformed the simple logistic regression as well as the other comparison measures.

Practical Considerations

Selecting Features

The selection of features merits further discussion as careful selection may lead to better models and minimize overfitting (and the opposite is true for inadequate selection). First, researchers should avoid cherry-picking their features by selecting those that produce the most accurate model on the test set. This cherry-picking may lead to models that produce overfitting on novel, untrained exemplars. Instead, feature selection should involve a rigorous approach. Researchers generally categorize feature selection methods in three broad categories: filter, wrapper, and embedded (Cai et al., 2018; Visalakshi & Radha, 2014). Filter methods typically involve keeping features with specific statistical properties (e.g., significant relationship with the outcome variable, correlation threshold). Wrapper methods consist of systematically searching different combinations of features to identify the one that produces the best outcome. Finally, embedded methods integrate feature selection within the machine learning algorithm by identifying or emphasizing features that produce the best predictions. Describing the advantages and disadvantages of these methods goes beyond the scope of this tutorial. We suggest that the reader consult Cai et al. (2018) and Visalakshi and Radha (2014) for a review of different feature selection methods.

In the tutorial, we selected three of our features because they had been shown to be correlated with the class label and displayed no multicollinearity, which is similar to a filter-based approach. Alternatively, our procedures could have involved hyperparameter tuning for feature selection (i.e., a wrapper method). In this alternative, the features included in the model would represent the hyperparameter. As indicated earlier, this approach is only viable if the selection of features relies on a validation set. We feel that it is important to repeat here that the selection of features should *never* rely on the results of the test set. Another consideration when selecting features is the measurement scale (e.g., nominal, ordinal, continuous). For the tutorial, we dichotomized two features. The dichotomization of the features was done to better balance the samples as the data were highly skewed. While this procedure may lower chances of overfitting, the reader should bear in mind that decreasing the number of degrees of freedom may result in a loss of power.

Selecting an Algorithm

We reviewed four different types of algorithms as part of the current tutorial. One important question remains: When to select one algorithm over another? Unfortunately, the research literature does not provide a straightforward answer to this question and the results from this tutorial should not be used as performance indicators as we examined a single specific dataset. One solution is to compare the results across algorithms (as we have done with hyperparameter tuning) and to select the algorithm that produces the best outcome. The advantages of each algorithm may also guide the selection. The random forest and the k-nearest neighbors algorithms are easy to explain, intuitive, and allow an analysis of why the samples are categorized the way they are. In contrast, stochastic gradient descent are like black boxes; even when very accurate, we cannot identify the underlying mechanisms that produced the outcomes. The k-nearest neighbors and support vector classifiers produce deterministic results, which renders them more stable than those that have a random component. Finally, the random forest may require little to no tuning to produce accurate predictions with small sets.

About Samples

Earlier in the tutorial, we suggested that the models could be trained with datasets with as few as 25 samples: a series of features and class labels for 25 exemplars on which you can make predictions. This rule-of-thumb is a lower limit. When everything else is kept equal, algorithms with more data will train more accurate models and reduce overfitting. The only dataset that we had at hand for the tutorial contained 26 samples, but we strongly recommend that you aim for more. Samples may take on many forms. For example, a sample may represent a participant and their responding to a treatment (as in our tutorial). In experimental research, a sample could involve the rate of lever presses by a rat within 1 min; each minute of the session would thus be a different sample. Alternatively, a sample could be a complete session if the models were designed to predict the percentage of behavior over longer periods of time. In this case, each session could count as a sample. Nevertheless, you would still want many different subjects (e.g., 10 subjects with 10 sessions) in order to measure and to validate the generalizability of the models within and across subjects.

Alternatives to Single Binary Classification

Our tutorial focused on one type of problem: binary classification. We can readily apply the same algorithms to multiclass classification problems. Assume that we want to predict the function of a challenging behavior. The output would involve four class labels (columns), one per challenging behavior function. Each class label would remain binary: 1 = positive, 0 = negative. Regarding the machine learning algorithms for small datasets, the only change in the code is providing data labels with multiple columns (rather than a single column as was done in the current study).

Another type of problem that can be solved using machine learning is predicting specific values. For example, a researcher may aim to predict the percentage of behavior during a session based on some other variables. In this case, we recommend using a regressor rather than a classifier. Fortunately, the packages that we have used for classification all have regressor equivalents: RandomForestClassifier becomes RandomForestRegressor, svm.SVC becomes svm.SVR, SGDClassifier become SGDRegressor, and KNeighborsClassifier becomes KNeighborsRegressor. The kappa and accuracy measures are not appropriate for regressors. Alternatives include the mean_square_error and mean_absolute_error functions from the scikit-learn package.

Cross-Validation

In the tutorial, we reviewed only one type of cross-validation: the leave-one out method. A second type of cross-validation is the holdout method, which divides datasets into a single training set and a single test set. The test set remains consistent across all analyses and is never used during training. Thus, we do not need to program a loop. To split the dataset, we run the following code:

```
from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size
     = 0.20, random_state = 48151)
```

The random_state parameter ensures that the results remain constistent across replications whereas the test_size parameter indicates the proportion of samples in the dataset that should be placed in the test set. Figure 4 (bottom panel) shows an example of holdout cross-validation with a hypothetical dataset containing 100 samples. In this case, a value of .20 produces a test set with 20 samples and a training set with 80 samples. Although generally applied when datasets are larger, Vabalas et al. (2019) found that a such approach to building and testing a machine learning model produced the least biased outcomes.

A third method relevant to behavioral researchers is the k-fold cross-validation method (Wong, 2015). The k-fold method is a hybrid between the leave-one out and holdout methods. In the k-fold method, the k represents the number of times the cross-validation is repeated. For example, a k of 5 involves running the cross-validation five times. Each iteration, the algorithm uses four fifths (80%) of the data for training and one fifth (20%) of the data for testing. The data in testing differs across each iteration so that all samples are included in the test set exactly once. To implement k-fold cross-validation, we need to import the algorithm using:

```
from sklearn.model_selection import KFold
kf = KFold(k)
```

In the example above, k represents the number of folds, which should be an integer. Then, we replace the loo.split(data_matrix) loop by the following code:

```
for train_index, test_index in kf.split(data_matrix):
```

The k-fold method is a strong alternative to the holdout method when the number of samples is limited as it rotates all the samples in the test set (see Cross Validation in Appendix).

Conclusion

As part of the current tutorial, we demonstrated how to apply four different machine learning algorithms to train models to predict whether specific parents would benefit from an interactive web training. We developed this tutorial to raise awareness of the potential use of machine learning to support decision-making in the field of behavior analysis. The purpose of our tutorial was to demonstrate how machine learning can aid researchers in analyzing small datasets and not to prove that machine learning always performs better than traditional statistics (which is not the case). Machine learning has the advantage of conducting nonlinear discrimination beyond the logistic regression and of analyzing small datasets that do not respect assumptions typically found in parametric tests. Thus, this paper presents an approach, which behavioral researchers may add to their toolbox to address questions important to our understanding of human behavior.

In our tutorial, we showed that models developed with machine learning may predict which parents could benefit from an interactive web training. Until independent researchers replicate our procedures with more data and carefully examine its social validity, we do not recommend the adoption of these models in practice. If these models are further validated, they could lead to better decision-making. Currently, behavior analysts rely on their professional judgment to decide whether a parent could benefit from a specific type of training. The machine learning models may support behavior analysts in making more consistent and more accurate decisions. The litmus test for such an approach will be comparing the decisions of the models with the decisions taken by trained behavior analysts, which goes beyond the scope of a tutorial on how to apply these machine learning algorithms.

The application of machine learning in behavior analysis is still in its infancy. If the rapid adoption of machine learning by other fields is any indication, we expect that behavior analysts will increasingly use this approach in their experimental work, applied research, and practice. Examples of uses wherein machine learning could support behavior analysts include the identification of novel variables that play a role in the development and maintenance of behavior, the prediction of intervention effects or rates of behavior within experimental settings, the measurement of behavior, the analysis of functional assessment data, and the inspection of single-case designs. The benefits may range from a better understanding of the causes behavior to practitioners making more reliable and accurate clinical and educational decisions. This tutorial may thus serve as a starting point for behavioral researchers looking for an introduction to machine learning and its applications.

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Table 1

Parallels Between Machine Learning and Behavior Analytic Terms

Machine Learning	Behavior Analysis
Algorithm	Teaching method
Model	Learner
Sample	Exemplar
Features	Discriminative stimuli
Class label	Correct response
Prediction	Learner's response
Hyperparameter	Teaching parameter

Table 2

Description of the Variables in the Dataset

Variable	Questionnaire	Type	Values
Feature 1			
Household income		Binary	0 = Less than $90 000 1 = $90 000 or higher
Feature 2			
Highest diploma		Binary	0 = College or lower 1 = University and higher
Feature 3			
Social functioning	ABAS-II - Social domain	Continuous	*z* score
Feature 4			
Parental use of behavioral interventions at baseline	Ad hoc questionnaire (see Turgeon et al. 2020)	Continuous	*z* score
Class Label			
Improvement in the frequency of child challenging behaviors	BPI	Binary	0 = No improvement 1 = Improvement

Note. BPI: Behavior Problem Inventory (Rojahn et al., 2001); ABAS-II: Adaptive Behavior Assessment System - Second Edition (Harrison & Oakland, 2011).

