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Impact de la représentation visuelle des recommandations basées sur l'intelligence artificielle en contexte de prise de décisions d'assortiment

par

Emilie Bigras

Sciences de la gestion
(Option Expérience utilisateur dans un contexte d'affaires)

Sous la codirection de
Pierre-Majorique Léger, Ph.D. et Sylvain Sénécal, Ph.D.

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La présente atteste que le projet de recherche décrit ci-dessous a fait l'objet d'une évaluation en matière d'éthique de la recherche avec des êtres humains et qu'il satisfait aux exigences de notre politique en cette matière.

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Chercheur principal :
Pierre-Majorique Leger,
Professeur titulaire, Technologies de l'information
HEC Montréal

Cochercheurs :
Marc-Antoine Jutras;
Emilie Bigras;
Elise Labonte-Lemoyne;
Sylvain Senecal;
David Brieugne;
Bertrand Demolin

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Maurice Lemelin
Président du CER de HEC Montréal

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Chercheur principal :
Pierre-Majorique Léger
Professeur titulaire, HEC Montréal

Cochercheurs :
Bertrand Demolin; David Brieugne; Sylvain Sénécal; Elise Labonté-Lemoyne; Emilie Bigras; Marc-Antoine Jutras

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Président du CER de HEC Montréal

Résumé

Pour créer un assortiment optimal de produits, un planificateur d'assortiment travaillant pour un détaillant doit considérer et évaluer l'importance d'une grande quantité d'informations. Lorsque surchargé d'informations, la qualité de décision d'un planificateur d'assortiment pourrait être affectée négativement. Ainsi, pour diminuer l'impact de la surcharge d'information, les planificateurs d'assortiment peuvent maintenant être assistés par des systèmes de recommandations basées sur l'intelligence artificielle (IA) lors de leur processus de prise de décision.

Ce mémoire par articles étudie donc l'impact de la représentation visuelle des recommandations d'un agent de recommandation (AR), ainsi que de leur contenu, sur les perceptions, le comportement d'utilisation et la qualité de décision des planificateurs d'assortiment. En se basant sur les études antérieures des ARs en commerce de détail, qui se sont principalement concentrées sur les consommateurs, une étude en laboratoire intra-sujet a été menée auprès de 20 participants. Les résultats de cette étude montrent l'importance d'atteindre un équilibre adéquat entre le besoin d'explications sur les recommandations d'un AR et l'effort cognitif nécessaire pour accéder et comprendre ces explications. D'ailleurs, les résultats de ce mémoire contribuent à combler le manque dans la littérature sur les ARs dans des contextes organisationnels et à identifier, d'un point de vue pratique, des lignes directrices pour les développeurs d'AR et les designers en expérience utilisateur.

Mots clés : Agent de recommandation, Intelligence artificielle, Processus de prise de décision d'assortiment, Explications, Effort cognitif, Perception, Comportement d'utilisation, Qualité de décision, Attention visuelle.

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Liste des abréviations

IA : Intelligence artificielle

AI : « *Artificial Intelligence* »

AR : Agent de recommandation

RA : « *Recommendation Agent* »

UX : Expérience utilisateur

UX : « *User Experience* »

Avant-propos

L'autorisation de rédiger ce mémoire par articles a été obtenue par la direction du programme de M.Sc. de HEC Montréal. Ce mémoire a donc été rédigé sous la forme de trois articles complémentaires. De plus, l'accord de tous les coauteurs de ces trois articles a été obtenu pour que ceux-ci soient présentés dans ce mémoire. Par ailleurs, en juillet 2017, le comité d'éthique en recherche (CER) de HEC Montréal a approuvé ce projet de recherche.

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Introduction

Mise en contexte de l'étude

Les décisions d'assortiment dans un contexte de commerce de détail reposent généralement sur un niveau élevé d'incertitude. Selon la littérature, une décision d'assortiment consiste à l'assortiment optimal de produits répondant à des critères qualitatifs et quantitatifs (Brijs et al., 1999). Ainsi, pour créer un assortiment optimal de produits, un planificateur d'assortiment travaillant pour un détaillant doit considérer un grand nombre de variables et parvenir à identifier un compromis adéquat entre celles-ci (Mantrala et al., 2009). Ces variables englobent les perceptions et préférences des consommateurs (p. ex., les consommateurs recherchent la variété et la flexibilité dans les produits disponibles d'un détaillant (McAlister, 1982)), les contraintes mises en place par le détaillant (p. ex., l'espace physique restreint d'un magasin (Corstjens et Doyle, 1981)) et les facteurs environnementaux (p. ex., les produits similaires de la concurrence (Fox et Sethuraman, 2006)) (Mantrala et al., 2009). Toutefois, la quantité importante d'informations qui doit être considérée par un planificateur d'assortiment pourrait affecter négativement la qualité de l'assortiment de produits générés (Lurie, 2004). D'ailleurs, un détaillant doit satisfaire les besoins des consommateurs pour maximiser ses ventes actuelles et futures (Mantrala et al., 2009). Créer un assortiment optimal de produits est donc une décision critique pour le détaillant qui est prise par le planificateur d'assortiment travaillant pour celui-ci.

Pour réduire le risque associé à l'incertitude d'une décision d'assortiment, les employés peuvent maintenant être assistés par des systèmes de recommandations basées sur l'intelligence artificielle (IA) lors de leur processus de prise de décision (Andrews et al., 2017). Par conséquent, obtenir une meilleure compréhension des caractéristiques d'un agent de recommandation (AR) influençant positivement l'adoption et l'utilisation continue d'un AR par les planificateurs d'assortiment est cruciale. Cependant, la plupart des études sur les ARs en commerce de détail se concentrent principalement sur les consommateurs (p. ex., Sénécal et Nantel, 2004; Wang et Benbasat, 2009). Ainsi, un manque dans la littérature sur les ARs dans des contextes organisationnels peut être relevé. De ce fait, certains résultats des études antérieures sur les ARs en commerce de détail se concentrant sur les consommateurs pourraient contribuer à comprendre l'adoption de tous les utilisateurs, tels que les employés dans des contextes organisationnels.

Les études antérieures, dans un contexte en ligne, montrent que les consommateurs qui ne perçoivent pas l'utilité des recommandations d'un AR seront portés à ignorer celles-ci durant leur processus de prise de décision (Zanker, 2012). D'ailleurs, ceci est principalement le cas lorsque le risque financier associé à un achat par un consommateur est identifié comme étant élevé (Herlocker et al., 2000; Dabholkar et Sheng, 2012). Ainsi, comprendre le raisonnement logique derrière les recommandations d'un AR à l'aide d'explications est crucial pour que les consommateurs acceptent et considèrent ces suggestions au cours de leur processus de prise de décision (Pu et Chen, 2006). Ces explications permettent d'exposer aux consommateurs les détails de l'algorithme responsable des recommandations d'un AR complètement ou partiellement (Vig et al., 2009; Gedikli et al., 2014). Les détails de l'algorithme responsable des recommandations d'un AR sont généralement exposés partiellement pour protéger les détails d'un algorithme, mais également pour ne pas surcharger les consommateurs cognitivement (Gedikli et al., 2014).

Lorsque les consommateurs sont surchargés d'informations à considérer durant leur processus de prise de décision, leur efficacité pour prendre une décision et l'efficience de leur décision sont atteintes négativement (Lurie, 2004). En effet, en considérant seulement les recommandations d'un AR lors d'un achat, les consommateurs perçoivent une diminution de leur effort cognitif investi (Bechwati and Xia, 2003). Par contre, en ajoutant des explications permettant aux consommateurs de comprendre le raisonnement logique derrière les recommandations d'un AR, l'effort cognitif de ceux-ci augmente (Gregor, 2001). Ainsi, sans explication, les recommandations d'un AR seraient ignorées par les consommateurs, mais avec des explications, les consommateurs pourraient être surchargés d'informations. Dans les deux cas, le processus de prise de décision des consommateurs serait affecté négativement. Par conséquent, le besoin d'explications et l'effort cognitif nécessaire pour accéder et comprendre ces explications doivent être correctement équilibrés dans le format de présentation des recommandations d'un AR.

Pour que les consommateurs considèrent les recommandations d'un AR lors de leur processus de prise de décision, ceux-ci doivent percevoir ces suggestions comme étant précises, crédibles, faciles à utiliser, satisfaisantes et utiles (Pereira, 2001; Wang et Benbasat 2005; Komiak et Benbasat, 2006; Xiao et Benbasat, 2007). Les perceptions, le comportement d'utilisation et le bénéfice associé à l'utilisation des consommateurs influencent donc l'adoption et l'utilisation continue d'un AR. La représentation visuelle des recommandations d'un AR et leur contenu doivent donc influencer positivement les perceptions, le comportement d'utilisation et la qualité de décision des consommateurs.

Questions de recherche

Dans un contexte organisationnel, les employés n'ont pas le choix d'adopter le système d'information de leur employeur (Karahanna et al., 1999). Cependant, sans comprendre le raisonnement logique derrière les recommandations d'un AR, les employés ne pourront pas justifier leurs décisions à leur supérieur (Heitmann et al., 2007). Il est donc crucial pour ceux-ci de comprendre le raisonnement logique derrière les recommandations d'un AR à l'aide d'explications pour considérer ces suggestions lors de leur processus de prise de décision (Gregor, 2001; Zanker, 2012). Par ailleurs, des études antérieures ont montré qu'un décideur tente constamment de maximiser la qualité de ses décisions et de minimiser son effort cognitif investi (Payne et al., 1993). Or, la représentation visuelle est un facteur important dans le déploiement de cet effort.

Ce mémoire par articles permettra d'explorer l'impact de la représentation visuelle des recommandations d'un AR, ainsi que de leur contenu, sur les perceptions, le comportement d'utilisation et la qualité de décision des planificateurs d'assortiment. Les études antérieures sur les ARs dans un contexte en ligne permettront de bâtir cette étude. Le format de présentation des recommandations d'un AR basées sur l'IA sera manipulé en considérant deux facteurs, soit le besoin d'explications (c.-à-d., sans ou avec des explications) et l'effort cognitif investi (c.-à-d., faible ou élevé). Les perceptions des planificateurs d'assortiment envers un AR (c.-à-d., crédibilité, sentiment de contrôle, qualité de la décision, satisfaction et intention d'adopter l'AR) seront observées à l'aide de données psychométriques (questionnaires) (Ohanian, 1990; Bradley et Land, 1994; Sirdeshmukh et al., 2002; Komiak et Benbasat, 2006). Des données oculométriques seront utilisées pour examiner le comportement d'utilisation des planificateurs d'assortiment envers un AR. La qualité de décision des planificateurs d'assortiment sera observée en comparant chaque assortiment optimal de produits créé par ceux-ci à l'assortiment optimal de produits préétabli par le partenaire. Cette étude tentera donc de répondre aux questions de recherche suivantes :

Dans quelle mesure le format de présentation des recommandations d'un AR basées sur l'IA influence les perceptions, le comportement d'utilisation et la qualité de décision des planificateurs d'assortiment envers cet AR ?

Quel format de présentation des recommandations d'un AR basées sur l'IA est considéré comme étant préférable en ce qui concerne les perceptions, le comportement d'utilisation et la qualité de décision des planificateurs d'assortiment envers cet AR ?

Objectif de l'étude et contributions potentielles

L'objectif de ce mémoire est d'identifier le format de présentation des recommandations d'un AR basées sur l'IA qui est préférable pour les planificateurs d'assortiment en ce qui concerne leurs perceptions, leur comportement d'utilisation et la qualité de leurs décisions. Ainsi, d'un point de vue théorique, ce mémoire contribue à combler le manque dans la littérature sur les ARs dans des contextes organisationnels, ajoutant ainsi aux connaissances dans la littérature sur l'interaction humain-machine. De plus, ce mémoire, d'un point de vue pratique, permet d'identifier des lignes directrices pour les développeurs d'AR et les designers en expérience utilisateur (UX). En effet, à l'aide des résultats de cette étude, des ARs influençant positivement l'adoption et l'utilisation continue des employés pourront être créés à l'aide d'un design adapté.