Table 3

Complete Dataset with Feature and Class Label Values

Household Income	Most Advanced Degree	Social Functioning	Parental Use of Behavioral Interventions	Improvement in the Frequency of Child Challenging Behaviors
0.5*	0	70	17	1
0	0	75	14	1
1	1	70	18	1
0	1	68	15	0
0	0	55	18	1
0	0	68	15	0
0	0	58	12	0
1	1	77	18	1
0	1	87	16	0
0	0	90	17	1
0	0	55	15	1
0	0	68	18	1
1	1	70	18	1
1	0	87	18	1
1	1	71	19	1
1	1	75	14	1
0	0	58	17	1
0	1	95	16	0
0	1	89	18	1
1	0	70	14	1
1	1	93	15	0
1	1	66	15	1
1	1	61	15	0
0	1	80	17	1
1	1	114	13	0
0	1	87	17	1

* Missing value

Table 4

Comparison of Accuracy and Kappa Scores Without and With Hyperparameter Tuning for Each Algorithm

	No Tuning		Hyperparameter Tuning	
Algorithm	Accuracy	Kappa	Accuracy	Kappa
Random Selection	.574	.000		
Highest Probability Response	.692	.000		
Logistic Regression	.731	.428		
Random Forest	.769	.458	.846	.639
Support Vector Classifier	.654	.264	.808	.532
Stochastic Gradient Descent	.692	.325	.731	.492
K-nearest Neighbors	.615	-.048	.808	.591

Figure 1

Screenshot for the Spyder Integrated Development Environment

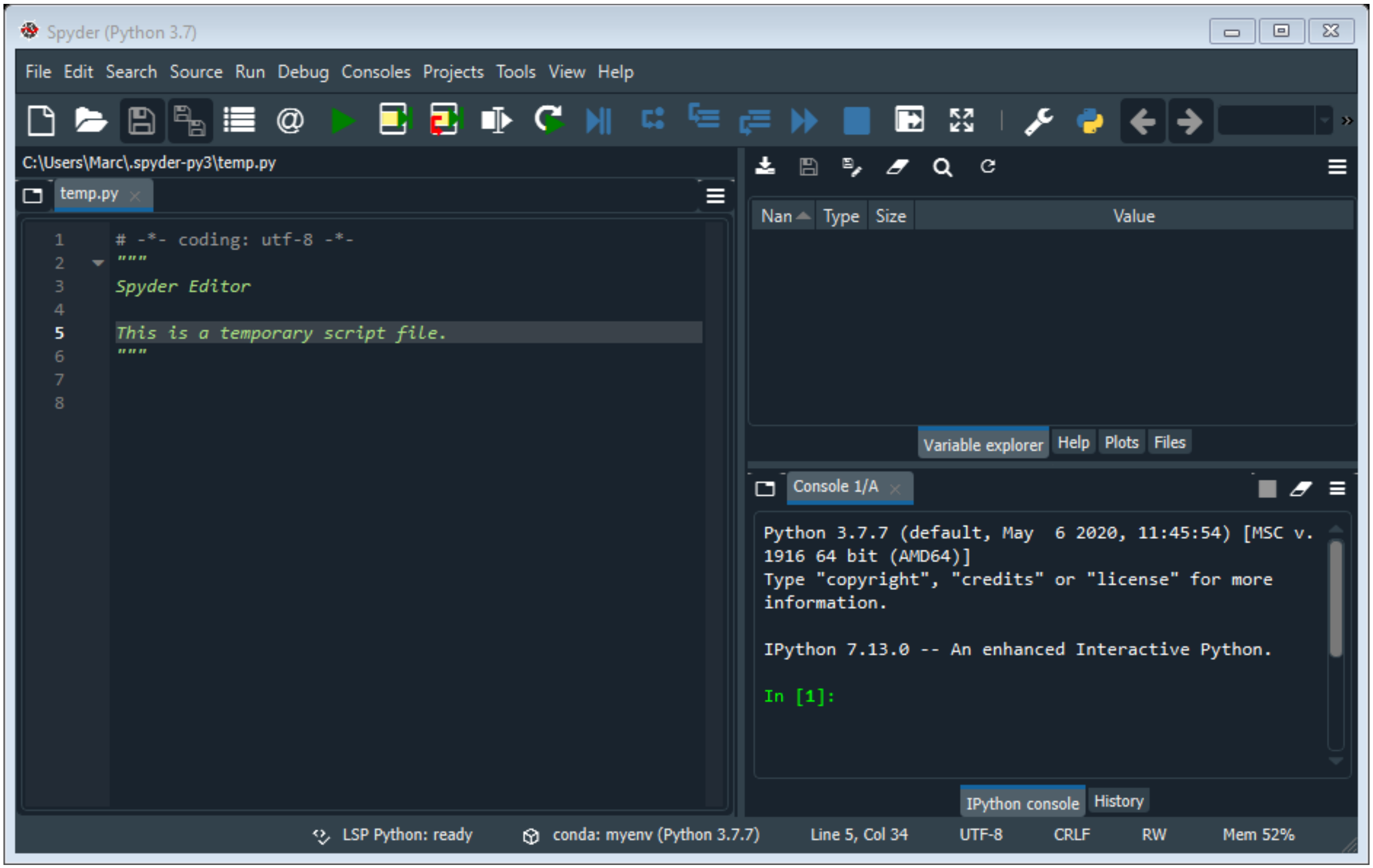


Figure 2

Visual Representation of the First Tree in the Random Forest

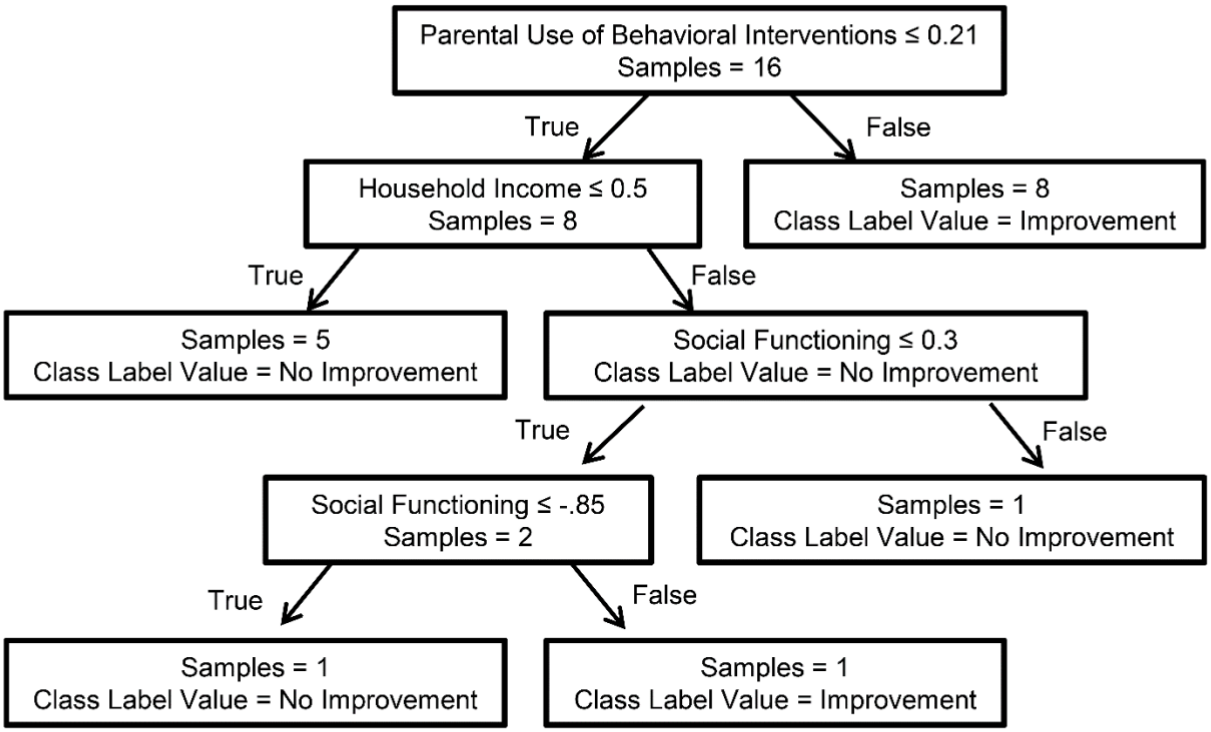
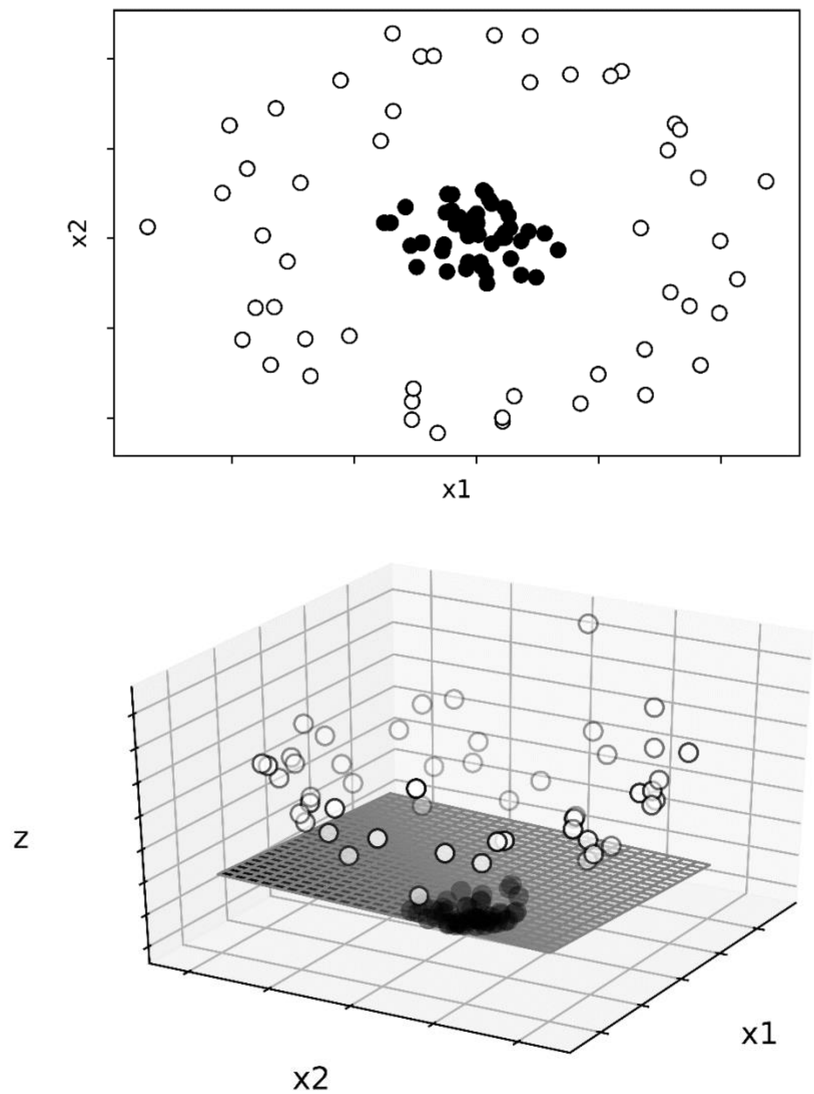


Figure 3

Example of a Dataset Separated by a Support Vector Classifier

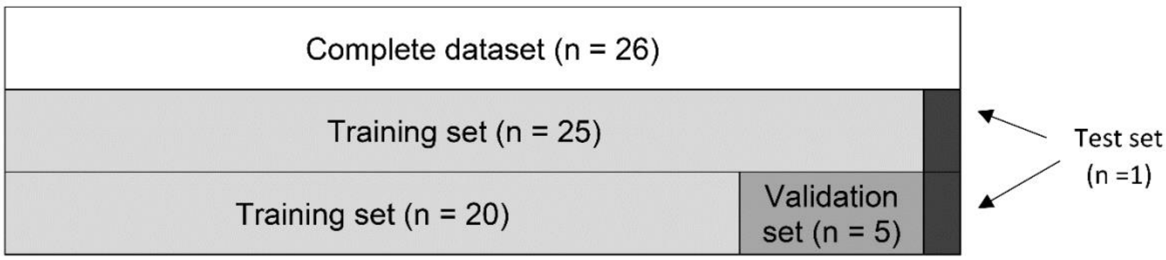


Note. The upper panel shows a two-dimensional graph representing two features: x1 and x2. Closed points represent one category and opened points a different category. The lower panel depicts the addition of a higher dimension (z) and a linear plane that separates the two categories.

Figure 4

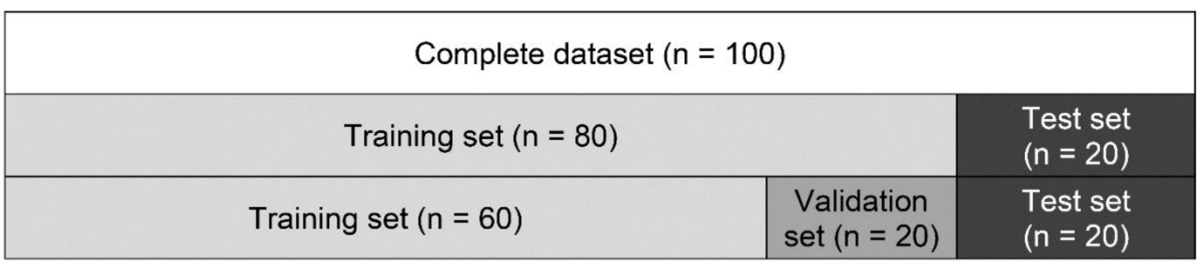
Visual Representations of Different Sets in the Leave-One Out Cross-Validation and the Holdout Cross-Validation

Leave-One Out Cross-Validation



Note. This process runs 26 times so that each sample is in the test set once.

Holdout Cross-Validation



Note. This process runs only once with each set being sampled randomly without replacement.

Appendix

Free Online Resources

Learn More About Python

Learn Python - https://www.learnpython.org/

Google's Python Class - https://developers.google.com/edu/python

Python for Beginners - https://www.python.org/about/gettingstarted/

Learn More About Machine Learning

An Introduction to Machine Learning - https://www.digitalocean.com/community/tutorials/an-introduction-to-machine-learning

Google's Introduction to Machine Learning - https://developers.google.com/machine-learning/crash-course/ml-intro

Introduction to Machine Learning for Beginners - https://towardsdatascience.com/introduction-to-machine-learning-for-beginners-eed6024fdb08

Learn More About Machine Learning in Python

Cross Validation in Python: Everything You Need to Know About - https://www.upgrad.com/blog/cross-validation-in-python/

An Implementation and Explanation of the Random Forest in Python - https://towardsdatascience.com/an-implementation-and-explanation-of-the-random-forest-in-python-77bf308a9b76

Implementing SVM and Kernel SVM with Python's Scikit-Learn - https://stackabuse.com/implementing-svm-and-kernel-svm-with-pythons-scikit-learn/

How To Implement Logistic Regression From Scratch in Python - https://machinelearningmastery.com/implement-logistic-regression-stochastic-gradient-descent-scratch-python/

Develop k-Nearest Neighbors in Python From Scratch - https://machinelearningmastery.com/tutorial-to-implement-k-nearest-neighbors-in-python-from-scratch/

Hyperparameter Tuning - https://towardsdatascience.com/hyperparameter-tuning-c5619e7e6624

Sci-Kit Learn: 3.2. Tuning the Hyper-Parameters of an Estimator - https://scikit-learn.org/stable/modules/grid_search.html

Transition entre les chapitres

Dans l'étude présentée au Chapitre II, 45% (n = 21) des parents recrutés pour l'étude n'ont pas complété la formation en ligne. En plus de ce haut taux d'attrition, le recrutement des parents par les réseaux sociaux a présenté un défi important. Notamment, suivant la publication de notre message de recrutement sur Facebook, certaines personnes ont tenté de décourager les gens à participer à notre étude en publiant des messages haineux à l'égard de la formation ou de l'approche sur laquelle était basée la formation. Puisque les réseaux sociaux sont une source d'influence importante du choix d'intervention des parents pour leur enfant, il est important de connaître ce à quoi sont exposés les gens lorsqu'ils naviguent ce type de site internet. Le Chapitre IV vise donc à mesurer la polarité et la validité de l'information sur l'AAC véhiculés dans les forums sur le TSA d'un site internet largement fréquenté par la population francophone. Les résultats pourraient aider à mieux diffuser la formation interactive à long terme.

Chapitre IV - Article 3: Perceptions of behavior analysis in France: Accuracy and tone of posts in an internet forum on autism

Perceptions of behavior analysis in France:

Accuracy and tone of posts in an internet forum on autism

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Abstract

Applied behavior analysis (ABA), which is often used as the basis for designing interventions for people with autism, is highly misrepresented and under-utilized in many countries. One country where ABA remains particularly difficult to access is France. One potential problem is that parents often rely on online resources such as social media to identify interventions for their child. Many of these sources of information do not accurately portray ABA or even openly disapprove of the science. To examine this issue, we used data mining methodology to extract, categorize, and analyze 897 messages on ABA published in a popular French internet forum based on their type, tone, and accuracy. Although messages were generally accurate and approving of ABA, our results showed that one in three messages fully or partially disapproved of the science and one in four messages contained some inaccurate information. Our analyses also indicated that parents were more likely to approve of ABA than individuals with an autism spectrum disorder. Finally, we found that the number of approving messages published in the internet forum decreased with time, especially over the last five years. Together, these results support the relevance of developing system-level approaches to dispel misconceptions about ABA in languages other than English.

Keywords: autism, behavior analysis, data mining, France, internet forum, perception.

Perceptions of Behavior Analysis in France:

Accuracy and Tone of Posts in an Internet Forum on Autism

Over 70 years ago, Ayllon and Micheal (1959) as well as Williams (1959) published the first studies using the principles of behavior analysis to solve problems of applied significance. Since then, research and clinical practice within the field of applied behavior analysis (ABA) have flourished and led to the creation of the Journal of Applied Behavior Analysis in 1968. More recently, concerns involving the practice of ABA has led to the development of the Behavior Analyst Certification Board "to meet professional certification needs identified by behavior analysts, governments, and consumers of behavior analysis services" (Behavior Analyst Certification Board, n.d.). Initially practiced predominantly in the United States of America, ABA has migrated to countries across all five continents (Ardila, 2006; Johnston et al., 2017). Researchers have studied the effectiveness of interventions based on ABA for a variety of populations (Fisher et al., 2013). Notably, the body of research on behavior analytic interventions for persons diagnosed with an autism spectrum disorder (ASD) has proliferated over the past decades (e.g., Leaf et al., 2016; Roth et al., 2014; Wong et al., 2015). With the consistent increase in prevalence of ASD (Fombonne, 2018), a majority of certified clinicians now work with individuals on the spectrum (Association of Professional Behavior Analysts, 2009; Deochand & Fuqua, 2016).

Behavior analytic interventions are functional procedures based on learning theory that aim to modify the antecedents and consequences associated with a behavior as well as to teach alternatives (Leaf et al., 2008). Researchers consider interventions based on behavior analytic principles as well established for individuals diagnosed with autism (National Autism Center, 2015). Many evidence-based interventions for ASD grounded in ABA have led to positive effects on a variety of communication, social, behavior, academic, adaptive, and cognitive outcomes (Hyman et al., 2020; Roth et al., 2014; Wong et al., 2015). In fact, behavior analytic interventions have the most empirical evidence for decreasing challenging behaviors and teaching adaptive skills to children with ASD (Roth, et al., 2014; Wong et al., 2015).

Despite the accumulation of empirical evidence for the efficacy of interventions derived from behavior analysis with individuals diagnosed with ASD, the science is persistently misrepresented in many countries, especially where access to training is limited (Freedman, 2016; Krapfl, 2016). One country where ABA remains particularly misrepresented and difficult to access is France (Amouroux, 2017). Although efforts have been put forward during the last two decades to develop recognized academic programs, French-speaking students only have access to three active verified course sequences that meet the requirements for certification by the Behavior Analyst Certification Board (Association for Behavior Analysis International, 2021a; 2021b). In contrast, English Canada has 35 training programs despite having less than half the population of France. Moreover, interventions grounded in ABA for persons diagnosed with ASD were not recommended by France's higher health authorities until 2012 (Haute Autorité de Santé and Agence Nationale de l'Évaluation et de la Qualité des Établissements et Services Sociaux et Médico-Sociaux [HAS], 2012). In 2012, the HAS finally recommended interventions derived from the science of ABA, but their report categorized them as "Grade B" (i.e., presumed scientific). Thus, the HAS still considers that ABA derived interventions have insufficient scientific proof to merit a "Grade A" recommendation (i.e., established as scientific). Such misinformation has hindered, and continues to hinder, the application of the science in practice.

Parents play a major role in selecting interventions for their child (Green, 2007; McPhilemy & Dillenburger, 2013). When identifying potential interventions, parents are faced with an overwhelming amount of information (Miller et al., 2012; National Autism Center, 2015). For example, hundreds of different interventions exist for children with ASD with varying proof of effectiveness (Goin-Kotchel et al., 2007; Miller et al., 2012; National Autism Center, 2015). These can range from drug treatments and diet therapies to behavioral, educational, and alternative interventions. Parents can seek information on potential interventions from a diversity of sources such as health professionals, books, newspapers, other parents, and the internet (Miller et al., 2012).