Informations sur les articles

L'auteur de ce mémoire a réalisé, avec le soutien d'une bourse de recherche de premier cycle (CRSNG), la phase de conception du design expérimental et les prétests de cette étude au cours de l'été 2017. À l'automne 2017, sous une bourse de la Chaire de recherche industrielle CRSNG-Prompt en expérience utilisateur, la collecte de données en laboratoire a été effectuée. Les résultats de cette étude ont permis à l'étudiante de ce mémoire de rédiger trois articles. Ainsi, suite à trois phases d'analyse, chaque article partage aux lecteurs un plus grand nombre de résultats. Tout d'abord, le premier article de ce mémoire a été présenté à la conférence scientifique *CHI 2018* (*The ACM CHI Conference on Human Factors in Computing Systems*) à Montréal en avril 2018 (Bigras et al., 2018a). Ensuite, le deuxième article de ce mémoire a été présenté à la conférence *HCI International 2018* (*Human-Computer Interaction International Conference*) à Las Vegas en juillet 2018 (Bigras et al., 2018b). Pour ce qui est du troisième article de ce mémoire, celui-ci est actuellement en préparation pour soumission dans la revue *Industrial Management & Data Systems*. Une version préliminaire de cet article est donc présentée dans ce mémoire.

Résumé du premier article

Les ARs basés sur l'IA peuvent aider les gestionnaires à augmenter la qualité de leurs décisions en traitant pour ceux-ci une grande quantité d'informations pertinentes. Les recherches observant les interactions entre un utilisateur et un AR montrent que les utilisateurs bénéficient lorsqu'ils adoptent un AR, mais que leur adoption présente certains défis. Par exemple, l'adoption d'un AR est seulement possible lorsque les utilisateurs ont confiance en celui-ci. Ainsi, cette étude examine comment la richesse de l'information fournie par un AR et l'effort nécessaire pour atteindre cette information influencent les perceptions et l'utilisation des utilisateurs. Une expérience en laboratoire intra-sujet a été menée auprès de 20 participants. Les résultats suggèrent que les perceptions à l'égard de l'AR (c.-à-d., confiance, crédibilité et satisfaction) sont influencées par la richesse de l'information d'un AR et non par l'effort nécessaire pour obtenir cette information. En plus de contribuer à la littérature sur l'interaction humain-machine, les résultats ont des implications pour la conception de meilleurs systèmes d'AR basés sur l'IA.

Résumé du deuxième article

Tout en créant un assortiment optimal de produits, les planificateurs d'assortiment doivent prendre en considération une quantité importante d'informations, ce qui cause un certain niveau d'incertitude. Les compromis faits par les planificateurs d'assortiment entre les différentes informations qu'ils doivent considérer peuvent diminuer la qualité des décisions d'assortiment prises par ceux-ci. Pour réduire l'impact de ces compromis, les planificateurs d'assortiment peuvent désormais utiliser des ARs basés sur l'IA tout au long de leur processus de prise de décision, bénéficiant ainsi de leur capacité à traiter une grande quantité d'informations pour améliorer leurs décisions. Cependant, les recherches observant les interactions entre un utilisateur et un AR montrent que l'adoption d'un AR par un utilisateur présente certains défis. Par exemple, l'adoption d'un AR est seulement possible lorsque les utilisateurs perçoivent les recommandations de l'AR comme étant crédibles. Ainsi, cette étude observe comment la richesse de l'information fournie par un AR et l'effort nécessaire pour accéder cette information influence le comportement d'utilisation (c.-à-d., attention visuelle) et les perceptions (c.-à-d., crédibilité, satisfaction, performance, intention d'adopter l'AR) des planificateurs d'assortiment. Une expérience en laboratoire intra-sujet a été menée auprès de 20 participants. Les résultats montrent l'importance des recommandations d'un AR qui incluent des explications facilement accessibles sur le comportement d'utilisation, les perceptions et la qualité de décision des planificateurs d'assortiment. Ces résultats contribuent à la littérature sur l'interaction humain-machine et à la théorie d'adoption d'un AR dans des contextes organisationnels en présentant des indications sur les fonctionnalités augmentant l'adoption d'un AR par les employés.

Résumé du troisième article

Le but de cet article est de rapporter les résultats d'une expérience en laboratoire qui a étudié comment les perceptions, le comportement d'utilisation et la qualité de décision des planificateurs d'assortiment sont influencés par la manière dont les recommandations d'un AR basées sur l'IA sont présentées. Une expérience en laboratoire intra-sujet a été menée auprès de 20 participants. Les perceptions des participants et leur comportement d'utilisation envers un AR durant leur processus de prise de décision ont été évaluées à l'aide d'échelles de mesure validées et une technologie d'enregistrement du mouvement oculaire. Les résultats de cette étude montrent les effets positifs des ARs partiellement transparents demandant un effort cognitif faible sur les perceptions, le comportement d'utilisation et la qualité de décision des planificateurs d'assortiment. Cette étude contribue à combler le manque dans la littérature sur les ARs basés sur l'IA dans des contextes organisationnels, faisant ainsi progresser les connaissances dans la littérature sur l'interaction humain-machine. Les résultats de cette étude ont des implications pour les développeurs d'AR et les designers en expérience utilisateur. En effet, ceux-ci permettent de contribuer à la création de meilleurs ARs basés sur l'IA pour les employés. Les études antérieures sur les ARs se sont principalement concentrées sur le contexte en ligne. Ainsi, cet article fournit un comparatif entre les consommateurs et les employées pour ce qui est de leurs perceptions envers les ARs, leur comportement d'utilisation et la qualité de leurs décisions.

Pour comprendre la contribution de l'étudiante de ce mémoire dans la rédaction des trois articles, un tableau descriptif a été élaboré (voir Tableau 1). Celui-ci identifie la contribution en pourcentage de l'étudiante de ce mémoire pour chaque étape du processus de recherche.