Advances in technology and increased accessibility to the internet make the latter an important source of knowledge acquisition for parents of children with ASD (e.g., Grant et al., 2016; Hall et al., 2016; Pham et al., 2019). While Gibson et al. (2017) found that parents prefer obtaining information relating to ASD from local resources (e.g., pediatricians, teachers, and local organizations), results from other studies have suggested that the internet is increasingly used as parents' primary source of information (Grant et al., 2016; Hall et al., 2016). A recent study by Shepherd et al. (2020) found that nearly 45% of the parents in their sample reported using social media for caregiving-related support. In another example, Clifford and Minnes (2013) noted that 31% of the parents of children with ASD in their study were actively using online support groups. Social media platforms, such as Facebook, Twitter, blogs, and internet forums, are online resources that are particularly interesting as they not only give the parent access to large amounts of information, but also allow parents to get emotional support, interact with others (e.g., parents, professionals, researchers, persons with a diagnosis of ASD) and get answers to specific questions such as intervention recommendations (Saha & Agarwal, 2016; Sherpherd et al., 2020). Although social media can be a helpful resource for parents of children with ASD, researchers have found that they contain an overabundance of information that is often unreliable and contradictory (Moorhead et al., 2013). Given that parents have reported that empirical evidence does not seem to influence their decision-making (Green et al., 2006) and that opinions or shared experiences of others are considered evidence of the effectiveness of interventions (Grant et al., 2016), relying on information found on social media can potentially result in parents selecting ineffective, or even dangerous, interventions for their child (Moorhead et al., 2013).

Considering that ABA is misrepresented in France (e.g., Richelle et al., 2006; Robert, 2017), it would be important to provide details of the extent of this problem. To address this issue, we examined messages about ABA in a French internet forum on ASD. The specific objectives of our study were to: 1) measure the perception of ABA by quantifying the information on accuracy and tone, 2) assess whether messages with varying tones differed in accuracy, 3) evaluate whether messages with varying tones differed across the type of user (parent or person with autism), and 4) examine whether the tone of more recent messages differed from older ones.

Method

Data Source

The first author identified a popular French internet forum for people with autism and their families using the Google search engine. This internet forum had at least 500 messages pertaining to ABA and is one of the most popular autism boards published in French, which is why we selected it for our analysis. The website divided the forum into multiple subforums with specific themes. We focused our analyses on subforums that had themes involving autism in general, parents of children with autism, and intervention.

As per the *Canadian Tri-Council Statement: Ethical Conduct for Research Involving Humans* (Canadian Institutes of Health Research, Natural Sciences and Engineering Research Council of Canada, & Social Sciences and Humanities Research Council of Canada, 2018), research involving publicly available data with no expectation of privacy does not require informed consent, nor ethical review. As anyone could access the website using a standard search engine and viewing the posts did not require the creation of a private account, the data were considered in the public domain. Nevertheless, we removed all usernames, timestamps, and message contents from our shared database so that it would be impossible to identify a participant if they were to delete their posts from the forum.

Data Extraction

Our data extraction process involved four steps. First, we hired a web data extraction service team to extract all messages as well as identification (message URL, message ID, and thread ID) and descriptive (subforum label, thread title, authors username, authors message ID, timestamp, and number of views) information for the targeted subforums. Second, a list of French keywords associated with ABA was created by the first author and approved by the second author (see Table 1 for the list of keywords). For the third step, we used Python as a keyword processing tool to identify messages relating to ABA that contained the keywords presented in Table 1. Finally, the first author manually searched each message to remove those with a confounded use of one of the keywords (e.g., GABA, *tabac* [tobacco], *abandonner* [abandon], or *thérapie comportementale cognitive* [cognitive behavior therapy]). Our final sample contained 897 messages.

Data Classification

Following the data extraction process, the first author manually coded each message in relation to three categories of characteristics: type of message, tone, and accuracy. While the type of message referred to the message as a whole, the remaining categories were coded based on the sections of the message pertaining to ABA (see Table 2 for definitions and examples for the characteristics of each category). To assess interrater reliability, an independent rater coded 25% (*n* = 224) of the messages, which were selected at random. Interrater reliability was quantified using the kappa coefficient to control for high accuracy scores resulting from chance when coding a binary variable (i.e., 50%; McHugh, 2012). Prior to calculating the kappa values, we transformed each characteristic to a binary variable. Kappa coefficients varied from .48 to .80 (mean = .67). With the exception of one value, all kappa values remained above .60, indicating that our interrater agreement for coding was moderate to strong.

The third objective involved identifying user status (i.e., parent or person with a diagnosis of ASD) so that we could conduct a more fine-grained analysis of tone. To address this issue, the first author also manually searched all user signatures at the end of each message in the internet forum. Within this signature, users often stated their relationship to ASD (e.g., father of two children with an ASD or diagnosed with Asperger's syndrome in 2011). When the signature did not clearly allow the identification of a user’s status, messages written by the user were hand searched to find this information. The dataset contained 193 different users in total: 85 users reported being a parent, 57 users reported having a diagnosis of ASD, 38 users reported neither being a parent or a person with ASD (e.g., pre-diagnosis, social communication disorder, students, practitioners), 9 users reported having both ASD and a child with ASD, and 4 users had unidentifiable statuses. We excluded the latter three categories from our analyses involving user status to focus exclusively on parents and persons with ASD.

Data Analysis

First, we used descriptive statistics to quantify the prevalence for each category of the three main characteristics. Second, contingency tables were drawn to obtain the frequency distributions and conditional probabilities for all pairs of characteristics of tone (i.e., approving, disapproving, mixed, or neutral) and accuracy (accurate, inaccurate, mixed, or accuracy does not apply). Third, a chi-square analysis was used to test whether messages differed significantly on accuracy (i.e., accurate and inaccurate) given tone (i.e., approving and disapproving). Fourth, messages of parents were compared to messages of individuals with ASD using a chi-square test to measure whether they differed by opposing tones (i.e., approving vs disapproving). Given that some users wrote more than one message and to meet the assumption of independence of observations, we ran our chi-square using the rounded integer mean of tone (i.e., 0 = disapproving or 1 = approving) for each user. Users (n = 8) with a mean of 0.5 were excluded from the analysis since the number of approving and disapproving messages published was equal; thus, the user could not be classified in one of the mutually exclusive categories. Furthermore, we also excluded parents and individuals with ASD who did not publish any messages with an approving or disapproving tone from this analysis. The final sample for our comparison of tone given user status contained the average rounded tone for 62 parents and 43 individuals with ASD. Finally, we ran a binary logistic regression to examine if and how time predicted the prevalence of messages with opposing tones. All statistical analyses were conducted using the R software version 4.0.3. The anonymized data (i.e., without username, timestamp and message content) and code are freely available at: https://osf.io/wceh3/.

Results

Sample Description

Our sample consisted of 897 messages from 193 different users published between 2005 and 2020. The user sought support or information in 68 (8%) messages while information or support was offered in 110 (12%) messages. Furthermore, the user provided general information in 321 (36%) messages or commented on another message in 398 (44%) instances. Figure 1 presents the frequency distributions for the number of words per message, the number of messages published per user, and the number of views per discussion thread following the removal of outliers (i.e., top 5%). Table 3 also presents descriptive statistics for frequency of publication by users and message length (i.e., number of words). Based on these results, the average user posted one or two messages that contained fewer than 500 words and garnered more than 1,000 views.

Perceptions of ABA

To examine perceptions of ABA, we first assessed the frequency distribution of messages with information on ABA for all four characteristics of tone (i.e., approving, disapproving, mixed, or neutral). More than one third of messages (n = 349; 39%) discussed ABA in an approving manner. On the other hand, nearly one in five (n = 178; 20%) messages disapprovingly referred to ABA. Additionally, 113 (13%) messages contained both approving and disapproving comments on ABA. Finally, 257 (29%) messages used a non-polarized tone (i.e., neutral).

We also qualified the accuracy of the information on ABA (i.e., accurate, inaccurate, mixed, accuracy not applicable). In all, 268 (30%) messages had information on ABA that was considered accurate and 158 (18%) messages contained inaccurate information on ABA. Moreover, 43 (5%) messages presented a mixed accuracy (i.e., containing accurate and inaccurate information). Finally, we classified 428 (48%) messages as not applicable (i.e., reporting anecdotal information [*n* =88] or without judgment [*n* =340]).

Accuracy Given Tone

Table 4 presents the frequency distribution and the conditional probability of accuracy given message tone. The results show that messages with an approving tone were most likely of being accurate (*n* = 172; 49%) whereas messages with a disapproving tone had the highest probability of being inaccurate (*n* = 110; 62%). To measure whether messages significantly differed based on accuracy and tone, we ran a chi-square analysis using polarized characteristics (i.e., accurate, inaccurate, approving, and disapproving). The results suggest that there was a significant association between message accuracy and tone, $\chi^2(1) = 201.31$, $p < 0.01$. Specifically, our result confirms our prior observation that approving messages were more likely to be accurate. Conversely, disapproving messages were dominantly inaccurate.

Tone Given User Status

Table 5 presents the frequency distribution of polarized tone given user status. Conditional probabilities suggest that parents were more likely to write messages approving of ABA than individuals on the spectrum. Specifically, we observed that 84% (*n* = 52) of parents wrote messages with an approving tone whereas only 16% (*n* = 10) of parents wrote messages with a disapproving tone. Results for users with ASD also suggest that they published more approving than disapproving messages. However, the contrast for users with ASD was not as important as the one observed for parents with 24 (56%) individuals publishing more approving messages versus 19 (44%) individuals publishing more disapproving messages. Our chi-square analysis revealed that messages significantly differ across tones and type of user $\chi^2(1) = 8.64$, $p < 0.01$.

Evaluating Tone as a Result of Time

Figure 2 shows that the number of approving messages was mostly homogenous from 2006 to 2014, then decreased from 2015 to 2020. On the other hand, the number of disapproving messages remains generally stable. Interestingly, the number of approving messages per year was consistently superior to the number of disapproving messages, except for 2018. The result of the logistic regression suggests that time was a significant predictor of whether a message was approving or disapproving, Wald(1) = 3.40, $p < 0.01$, with the probability of a message being approving decreasing across years.

Discussion

The objectives of our study were to measure the accuracy and tone of messages about ABA in an internet forum, investigate the relationship between the tone and accuracy of messages, compare the tones across types of users (parents vs. persons with ASD), and examine the evolution of tone over time. Although messages were generally approving of ABA, our results suggest that the applied branch of our science remains contested and misunderstood in France. In fact, nearly one in four messages contained some inaccurate information on ABA while one in three messages fully or partially disapproved of ABA. Moreover, we found that the number of approving messages on ABA decreased with time, indicating that the perception of ABA published in the French internet forum has deteriorated since 2005. One potential explanation for this result involves the mass exposure of the population to misinformation and negative publicity from public events (e.g., trials, protests), media coverage, and advances in technology (e.g., social media that facilitates and accelerates the spread of misinformation; Freedman, 2016; Keenan & Dillenburger, 2018, n.d.). That is, parents and persons with autism may consume inaccurate information, which may lead to misinformed posts. Our analyses also showed that messages that approved of ABA were most likely to be accurate whereas messages classified as disapproving of ABA had a higher probability of being inaccurate. Finally, we observed that parents and individuals with ASD perceived ABA differently. Specifically, parents were more likely to post messages approving of ABA than individuals on the spectrum.