Tableau 1 – Contributions dans la rédaction des articles

Étape du processus	Contribution
Définition des besoins du partenaire	Identifier les besoins d'affaire du partenaire et transformer ceux-ci en questions de recherche scientifique – 60 % • Le reste de l'équipe de recherche a contribué à identifier les besoins d'affaire du partenaire et à transformer ceux-ci en un objectif de recherche précis
Revue de la littérature	Communiquer directement avec le partenaire pour concevoir les stimuli – 60 % • Contribuer au développement des stimuli

	• Marc-Antoine Jutras, coauteur des trois articles, a finalisé le prototype sur Axure RP. 8 des stimuli à l'aide des gabarits fournis par le partenaire Élaborer et rédiger la revue de littérature pour identifier les construits observés dans les études antérieures sur les ARs en commerce de détail – 100 % Définir et proposer les outils de mesure à utiliser selon les construits choisis en communiquant directement avec le partenaire – 80 % • Le reste de l'équipe de recherche s'est assuré que les outils de mesure sélectionnés permettaient de tester les construits choisis
Conception du design expérimental	Compléter la demande au CER et les demandes de modification de projet par la suite – 100 % • Le reste de l'équipe de recherche s'est assuré que toutes les demandes complétées au CER soient adéquates Élaborer et rédiger le protocole d'expérimentation – 100 % Assurer la mise en fonction du système oculométrique Smart Eye Pro – 90 % • Élaborer et effectuer des prétests techniques permettant de découvrir le fonctionnement de ce système de la collecte à l'extraction des données oculométriques • Marc-Antoine Jutras, coauteur des trois articles de ce mémoire, a été impliqué dans la mise en fonction de ce système Organiser la salle de collecte – 100 %
Recrutement des participants	Élaborer et rédiger le questionnaire de recrutement – 100 % Recruter et gérer des participants – 100 % Administrer les compensations – 100 %

<table>
<tr><td></td><td>Concevoir et assembler le cartable d’expérience pour le suivi des participants – 90 %

• Marc-Antoine Jutras, coauteur des trois articles de ce mémoire, a contribué à l’assemblage du cartable d’expérience pour le suivi des participants</td></tr>
<tr><td>Prétests et collecte de données</td><td>Chargé des opérations lors des collectes de données – 50 %

• Marc-Antoine Jutras, coauteur des trois articles de ce mémoire, a été présent pour toutes les collectes de données

Soutien technique et appui aux assistantes de recherche en cas d’un problème – 50 %

• Cette responsabilité a été partagée avec Marc-Antoine Jutras, coauteur des trois articles</td></tr>
<tr><td>Extraction et transformation des données</td><td>Extraction et mise en forme des données psychométriques et oculométriques – 30 %

• Marc-Antoine Jutras, coauteur des trois articles, a contribué à l’extraction et la mise en forme des données psychométriques et oculométriques</td></tr>
<tr><td>Analyse des données</td><td>Analyse des données oculométriques – 50 %

• Préparer six gabarits d’aires d’intérêt (2 scénarios x 3 conditions)

• Marc-Antoine Jutras, coauteur des trois articles, a créé des aires d’intérêt pour chaque pop-up ou nouvelle page consultée par les participants

Retranscription et analyse des verbatim des entrevues – 50 %

• Regrouper par sujet et analyser les verbatim des entrevues

• Un assistant de recherche faisant partie de l’équipe de recherche a retranscrit les verbatim des entrevues</td></tr>
</table>

	Analyses statistiques du mémoire – 100% • Interpréter les résultats statistiques • Aide d'un statisticien de l'équipe de recherche a effectué les tests statistiques à l'aide de SAS 9.4
Rédaction des articles	Contribution dans l'écriture des articles du mémoire – 100 % • Les articles ont été améliorés à l'aide des commentaires des coauteurs

Structure du mémoire

Les trois prochains chapitres de ce mémoire présenteront l'entièreté des résultats de cette étude. Tout d'abord, le prochain chapitre de ce mémoire présentera le premier article qui a été publié à la conférence scientifique *CHI 2018*. Ensuite, le chapitre 3 de ce mémoire présentera le deuxième article qui a été publié à la conférence scientifique *HCI International 2018*. Pour ce qui est du troisième article, celui-ci se retrouve dans le chapitre 4 de ce mémoire et est actuellement en préparation pour soumission dans la revue *Industrial Management & Data Systems*. À noter que les résultats du premier article se retrouveront dans le deuxième article et ainsi de suite. Pour conclure, le chapitre 5 rappellera les résultats complémentaires des trois articles répondant aux questions de recherche ainsi que leurs contributions. Ce chapitre abordera également les limitations de cette étude et les futures avenues de recherche.

Chapitre 2 : Premier Article

Working with a Recommendation Agent: How Recommendation Presentation Influences Users' Perceptions and Behaviors

Emilie Bigras[1], Marc-Antoine Jutras[1], Sylvain Sénécal[1], Pierre-Majorique Léger[1], Marc Fredette[1], Chrystel Black[2], Nicolas Robitaille[2], Karine Grande[2], and Christian Hudon[2]

[1] HEC Montréal, Montréal, QC H3T 2A7, Canada
{emilie.bigras, marc-antoine.jutras, sylvain.senecal, pierre-majorique.leger, marc.fredette}@hec.ca
[2] JDA Labs, Montréal, QC H2W 2R2, Canada
{Chrystel.Black, Nicolas.Robitaille, Karine.Grande, Christian.Hudon}@jda.com

Abstract

Artificial intelligence (AI)-based recommendation agents (RA) can help managers make better decisions by processing a large quantity of decision relevant information. Research on user-RA interactions show that users benefit from RA, but that there are some challenges to their adoption. For instance, RA adoption can only happen if users trust the RA. Thus, this study investigates how the richness of the information provided by an RA and the effort necessary to reach this information influence users' perceptions and usage. A within-subject lab experiment was conducted with 20 participants. Results suggest that perceptions toward the RA (trust, credibility, and satisfaction) are influenced by the RA information richness, but not by the effort needed to reach this information. In addition to contributing to HCI literature, the findings have implications for the design of better AI-based RA systems.

Keywords: Recommendation agent • Artificial intelligence • Trust • Perception • Behavior • Eye tracking.

1 Introduction

As artificial intelligence (AI)-based recommendation agents (RA) become more common in the workplace, investigating how to best present decision recommendations to users becomes important for their adoption and continuous usage. Most research on RA adoption has focused on consumer adoption, not employee adoption (Sénécal and Nantel, 2004; Wang and Benbasat, 2009). Thus, a better understanding of how professionals use and perceive RAs and more importantly which RA characteristics promote their adoption will enrich theory development. In addition, it will inform the human interaction community in the design of better RA interactions.

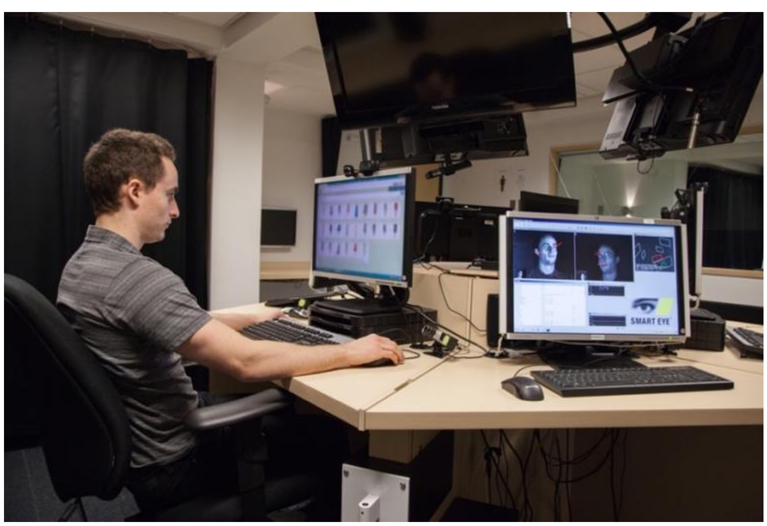
This study investigates how the way recommendations are presented to professionals influences their usage behavior and perception of the RA. It aims at answering the following questions: Which recommendation representation will planners trust and use the most? Are they likely to prefer a simple recommendation represented as a product score (low information richness) or a product score which provides information on the different variables included in its calculation (high information richness). Also, will users prefer to get less information faster on the product score (low effort) or more information which may be longer to access (high effort). To answer these questions, the recommendation representations were manipulated with two factors in the study: effort required to access information (low or high) and information richness (low or high). The effort is associated to the number of steps required to get to the information (e.g., number of screens) and the information richness is associated with the amount of information provided by the RA to assist assortment planners through their decision-making process. The latter has been demonstrated to influence the RA perceived credibility (Heesacker et al., 1983). We suggest that these two factors will impact users' RA perceptions.

The context of the study is retail assortment decisions. In order to create an optimal assortment of products, assortment planners need to take into consideration qualitative and quantitative criteria while making a decision (Brijs et al., 1999). These criteria include an important number of variables (e.g., past sales, retail trends, inventory, sales forecast, customers' needs) which creates a certain level of uncertainty. AI-based recommender systems can now be used as an aid by assortment planners through their decision-making process (Wang et al., 2015). Research shows that RAs reduce the volume of information to process (Wang and Benbasat, 2005), enhance decision-making process (Aljukhadar et al., 2012), and improve user satisfaction (Cearley et al., 2017). But, some challenges affect their adoption. For instance, one challenge resides in building RA credibility in order for users to trust recommendations and adopt the RA (Xiao and Benbasat, 2003; Lemoine and Cherif, 2012; Hengstler et al., 2016).

2 Method

A within-subject laboratory experiment was conducted using the experimental RA prototype for assortment planning developed by JDA Labs (Montreal, Canada). Twenty logistics and marketing professionals (M_{age} = 26, SD = 3.92; 9 women) participated in the study. Participants had to make assortment decisions for two fictitious scenarios and for each scenario they were exposed to 3 conditions in a counterbalanced order: Task 1 represented a low effort & low richness condition (T1), Task 2 reflected a low effort & high richness condition (T2), and the third task was a high effort & high richness condition (T3). Due to time constraints, the high effort & low richness condition was not included in the experiment. Each scenario started with a practice task with no RA to familiarize participants with the assortment planning software. They each received a $30 gift card as a compensation. This experiment was approved by the IRB of our institution.

Figure 1 – Experimental set-up.



For each task of each scenario, 24 different products were presented to participants. Through their decision-making process, participants needed to make an assortment decision by selecting, from the 24 products displayed, the optimal assortment of products. Each scenario specified the total number of products (ranging from 6 to 7) that needed to be selected by the participants for their optimal assortment for each condition. Figure 2 represents the elements that were displayed for each product and in each condition to the participants. The product score, i.e., the RA's recommendation, has a value between 0 to 100 and provides the AI-based forecast based on the RA. For T1, the product score represented in Figure 2 was the only source of information made available to the participants.

Figure 2 – Each product was presented with an image, its name including its brand, and its product score (i.e., RA's recommendation).

For T2 and T3, the product score was also made available to the participants, but, by clicking on the products, participants had also access to more information. This additional information included various product characteristics (e.g., attributes, past sales, margin, comparative products). However, the effort required to reach this additional information varied between T2 and T3. For T2, the information was made available through a modal window (Figure 3). As for T3, the information was accessed with additional navigation through a new page (Figure 4).

Figure 3 – For T2, each product had a modal window presenting additional information on the variables included in its product score calculation.