Parents play a major role in selecting interventions for their children. When parents are faced with challenges such as those associated with ASD (e.g., speech impairment or challenging behaviors), they often turn to social media to identify potential interventions (Grant et al., 2016; Hall et al., 2016). Grant et al. (2016) have found that parental choice of intervention is highly influenced by opinions or shared experiences of others. Our results are concerning given that the information found on one internet forum contained many inaccuracies. The presentation of inaccuracies pertaining to ABA was especially disconcerting because of the ramifications for public policy. Notably, nearly half (43%) of the messages with a non-neutral tone contained some inaccurate information. Beyond disapproving messages portraying ABA inaccurately (e.g., stating that there is no evidence that ABA is effective or that ABA always leads to post-traumatic stress disorder), some messages approving of ABA also presented inaccurate information (e.g., ABA heals one in five people of ASD or ABA therapy is the best resource to treat anxiety and negative thoughts). Relying on such inaccurate and confusing information may result in parents considering ABA as ineffective, which may ultimately lead them to select alternative, invalidated, and potentially dangerous interventions for their child (e.g., Arnold et al., 2003; Brown et al., 2006; Heiger et al., 2008). In contrast, overgeneralizations and inexact positive effects presented in the internet forum may produce false hope or lead to the inappropriate use of behavioral interventions.

Our results stress the importance of being exposed to accurate information when selecting an intervention. To achieve this purpose, different steps should be taken. First, efforts must be put forward to ensure that practitioners, researchers and policymakers are cognizant of current evidence-based interventions. This action is especially important given France's long history with psychoanalysis as the preferred intervention for ASD (e.g., Bates, 2020; Bishop & Swendsen, 2020; Houzel, 2018) and recent research suggesting that ABA remains misrepresented and difficult to access in France (Amouroux, 2017). Despite more than 40 years of empirical evidence (Keenan & Dillenburger, 2018), the HAS (2012) has categorized ABA-based interventions as "Grade B", stating that there was insufficient evidence for the science to be classified as established. "Fake news", "propaganda" and "myths" about ABA as well as a lack of knowledge regarding the concepts, methods, principles, and vocabulary used in behavior analysis can result in misconceptions regarding its ethical and effective use (Freedman, 2017; Keenan, 2015; Krapfl, 2016) and can even negatively impact policy development (Keenan & Dillenburger, 2018, n.d.). As a result, families can be deprived of effective interventions for their child. This result stresses the importance that researchers and practitioners work together to disseminate factual evidence and help educational agencies, health authorities and policymakers better understand the science of ABA.

Building an accurate understanding of ABA for addressing core features or associated conditions of ASD also requires that information is disseminated and accessible to parents and key stakeholders in multiple languages. Special attention must be given to the French translation of vocabulary relating to ABA to limit misinterpretation of the science. For example, the use of the word *punition* to refer to “punishment” may lead parents to believe that we are using immoral practices because this term is not understood as a functional technical procedure by the general public (Rivière, 2015).

As indicated in the introduction to this paper, the limited number training programs also remains an issue. Investing in the development of recognized certification programs could limit the widespread of misinformation pertaining to ABA by increasing the number of behavior analysts that can disseminate accurate information on the science in communities and allowing families to experience ABA-based interventions implemented by a competent professional. Finally, parents need to be guided on how and where to get accurate information on interventions for their child with a diagnosis of ASD, especially when they do not have access to professional intervention services (e.g., during the diagnosis process or when on a waiting list for intervention services).

Readers should bear in mind the limitations of our study when considering the results. First, data mining social media platforms allowed us to have access to a large dataset, but the amount of descriptive information extractable remained limited. Hence, variables such as gender, age, ethnicity, and education could not be analyzed to identify potential moderators across the tone and accuracy of messages. Furthermore, the nature of our design prevents us from reaching conclusions regarding the causes of our observations. Our results must be interpreted carefully given that our level of interrater agreement was moderate for some categories. Notably, two issues seemed to limit the agreement between the raters: the average length of each message and the use of overlapping categories for tone and accuracy (i.e., the presence of a mixed category resulted in overlap with two other categories). A large number of messages contained more than 500 words, which made their categorization challenging as these messages discussed multiple topics. Misreading a single word in the message could lead to it being rated in one category rather than another, which could explain the moderate interrater agreement observed for some categories. Similarly, another methodological limitation is the absence of an interrater procedure for the selection of keywords used for our data extraction. For example, we chose not to include the keyword BCBA as it is an English abbreviation that we thought was uncommon in French. Therefore, our initial search may have failed to include some messages about ABA.

Despite being based in France, the forum had no restrictions regarding the location of its users. Even though all participants were French speakers, some messages may thus have been posted by users in other countries (e.g., Canada, Belgium, Switzerland). Finally, our design does not allow us to generalize our findings to other social media platforms. Future research should replicate this study with other social media used by parents to see how our results would compare to popular platforms such as Twitter. Researchers should also develop strategies to effectively disseminate information on ABA in non-English speaking communities and examine their effects on the perception of behavior analysis using experimental designs.

Compliance with Ethical Standards

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Ethical Approval: This project did not require ethical approval as the data were publicly available over the internet and the researchers did not participate in the forum.

Conflict of Interest: On behalf of all authors, the corresponding author states that there is no conflict of interest.

Availability of Code and Data: The code and data are freely available at https://osf.io/wceh3/.

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Table 1

List of French and Translated Keywords used in Python Code for Message Extraction

French	English
aba	aba
*analyse appliqu**	applied analysis
*intervention comportemental**	behavioral intervention
*interventions comportemental**	behavioral interventions
comportementalisme	behaviorism
*thérapie comportement**	behavior* therapy
thérapies comportement*	behavior* therapies
aac	aac
*analyse comportementale appliqu**	applied behavior analys*
Comportementaliste	behaviorist
*méthode comportement**	behavior* method
*méthodes comportement**	behavior* methods
*behavioris**	behavioris
*approche comportemental**	behavior* approach

Note. The asterisk denotes keywords with incomplete endings to identify posts that contain variations of the same word or expression. For example, searching comportement* identifies the words comportement, comportemental, comportementaux.

Table 2

Definitions and Examples of Each Category for Type of Message, Tone and Accuracy

Category		Definition	Example (translated to English)
Type of message			
	1	Question/seeking information/seeking support.	My son was recently diagnosed. What is your experience with ABA?
	2	Answering a question/responding to someone seeking information or support.	No, many schools don't offer accommodations. We were told that we had to change schools to get access to support from behavior analyst.
	3	Giving general information or suggesting a resource. This category excludes responses to another person's message or question.	I found the following article on ABA, I think it is interesting. Here is the link https://....
	4	Commenting on another message or subject.	I think what you are describing is CBT and not ABA.
Tone			
	1	Approving: Message that promotes ABA, describes its benefits, or mentions positive experiences with ABA.	We saw great improvements after only a couple of months of interventions.
	2	Disapproving: Message that discourages the use of ABA, describes the harmful/negative effects or talks about negative experiences with ABA.	We should accept our children as they are and not try to change them using ABA.
	3	Mixed: Message with an approving and disapproving tone about ABA.	I have some friends that loved their experience and others that didn't. There are some competent professional and others not so competent.

	4	Neutral: Message that mentions ABA without using a polarized tone.	ABA means applied behavior analysis. You can get information here https://....
Accuracy			
	1	Accurate: Message that accurately describes the procedures, methods, interventions or effects of ABA. This category excludes anecdotal information.	You should get support from a behavior analyst. They can help with your child aggressive behaviors.
	2	Inaccurate: Message that inaccurately describes the procedures, methods, interventions or effects of ABA. This category excludes anecdotal information.	ABA is a sub-branch of CBT.
	3	Mixed: Message presenting accurate and inaccurate information on ABA. This category excludes anecdotal information.	ABA can be helpful for younger children, but it is ineffective for adults.
	4	Non-applicable: Messages without judgment on ABA or reporting anecdotal information on ABA.	A behavior therapist worked with my daughter. After only one month, she was able to use the bathroom alone. However, we did not see an improvement in her food selectivity.

Note. Values associated for each category represent the values in the dataset available at https://osf.io/wceh3/. The examples presented are based on messages extracted from the Forum. ABA: applied behavior analysis; CBT: cognitive-behavior therapy.

Table 3

Descriptive Statistics for our Sample

Characteristic	Median	Mean	SD	Min	Max
Number of messages published by user	2	4.65	21.96	1	303
Number of words per message	263	450.74	547.85	9	5147
Number of views per discussion thread	2,631	7,358	19,702	294	308,218

Table 4

Frequency Distribution and Conditional Percentage of Accuracy Given Tone

	Tone			
Accuracy	Approving	Disapproving	Mixed	Neutral
Accurate	172(49%)	11(6%)	39(35%)	46(18%)
Inaccurate	17(5%)	110(62%)	14(12%)	17(7%)
Mixed	11(3%)	6(3%)	24(21%)	2(1%)
Accuracy not applicable	149(43%)	51(29%)	36(32%)	192(75%)
Total	349(100%)	178(100%)	113(100%)	257(100%)