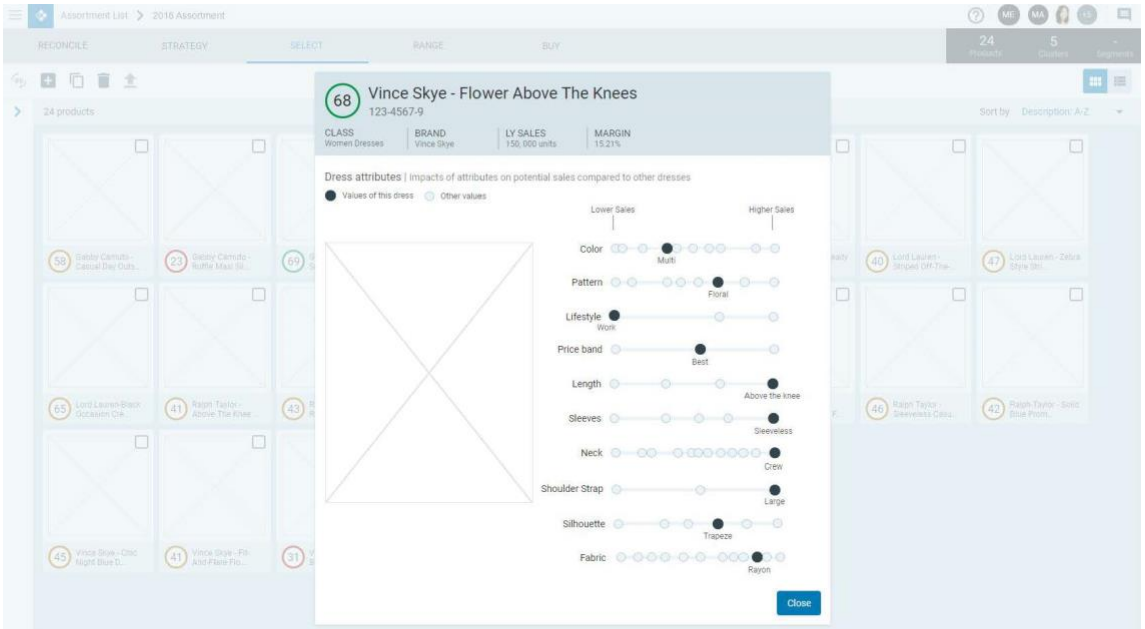
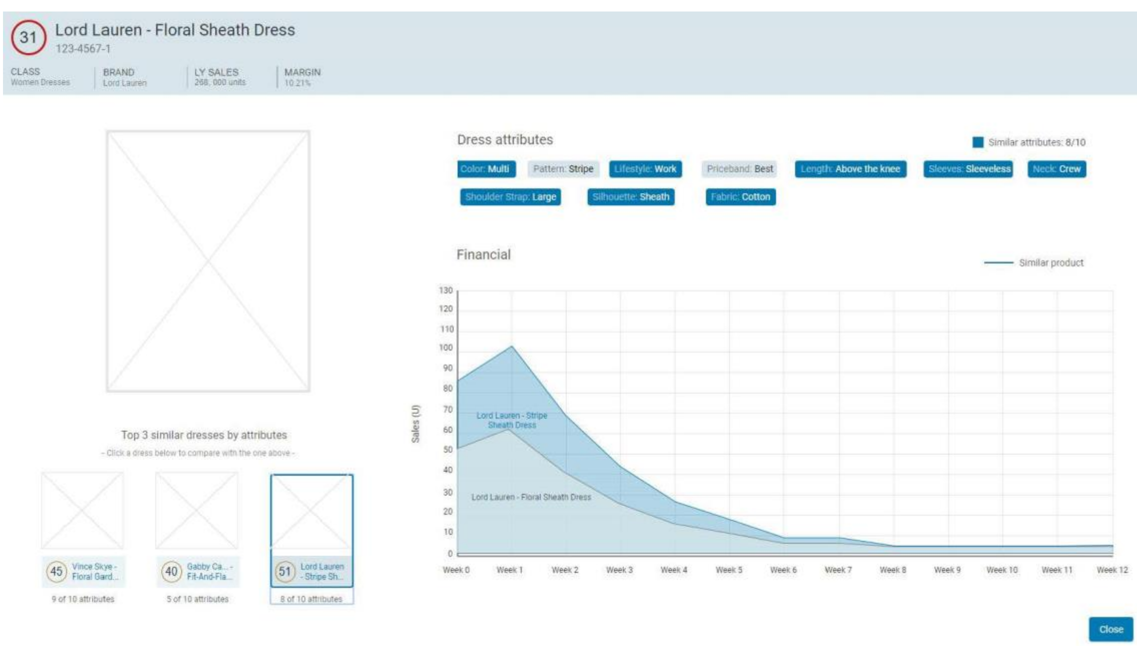


Figure 4 – For T3, each product had a new page to access the additional information which required more effort.



3 Apparatus and Measures

The experimental prototype for assortment planning by JDA Labs (Montreal, Canada) was presented through Axure RP 8. Task stimuli were presented on a monitor with a 1680 x 1050 resolution. All statistical analyses were performed with SAS 9.4.

3.1 Psychometric Measures

After each task, participants completed a questionnaire. It measured users' perceptions toward the RA in terms of trust (Komiak and Benbasat, 2006), credibility (Ohanian, 1990), satisfaction (Sirdeshmukh et al., 2002) and type of future usage (i.e., RA used as a decision aid or as a delegated agent (Komiak and Benbasat, 2006)).

3.2 Behavioral Measures

In addition to self-reported measures, exploratory observational measures were also used. A Smart Eye Pro system (Gothenburg, Sweden) was used to track users' visual attention in each task (at a 60Hz sampling rate). A 9-point (3 x 3) calibration grid was used. Calibration was repeated for each participant until sufficient accuracy was reached (± 2 degrees of accuracy). The eye tracking data was analysed with the MAPPS 2016.1 software. Areas of interest (AOIs) were created for each RA product score presented in Figure 2 (1 AOI x 24 products x 6 tasks) and for each modal window or a new page with additional information that was consulted by participants. For each AOI, the number and duration of ocular fixations were measured. Based on Rayner (1998), the fixation threshold set at 200 milliseconds.

4 Results

4.1 Users' Perceptions

A linear regression with random intercept was used to test the difference between the means of users' perceptions (Table 1). First, no difference between low effort & high richness (T2) and high effort & high richness (T3) was found, indicating that the effort required to access the information does not have an impact on user perceptions. Second, results suggest that information richness plays a key role in users' positive perceptions since RA trust, credibility, satisfaction and intention to adopt are all greater in high information conditions (T2 and T3) than in the low richness condition (T1). In addition, a Wilcoxon signed rank test with a two-tailed level of significance was also performed to compare the difference between the intention to adopt the RA as a delegated agent and the intention to adopt the RA as a decision aid for each condition. Results suggest that participants are more willing to adopt the RA as a decision aid than as a delegated agent for all three conditions (T1: $p \leq .0001$; T2: $p \leq .0001$; T3 $p \leq .0001$).

Table 1 – User Perception Results

	Result	Estimate	p-value[1]
Trust	T2 > T1	0.8748	***
	T3 > T1	0.7070	***
The Intention to Adopt the RA as a Delegated Agent	T2 > T1	0.8503	***
	T3 > T1	0.5647	*
The Intention to Adopt the RA as a Decision Aid	T2 > T1	1.0705	***
	T3 > T1	0.9681	***
Credibility	T2 > T1	0.7055	***
	T3 > T1	0.6139	***
Satisfaction	T2 > T1	0.6068	**
	T3 > T1	0.5103	*

[1] Two-tailed level of significance: * $p \leq 0.05$; ** $p \leq 0.01$; *** $p \leq 0.001$

4.2 Users' Behaviors

First, a linear regression with a mixed model adjusted for multiple comparisons with a two-tailed level of significance was used to test the difference between the least square means of the duration for the AOIs of the different conditions. The difference between the least square means of the number of fixations for the AOIs of the different conditions was also tested with a Poisson regression with a mixed model adjusted for multiple comparisons. When additional information is available (T2 and T3), participants spend less time on product scores, but consult them more frequently (T2 and T3 greater than T1, respectively 1.1642, $p = .0003$ and -1.0554, $p \leq .0001$; 1.3147, $p \leq .0001$ and -1.3978, $p \leq .0001$).

Second, a Wilcoxon signed rank test with a two-tailed level of significance was performed to compare the difference between the first 25% and the last 25% of the task duration and the number of fixations for each AOI of each condition. Results show no difference in the time and the frequency that the product score was consulted by the participants through time. However, it revealed that when in the low effort & high richness condition (T2), participants consulted the additional information more frequently and for a longer period of time at the beginning of the task ($p = .0274$ and $p = .0342$, respectively). It also showed that in the high effort & high richness condition (T3), participants consulted the additional information for a longer period of time, but not more frequently at the beginning of the task ($p = .0559$ and $p = .1104$, respectively). A similar test was also performed to compare the difference between the first 40% and the last 40% of the task duration and the number of fixations for each AOI of each condition. Results were in line with the above results.

5 Discussion and Concluding Comments

Our results show that in a professional context, the way recommendations from RA are presented influences users' perceptions and behaviors. First, an RA providing rich information is perceived as more trustworthy, credible, and satisfactory. In addition, users are more willing to adopt the RA as a decision aid than as a delegated agent and this perception is increased when the RA provides rich information. That being said, users seem to prefer a product score that is enhanced with additional information on the variables included in its calculation. The effort to reach this information does not seem to impact users' satisfaction. Second, results suggest that when assortment planners have access to richer information, they consult for a longer period of time, but less frequently, this information. Furthermore, users are referring more to this additional information at the beginning of their decision-making process, compared to the product score that is consulted consistently through their decision-making process.

As AI-based RA provide recommendations based on a tremendous amount of data, the way the information needed by the users must be presented is a formidable challenge. Although a condensed visual representation needs to be created by designers of such tools in order to manage this amount of data (Nilsson, 2014), our findings suggest that users still need to open the black box and access additional information for them to trust and be satisfied with the RA. As AI will eventually become common in the workplace (Andrews et al., 2017), it is crucial to understand how to best present AI-based recommendations in order to have employees trust these recommendations. Best practices in UX design for AI can then be generated based on such insights.

Obviously, more research is needed to better understand how professional users interact with RAs and provide more guidelines to UX designers. The effort/accuracy decision-making framework (Payne et al., 1993) could be useful to investigate the tradeoff between decision effort and accuracy users are willing to make in their professional context. As user behavior changes over time (Knijnenburg et al., 2012; Sénécal et al., 2015), longitudinal studies of RA usage will also contribute to understanding how the user-RA relationship evolves in terms of perceptions and behaviors.

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Chapitre 3 : Deuxième Article

In AI We Trust: Characteristics Influencing Assortment Planners' Perceptions of AI Based Recommendation Agents

Emilie Bigras[1], Marc-Antoine Jutras[1], Sylvain Sénécal[1], Pierre-Majorique Léger[1], Chrystel Black[2], Nicolas Robitaille[2], Karine Grande[2], and Christian Hudon[2]

[1] HEC Montréal, Montréal, Canada
emilie.bigras@hec.ca
[2] JDA Labs, Montréal, Canada

Abstract

While creating an optimal assortment of products, assortment planners need to take into account an important amount of information, which leads to a certain level of uncertainty. These trade-offs can diminish the quality of the assortment decisions made by the planners. To reduce their impact, assortment planners can now use artificial intelligence (AI)-based recommendation agents (RAs) throughout their decision-making process, thus benefiting from their ability to process a large quantity of information to improve their decisions. However, research on user-RA shows that there are some challenges to their adoption. For instance, RA adoption depends on the users perceived credibility of its recommendations. Hence, this study investigates how the richness of the information provided by the RA and the necessary effort to access this information influences the assortment planners' usage behavior (visual attention) and perceptions (credibility, satisfaction, performance, intention to adopt the RA). A within-subject lab experiment was conducted with twenty participants. The results show the importance of the RA's recommendations that include easily accessible explanations of the variables included in their calculations on the usage behavior, perceptions, and decision quality of the assortment planners. These findings contribute to the HCI literature and the theory of RA adoption in B2B contexts by providing insights on features enhancing employee adoption.