Table 5

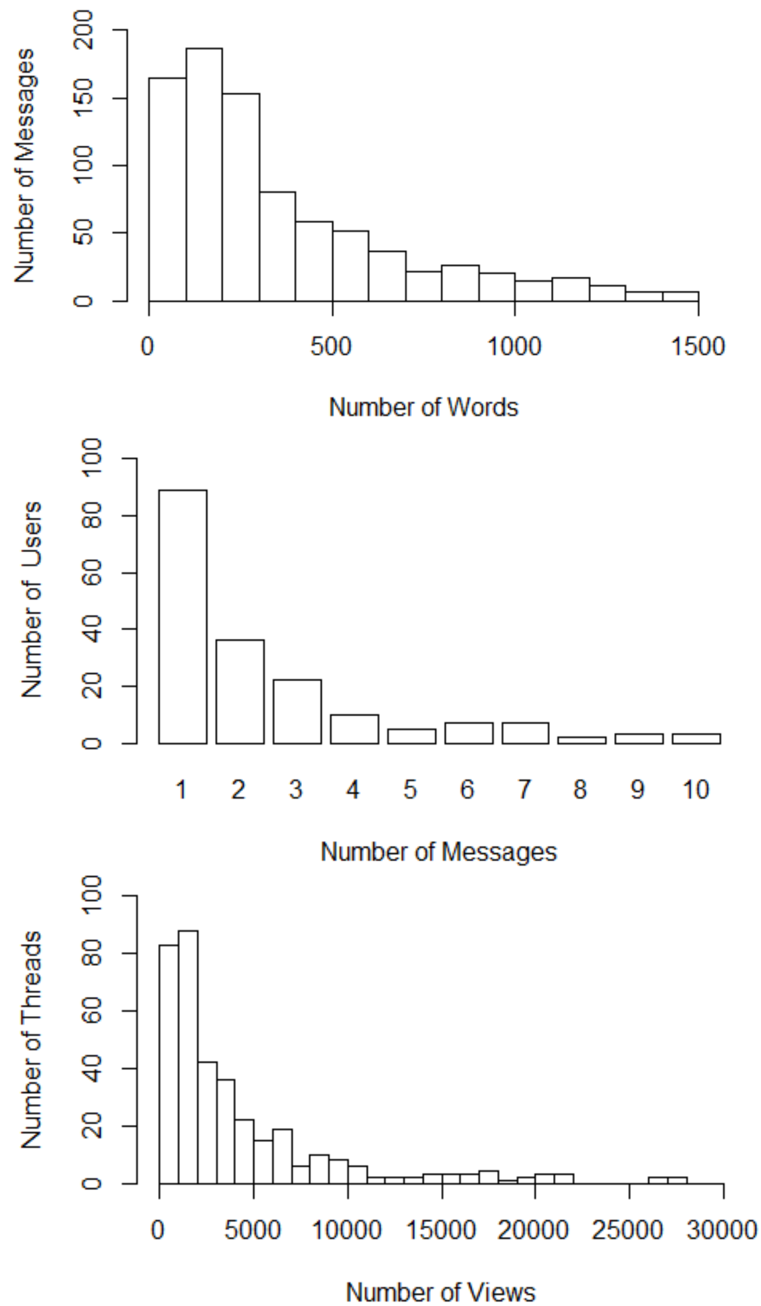
Frequency Distribution and Conditional Percentage of Polarized Tone Given User Status

	User Status	
Tone	Parents	Individuals with ASD
Approving	52(84%)	24(56%)
Disapproving	10(16%)	19(44%)
Total	62(100%)	43(100%)

Note. ASD = Autism spectrum disorder.

Figure 1

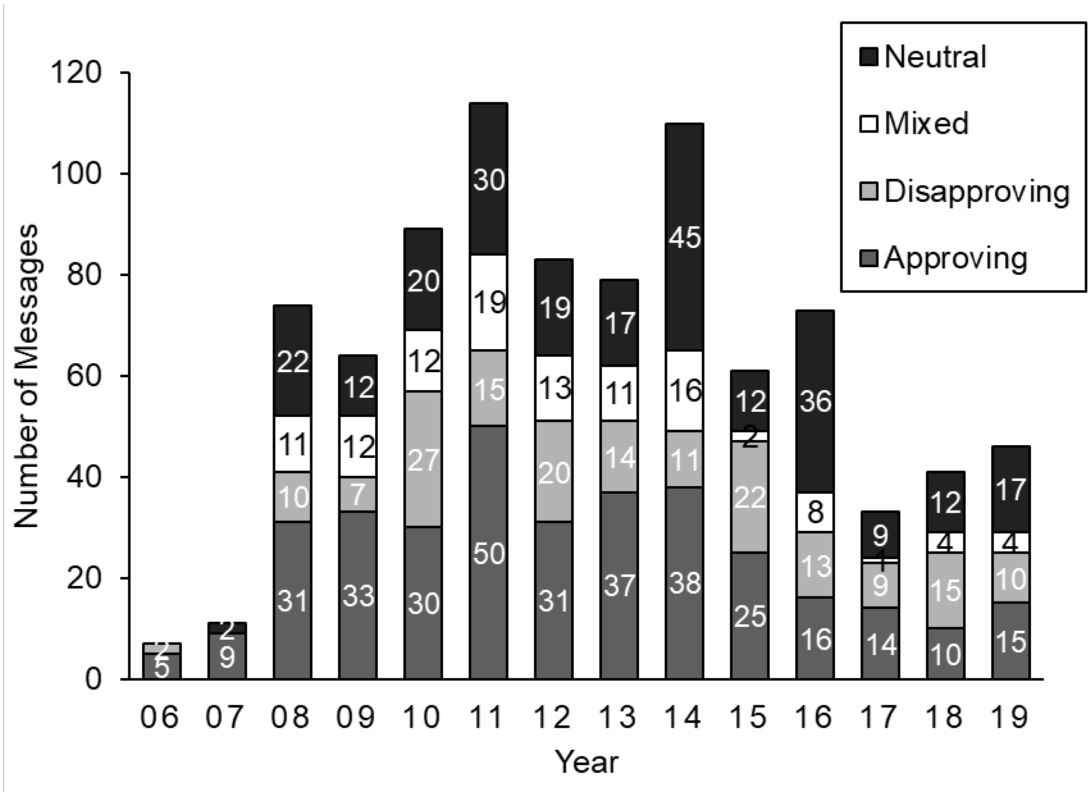
Frequency Distribution of the Number of Words in a Message, the Number of Messages Published per User, and the Number of Views per Thread.



Note. The outliers (i.e., top 5%) were removed from the graphs.

Figure 2

Number of Messages for Each Tone Published on the Internet Forum by Year.



Note. We excluded messages published in 2005 and 2020 from the histogram as data were unavailable for all months of those years.

Chapitre V : Discussion générale et conclusion

Résumé des principaux résultats empiriques

L’objectif principal poursuivi dans le cadre de ma thèse doctorale était d’utiliser la technologie pour présenter des solutions potentielles ou mieux comprendre les enjeux d’accessibilité, de connaissances des facteurs sous-jacents à l’efficacité des interventions et de perception découlant de l’AAC. Pour ce faire, il a été question de (a) évaluer les effets d’une formation interactive en ligne basée sur les principes de l’AAC sur les comportements des parents et sur les comportements problématiques de leur enfant, (b) présenter comment des algorithmes d’apprentissage automatiques peuvent être utilisés pour prédire si une intervention produira ou non des effets chez une personne et (c) mesurer la perception de l’AAC dans un forum internet français.

Les résultats de la première étude de ma thèse doctorale révèlent qu’une formation interactive en ligne complètement auto-guidée peut mener à des améliorations chez les parents et leur enfant. Spécifiquement, la fréquence d’utilisation des interventions découlant de l’AAC par les parents, dont le sexe féminin était dominant, a significativement augmenté, alors que la fréquence et la sévérité des comportements problématiques des enfants de moins de 12 ans ayant un TSA ont significativement diminué suivant l’intervention. Toutefois, aucune différence significative n’a été observée pour la mesure des pratiques parentales. De plus, les analyses réalisées ne permettent pas de connaître la qualité de l’implantation des pratiques par les parents. Parallèlement, elles ne permettent pas de comprendre pourquoi seulement certains parents ont bénéficié de la formation, ni de connaître les raisons entourant le haut taux d’attrition. Considérant que des effets iatrogènes peuvent découler d’une utilisation inexacte des méthodes comportementales enseignées dans la formation (St. Peter et al., 2016; Wilder, 2006), les résultats de cette première étude sont insuffisants pour recommander cette formation en ligne sans le soutien d'un professionnel.

Ma deuxième étude suggère que des algorithmes d'apprentissage automatique peuvent être utilisés avec des échantillons de petite taille pour prédire les effets d'une intervention avec des degrés de précision acceptables à élevés. La présentation détaillée du fonctionnement et des caractéristiques des algorithmes permet au lecteur de s'initier aux mécanismes sous-jacents aux algorithmes d'intelligence artificielle. Considérant le potentiel des algorithmes d'intelligence artificielle pour soutenir la prise de décision et l'intervention clinique, ce tutoriel devient un outil important permettant au professionnel d'interpréter les résultats qui découleront du modèle construit à partir d'algorithmes. Cependant, les connaissances fournies dans ce tutoriel ne sont pas suffisantes pour permettre l'appropriation, la création et la validation des modèles (p.ex. : dans le tutoriel il est question de performance, mais l'évaluation du fonctionnement du modèle, qui n'est pas discutée, est encore plus importante; Ribeiro et al., 2016).

Enfin, l'analyse des messages effectuée dans le cadre de ma troisième étude suggère que l'information publiée sur le forum internet présente souvent une désapprobation de l'AAC ou de l'information inexacte sur les méthodes, les interventions ou les effets qui en découlent. Enfin, les analyses démontrent que les messages plus récents ont une plus petite probabilité d'approuver de l'AAC que les messages plus anciens. Grâce à la technique de forage de données utilisée, il a été possible de quantifier l'ensemble de l'information portant sur l'AAC dans un forum populaire français sur le TSA. Ces résultats suggèrent qu'il y a de la désinformation sur la science de l'analyse du comportement qui circule sur le forum internet sélectionné. Les données nous amènent donc à nous interroger sur la quantité d'informations erronées présente à travers les divers réseaux sociaux et leur impact potentiel sur l'adoption d'interventions découlant de cette science, telles que la formation en ligne proposée dans ma première étude. Malgré les biais d'échantillonnage (p.ex. : âge, genre) qui peuvent découler du forage de données d'une plateforme de réseaux sociaux, une telle procédure donne accès à de grands échantillons de données, difficilement atteignables par des méthodes de recrutement traditionnelles. De manière plus générale, cette étude soutient que le forage de données permet d'extraire de l'information quant aux interventions utilisées dans notre profession. Le nombre de messages, de consultations (*views*) et de participants à un forum indique que les réseaux sociaux constituent une source d'information pour les parents d'enfant ayant un TSA. Les réseaux sociaux peuvent facilement mener à la diffusion d'informations inexactes, mais peuvent également devenir un outil efficace de transfert de connaissances pour les professionnelles, et ainsi servir à démystifier les mythes entourant l'AAC.

Ma thèse s'insère dans une ère de changement, où le numérique et la technologie font partie intégrante de nos vies (p.ex. : Chen et al., 2019; Schwab, 2017; Syam & Sharma, 2018). Ensemble, les résultats de ma thèse suggèrent que la technologie peut soutenir les psychoéducateurs dans plusieurs opérations professionnelles. Néanmoins, chacune des études a soulevé des limites face aux différents outils ou aux méthodes qui ont été évalués. Ainsi, la technologie (l'intelligence artificielle et le forage de données) et les outils (p.ex. : des formations en ligne) qui en découlent peuvent soutenir la pratique psychoéducative, mais ne doivent pas remplacer les professionnels ou leur jugement clinique.

Implications pour la recherche

Ensemble, les trois études de ma thèse contribuent aux connaissances dans le champ d'application de l'AAC auprès des personnes ayant un TSA, mais aussi à la compréhension du potentiel de la technologie pour soutenir la recherche et la pratique clinique s'insérant dans cette science. Comme soulevé dans l'introduction générale, les comportements problématiques peuvent engendrer des conséquences négatives sur le fonctionnement ainsi que le développement des individus ayant un TSA (Postorino et al., 2017; Prata et al., 2018). Intervenir tôt est associé à un pronostic plus favorable (Virués-Ortega, 2010; Wong et al., 2015). Cependant, des enjeux importants existent quant à l'accessibilité aux interventions fondées sur les meilleures pratiques, c'est-à-dire sur l'AAC (Csanady, 2015; Kogan et al., 2008; Protecteur du citoyen, 2015). Les formations pour parents, plus particulièrement les formations en ligne, s'avèrent des ressources prometteuses pour augmenter l'accessibilité aux interventions efficaces pour la gestion des comportements problématiques. Toutefois, aucune étude portant sur des formations en ligne pour parents complètement auto-guidée n'avait mesuré leurs effets sur les pratiques parentales ou les comportements problématiques des enfants ayant un TSA avant le début de mon projet de thèse. De plus, la compréhension des variables qui modèrent leur efficacité et la perception des gens de l'AAC est encore à un stade préliminaire. Le nombre et la qualité des études ayant évalué des formations en ligne complètement auto-guidée sont insuffisants pour recommander l'utilisation de ce type de ressource sans supervision. L'ajout d'une modalité de soutien en ligne (p.ex. : un forum de type questions-réponses supervisé par des professionnels compétents) pourrait rendre la formation en ligne accessible aux familles, et ce, dans un cadre supervisé, tout en nécessitant très peu de ressources humaines et financières.

Les études réalisées en aval de ma première étude de thèse ont montré que les formations interactives en ligne complètement autoguidées peuvent servir au développement des connaissances des parents (Blackman et al., 2020; Jang, et al., 2012; Marleau et al., 2018).

Mon étude contribue aux connaissances en indiquant que ce type de formation peut produire des améliorations comportementales chez les parents et leur enfant. L'absence d'un critère d'inclusion lié au niveau de fonctionnement des enfants ayant un TSA et l'inclusion d'enfants de plus de huit ans dans mon étude ont des retombées scientifiques, car elle permet une meilleure représentativité de cette population dans mes analyses. Ceci s'oppose à la majorité des données sur les formations pour parents d'enfant ayant un TSA qui portent sur des enfants de moins de huit ayant des habiletés de communication verbale (Ilg et al., 2017; Postorino et al., 2017; Suess et al., 2016; Wacker et al., 2013a; 2013b).

Mon deuxième article contribue à l'avancement des connaissances liées aux stratégies analytiques pour la recherche dans le domaine de l'AAC en servant d'introduction au potentiel, au fonctionnement et à l'application des algorithmes d'apprentissage automatique pour soutenir la recherche et l'intervention. Les études portant sur l'analyse du comportement sont souvent caractérisées par de petits échantillons, limitant l'exploitation d'analyses statistiques avancées nécessitant une puissance importante ou des données paramétriques (Lehmann, 2012). Le tutoriel présenté dans ma deuxième étude contribue à la recherche en sensibilisant les chercheurs aux avantages et aux champs d'exploitation des algorithmes d'apprentissage automatique pour la recherche avec de petits échantillons, favorisant ainsi leur utilisation en recherche appliquée. La combinaison de cette étude et d'autres articles récents (p.ex. : Dufour et al., 2021; Trudel, 2021) sert de point de départ pour l'élargissement de la recherche en psychoéducation, en autisme et en analyse appliquée du comportement portant sur l'intelligence artificielle.

Certains chercheurs ont rapporté que la perception des gens de l'AAC est négative (p.ex. : Freedman, 2016). Plusieurs familles utilisent les réseaux sociaux pour identifier des interventions pour leur enfant (Clifford and Minnes, 2013; Shepherd et al., 2020). Toutefois, aucune étude repérée dans la littérature n'a empiriquement mesuré l'information sur l'AAC à laquelle sont exposées les familles qui naviguent les réseaux sociaux. L'utilisation du forage de données pour analyser la polarité et l'exactitude des messages publiés sur un forum internet populaire en TSA est un aspect méthodologique novateur de ma troisième étude. En ce qui a trait aux résultats, ils permettent une meilleure compréhension de l'information sur l'AAC à laquelle sont exposées les familles qui fréquentent le forum en ligne ciblé. Un aspect important à noter est que le nombre de messages approbateurs publiés sur l'AAC a diminué avec le temps. Considérant l'importance qu'accordent les parents à l'expérience des autres pour leur choix d'intervention (Grant et al., 2016), il est possible que ce changement influence négativement la sélection des interventions comportementales par les parents qui fréquentent le forum étudié. Les chercheurs doivent ainsi tenter de mieux comprendre ce qui influence la perception de la population sur l'AAC, sans quoi son utilisation risque d'être limitée, et ce, malgré que la littérature scientifique appuie son efficacité pour intervenir auprès des personnes ayant un TSA (Wong et al., 2015; Roth et al., 2014). Le forage de données devient ainsi un outil intéressant à cet égard.

Implications pour la pratique psychoéducative

Les psychoéducateurs interviennent auprès des personnes vivant des difficultés d'adaptation en misant plus particulièrement sur les manifestations comportementales qui interfèrent avec leur fonctionnement dans différentes sphères de vie (Ordre des psychoéducateurs et psychoéducatrices du Québec [OPPQ], 2020). La croissance de la prévalence du TSA a mené à une augmentation du nombre de psychoéducateurs qui travaillent auprès de cette population (Paquette, 2017). Étant donné qu'une proportion importante de personnes ayant un TSA émet des comportements problématiques qui peuvent nuire à leur fonctionnement et à leur développement (Baghdadli et al., 2003; Matson et al., 2009; McTiernan et al., 2011), il est important que les psychoéducateurs aient accès à des ressources d'intervention efficaces visant leur gestion. Ensemble, les trois études de ma thèse doctorale ont une portée pour la pratique psychoéducative, plus particulièrement pour l'utilisation d'outils technologiques pour soutenir la pratique professionnelle entourant l'intervention sur les comportements problématiques des personnes ayant un TSA.

Dans un premier temps, les résultats de ma première étude suggèrent que la formation en ligne peut servir d'outil d'intervention efficace pour les psychoéducateurs. Étant accessible gratuitement, la formation peut être utilisée par les psychoéducateurs dans divers contextes afin de favoriser le potentiel adaptatif (PAD) des personnes ayant un TSA. D'une part, elle pourrait être suggérée aux familles qui sont en attente de services psychoéducatifs. Offrir une formation aux familles basée sur les meilleures pratiques pour la gestion des comportements problématiques des personnes ayant un TSA permettrait d'augmenter le potentiel expérientiel (PEX) de l'individu par le développement du savoir et du savoir-faire des parents sur l'AAC. D'autre part, la formation en ligne évaluée dans le cadre de ma première étude peut être utilisée par les psychoéducateurs comme outil d'intervention pour former les parents avec qui ils travaillent. Puisque les psychoéducateurs ont l'obligation professionnelle d'intervenir selon les données probantes et les meilleures pratiques (OPPQ, 2018), la formation en ligne offre un outil efficace et peu coûteux pour former les parents sur l'AAC, augmentant ainsi la cohérence entre les interventions du professionnel et de la famille. En sus, former les parents pour intervenir efficacement a le potentiel d'améliorer le PAD des personnes ayant un TSA en favorisant la généralisation des acquis (p.ex. : réduire les comportements problématiques dans divers contextes; Crone et Mahta, 2016; Postorino et al., 2017; Prata et al., 2018). Intégrer la formation en ligne dans le répertoire d'outils d'intervention des psychoéducateurs pourrait aussi accroître la cohérence entre la pratique des professionnels. La formation interactive présente une ressource particulièrement intéressante pour les psychoéducateurs puisqu'elle est validée auprès d'une population québécoise. Enfin, cet outil d'intervention est gratuit et offre une administration flexible de courte durée, ce qui s'agence bien avec les horaires chargés des familles. Néanmoins, il importe de noter qu'offrir une formation en ligne complètement autoguidée comporte des enjeux éthiques, en particulier en l'absence de soutien ou de supervision offert par un professionnel. Ainsi, pour assurer que l'intervention produise les effets souhaités, il est essentiel qu'un professionnel vérifie que les interventions apprises sont fidèlement implantées par les parents, sans quoi, des effets iatrogènes dont l'aggravation ou l'apparition de nouveaux comportements problématiques pourraient s'observer (St. Peter et al., 2016; Wilder, 2006).

Dans un deuxième temps, la seconde étude de ma thèse doctorale contribue au savoir-faire des psychoéducateurs en offrant des outils pour soutenir l'évaluation pré-intervention. L'OPPQ dicte que le psychoéducateur doit éviter « […] d'effectuer ou de multiplier des actes professionnels sans raison suffisante et s'abstient d'effectuer un acte inapproprié ou disproportionné au besoin de son client. » (Article 36 du Code de déontologie des psychoéducateurs et psychoéducatrices). Il est donc important que le psychoéducateur prenne en considération le PAD et le PEX d'un individu afin d'assurer le niveau de convenance de l'intervention qu'il souhaite proposer (Bluteau et al., 2012). Ainsi, ma deuxième étude soulève la pertinence des algorithmes d'apprentissage automatique pour permettre aux psychoéducateurs de prédire les individus qui sont les plus enclins à bénéficier d'une intervention, c'est-à-dire ceux pour qui le niveau de convenance est approprié. Ce tutoriel ne permet pas aux psychoéducateurs d'acquérir les compétences requises pour développer et valider de tels modèles de prédiction, mais sert de point de départ pour permettre aux psychoéducateurs de comprendre l'utilité et le fonctionnement des algorithmes d'apprentissage automatique. Cette sensibilisation pourrait ainsi permettre aux professionnels d'utiliser et de nuancer les résultats des outils d'évaluation ou d'interventions qui découlent d'algorithmes d'apprentissage avec lesquelles ils pourraient éventuellement être amenés à travailler. En bref, les algorithmes proposés dans la seconde étude de ma thèse doctorale sont des outils d'évaluation objectifs qui peuvent soutenir les psychoéducateurs dans leur choix d'intervention afin de maximiser l'adaptation psychosociale des personnes auprès de qui ils travaillent. Or, ces algorithmes ne doivent pas remplacer le jugement clinique du psychoéducateur, lequel doit reposer sur une compréhension globale de l'individu en interaction avec son environnement ainsi que s'appuyer sur les connaissances scientifiques ou des théories reconnues (OPPQ, 2014)

La pratique psychoéducative a évolué depuis sa fondation (Bienvenue, 2020). Au travers des années, le nombre d'heures passé sur le terrain a diminué et la place de l'exercice du rôle-conseil a augmenté (OPPQ, 2014). L'objectif principal du rôle-conseil est d'assurer une réponse efficace aux besoins d'adaptation de la ou des personnes ciblées par l'intervention (Caouette, 2015). Présentement, les interventions découlant de l'AAC ont le plus de soutien empirique pour réduire les comportements problématiques des enfants ayant un TSA et pour enseigner de comportements alternatifs adaptés (Wong et al., 2015). Ensemble, le taux d'attrition de ma première étude, les difficultés au niveau du recrutement de parents pour suivre la formation en ligne et les données de ma troisième étude soulignent l'importance de s'assurer que le psychoéducateur a une compréhension juste des approches et des interventions qu'il utilise. Le travail des psychoéducateurs est d'offrir des interventions efficaces et fondées, mais aussi de travailler en amont pour assurer une compréhension plus juste de l'AAC et des interventions qui en découlent pour intervenir auprès des personnes ayant un TSA. Ce travail de sensibilisation doit être fait tant auprès des intervenants et des organisations qui œuvrent auprès des personnes ayant un TSA qu'auprès de la population générale. Arrimer les connaissances sur l'AAC est d'autant plus important considérant l'étendue des conséquences qui peuvent émerger, persister ou s'aggraver en l'absence d'interventions efficaces pour réduire les comportements problématiques (Postorino et al., 2017; Prata et al., 2018). Par exemple, informer les professionnels de première ligne des meilleures pratiques et leur transmettre une liste de ressources d'intervention efficaces pouvant être utilisées durant la période d'attente pourrait empêcher certaines familles de se tourner vers d'autres ressources, y compris les réseaux sociaux, pour choisir des interventions potentiellement inefficaces, voire dangereuses.

Forces et limites de l'étude doctorale

Recrutement et échantillon

Le recrutement de parents par l'intermédiaire des réseaux sociaux, plus spécifiquement via la plateforme Facebook, fut un succès dans le cadre de la première étude de ma thèse doctorale. Cette stratégie a permis de recruter la taille d'échantillon prévue, tout en respectant les délais prévus du protocole de recherche. Recruter les participants par l'entremise de Facebook comporte plusieurs avantages dont permettre de diffuser l'annonce de recrutement à un grand nombre de personnes de manière efficiente. D'autre part, cette stratégie de recrutement permet de solliciter des personnes issues de divers statuts socioéconomiques et culturels. En contrepartie, effectuer le recrutement à l'aide de réseaux sociaux peut mener à un échantillonnage non-représentatif vu son utilisation hétérogène au travers de la société (Clément, 2020). Par exemple, près de trois utilisateurs Facebook sur quatre sont âgés entre 18 ans et 44 ans. Dans le cadre de mon étude, l'objectif était de recruter des parents d'enfants de moins de 12 ans, ce qui répond généralement aux utilisateurs de Facebook. Des limites similaires s'appliquent à la représentativité de l'échantillon de ma troisième étude qui provient d'une même source, soit un forum en ligne. La même stratégie de recrutement n'a pas été aussi fructueuse pour recruter des participants anglophones pour suivre la formation en anglais (étude annulée en raison de la pandémie). Il devient ainsi important de se pencher sur facteurs pouvant favoriser ou nuire au recrutement des parents pour des interventions en ligne.

D'autre part, le nombre de parents ayant complété ma première étude était relativement petit. Cependant, mon échantillon comprenait des profils d'enfants grandement diversifiés. La majorité des études portant sur les formations pour parents d'enfants ayant un TSA incluent seulement les enfants de moins de huit ans avec un certain niveau de fonctionnement adaptatif ou de capacités verbales (p.ex. : Ilg et al., 2017; Postorino et al., 2017; Suess et al., 2016; Wacker et al., 2013). De la sorte, l'inclusion d'enfants de 12 ans et moins sans critère pour le niveau de fonctionnement contribue à mieux comprendre l'efficacité des formations pour parents comme outil d'intervention pour les enfants sur l'ensemble du spectre de l'autisme.

Méthodologie.

Mon premier article constitue, à la lumière de mes lectures, la première étude portant sur une formation interactive en ligne pour parents complètement autoguidée basée sur l'AAC, qui inclut des mesures sur les comportements des parents et de leur enfant ayant un TSA. L'utilisation d'un devis randomisé avec liste d'attente est une force de l'étude, car ce devis permet à tous les participants d'avoir accès à la formation, tout en maintenant une bonne validité interne (Marchand et al., 2011; Ronaldson et al., 2014). De plus, l'utilisation d'une randomisation par bloc a permis d'assurer l'équivalence des groupes malgré la petite taille d'échantillon (N =47). Toutefois, l'utilisation exclusive de mesures auto-rapportées par les parents comporte une limite importante.

Dans le cadre de la deuxième étude, l'utilisation d'algorithmes d'apprentissage automatique est une pratique novatrice pour la psychoéducation et peut servir à appuyer le jugement clinque des professionnels. En revanche, la stratégie utilisée pour sélectionner les variables intégrées aux algorithmes présentait des limites importantes pouvant nuire à l'interprétation des résultats présentés dans le tutoriel. En ce qui a trait à ma troisième étude, la réalisation du forage de données [*data mining*] de quatre sous-forums d'un forum internet pour mesurer l'information sur les réseaux sociaux portant sur l'AAC représente une force. Cette stratégie permet d'obtenir de grands échantillons de données de manière efficiente tout en évitant les biais de désirabilité sociale que peuvent entraîner d'autres outils de collecte de données traditionnelles (p.ex. : des entrevues ou des questionnaires). Toutefois, elle ne permet pas de généraliser les caractéristiques des données à tous les réseaux sociaux. Enfin, toutes les données de l'étude ont dû être manuellement codées, par défaut de programme permettant d'extraire les caractéristiques souhaitées de textes rédigés en français. Comme appuyé par les valeurs de coefficients kappa, la procédure de codification demeure un exercice subjectif qui peut avoir influencé les résultats obtenus.

Futures études

Ma thèse doctorale offre une meilleure compréhension de la place et du potentiel des outils technologique pour soutenir l'intervention découlant de l'AAC pour répondre aux besoins des personnes ayant un TSA. En raison des limites méthodologiques de la première étude et de l'étendue des connaissances sur les formations en ligne pour parents visant la gestion des comportements problématiques des enfants avec un TSA, il est important de reproduire cette étude avec un plus grand échantillon. Il serait pertinent d'intégrer des mesures observationnelles ou complétées par différents observateurs à ces études de réplication pour mieux comprendre la portée de cette modalité d'intervention. De plus, les chercheurs devraient comparer les effets des formations autoguidées pour les parents qui ont et qui n'ont pas accès à des ressources d'intervention pour mieux comprendre dans quels contextes cet outil devrait être proposé. Des études doivent aussi être réalisées pour mieux comprendre quels facteurs médiatisent ou modèrent les effets des formations pour les parents. Considérant que les comportements problématiques peuvent être présents dans toutes les sphères de vie d'une personne, il serait important de développer et d'évaluer l'efficacité des formations en ligne auto-guidées pour différents acteurs qui travaillent auprès des personnes ayant un TSA (p.ex. : enseignants, intervenants, fratrie, ou famille éloignée) pour assurer la cohérence dans les interventions utilisées d'un contexte à l'autre. Finalement, il serait important que les chercheurs ajoutent des composantes pour mesurer les raisons qui motivent les parents à prendre part aux interventions proposées et comprendre les facteurs qui les incitent à compléter ou non la formation. L'ajout d'une composante de méthodologie qualitative (p.ex. : entrevues individuelles ou de groupes) pourrait permettre d'obtenir de telles informations.

L'utilisation d'algorithmes d'apprentissage automatique peut apporter une contribution importante pour la recherche et l'intervention. Toutefois, il est nécessaire 1) de déterminer l'efficacité des algorithmes proposés dans le tutoriel pour prédire les effets des interventions; 2) de mesurer sa convivialité pour des chercheurs et des cliniciens; 3) de déterminer les balises pour encadrer son utilisation (p.ex. : taille d'échantillon pour réduire les erreurs de type I et de type II, le nombre et les types de variables [*features*] à inclure dans les algorithmes, réglage optimal des hyperparamètres).

Enfin, bien que la troisième étude de ma thèse permette une meilleure compréhension de l'information à laquelle est exposé un parent qui navigue les réseaux sociaux dans le but d'identifier des interventions pour son enfant, les résultats ne peuvent pas être généralisés à d'autres réseaux sociaux ou échantillons. Davantage d'efforts doivent être mis de l'avant pour mieux comprendre ce qui influence la perception des personnes quant à l'AAC et identifier des stratégies efficaces pour augmenter leur utilisation par les familles, mais surtout pour s'assurer que les interventions qui leur sont offertes répondent à leurs besoins et correspondent à leurs valeurs.

Conclusion

Ma thèse présente trois outils technologiques qui permettent d'améliorer ou de mieux comprendre certains enjeux entourant l'AAC. Somme toute, les résultats de cet ouvrage offrent aux psychoéducateurs un outil d'intervention et un outil d'évaluation pour soutenir leur pratique clinique. Ils soulèvent également l'importance de soutenir les parents dans le choix d'intervention pour leur enfant et de leur rappeler à quel point le rôle-conseil qu'ils occupent est essentiel pour assurer une compréhension et une utilisation justes des meilleures pratiques en TSA. Aujourd'hui, l'accroissement des connaissances et de l'accessibilité à la technologie offre des opportunités d'intervention et de recherche considérables. Or, il est important de se rappeler que nous travaillons avec des êtres humains et que les outils présentés comportent des limites qui doivent être prises en considération lors de leur utilisation. Un travail de collaboration entre les chercheurs, les cliniciens et les familles deviendra essentiel pour assurer que les outils développés et validés aient un réel impact sur le fonctionnement et la qualité de vie des personnes ayant un TSA.

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