Keywords: Recommendation agent • Artificial intelligence • Credibility • Perception • Behavior • Eye tracking.

1 Introduction

Creating an optimal assortment of products is one of the most basic yet critical decision assortment planners must make for retailers (Mantrala et al., 2009). In order to create an optimal assortment of products, assortment planners need to take into consideration qualitative and quantitative criteria (Brijs et al., 1999). These criteria include a great number of variables (e.g., past sales, retail trends, inventory, customers' needs, sales forecast) that must be taken into account by the assortment planners, which creates a certain level of uncertainty. This level of uncertainty results from the important amount of information that needs to be considered by the assortment planners throughout their decision-making process. Hence, the information load could negatively impact the assortment decision quality (Lurie, 2004) which could lead to losses in both current and future sales due to customers exits (Mantrala et al., 2009).

To reduce the impact of these trade-offs, artificial intelligence (AI)-based recommender systems can be used as an aid by assortment planners throughout their decision-making process (Wang et al., 2015). By processing a large quantity of decision relevant information, AI-based recommendation agents (RAs) can help assortment planners define an optimal assortment more easily (Dellaert and Häubl, 2012). Though AI-based RAs are becoming more present in the workplace, most research on RA adoption has focused on consumer adoption, not employee adoption (Sénécal and Nantel, 2004; Wang and Benbasat, 2009). Understanding the way professionals use and perceive RAs, and more importantly, what RA characteristics encourage their adoption and continuous usage will contribute to advancing knowledge in the human-computer interaction (HCI) literature. In addition, it will inform the human interaction community on how to best present decision recommendations in order to create better RA interactions.

Therefore, the main objective of this study is to investigate how assortment planners' usage behavior and perceptions of RAs are influenced by the way recommendations are presented. This study contributes to theory on RA adoption in B2B contexts and has implications for RA developers by providing insights on features that would enhance RA adoption by employees.

2 Development of Hypotheses

In the RA literature, two main factors have been investigated (Wang, 2005; Aljukhadar et al., 2012). The first factor, information richness, is associated with the amount of information provided by the RA to assist assortment planners throughout their decision-making process. The scientific literature shows that users acceptance towards RAs increases with perceived transparency (Pu and Chen, 2006). The perception of transparency is recognized when the logical reasoning behind an RA is explained (Nilashi et al., 2016; Swearingen and Sinha, 2001). The need for explanations and justifications are specifically triggered when users are supporting their decisions through knowledge-based systems (Gregor, 2001). The second factor, effort, is related to the number of steps required to get to the information (e.g., number of screens). Thus, in a high effort condition, the number of steps required to get to the information is greater than in a low effort condition. In addition to processing information, assortment planners need, in order to make an assortment decision, to gather the decision-relevant information which can lead to information load (Pu and Chen, 2006). Due to the limited capacity of individuals to process information, information overload can result in cognitive fatigue and confusion (Eppler and Mengis, 2004). Hence, processing and obtaining a large quantity of information can negatively affect the assortment planners' decision-making process by reducing the quality of their decisions (Lurie, 2004).

According to the literature, explanations about the recommendations presented have been demonstrated to positively influence the RA's perceived credibility (Heesacker et al., 1983), satisfaction (Xiao and Benbasat, 2007), and performance (i.e., decision quality) (Wang, 2005). In this study, the source credibility dimensions of trustworthiness (i.e., the recommendations of the RA are identified by the users as reliable) and expertise (i.e., the RA is recognized by the users as knowing the right answer) have been observed (Ohanian, 1990). In order to establish trust and show the expertise behind the recommendations of the RA, transparency of the recommendation process is crucial (Sinha and Swearingen, 2002). Explaining this process increases users trust in the RA's recommendations (Pu and

Chen, 2006). Furthermore, the perceived ease of use of the RA is also related to RA trust (Wang and Benbasat, 2005). According to Pereira (2001), the cognitive load of gathering and processing information can negatively impact the perceived satisfaction and performance of the decision-making process. Therefore, finding a balance between information richness and effort seems to be crucial.

H1: Assortment planners' perceptions toward the RA regarding credibility (H1a), satisfaction (H1b), and performance (H1c) will be more positive when the RA's recommendations include easily accessible explanations.

Moreover, trust towards RAs is needed to foster their adoption, but trust in RAs is difficult to build (Lemoine and Cherif, 2012). Initial trust is thus essential in influencing users' continuous usage (Wang and Benbasat, 2007; Hengstler et al., 2016). However, users experiencing information overload, even in the absence of trust, are likely to consult the RA's recommendations more frequently (Aljukhadar et al., 2012). Thus, accepting the recommendations of the RA due to cognitive fatigue of confusion (Eppler and Mengis, 2004).

H2: Assortment planners will consult each recommendation of the RA more frequently when the RA's recommendations are enhanced with explanations that are difficult to access.

Research also shows that when trust is built, the risk perceived in adopting the RA's recommendations is then diminished (Hengstler et al., 2016). Hence, when RA trust increases, the usage of the RA follows (Komiak and Benbasat, 2006). Without knowledgeable explanations that are perceived as credible by the users, the recommendations of the RA are expected to be ignored (Wang and Benbasat, 2005; Zanker, 2012). Therefore, understanding the logical reasoning behind the recommendations of the RA seems to be important for users.

H3: When the RA's recommendations are explained, assortment planners will allocate their visual attention more towards the information explaining these recommendations at the beginning of the decision-making process, rather than at the end.

According to the literature, the presence of information load diminishes users' reluctance towards using RA recommendations (Aljukhadar et al., 2012). By perceiving the usefulness of the RA's recommendations through explanations, users are more inclined in adopting these recommendations during their decision-making process (Wang and Benbasat, 2005; Qiu and Benbasat, 2009). The users' intention in adopting the RA also increases when RA credibility is perceived (Xiao and Benbasat, 2003; Lemoine and Cherif, 2012; Hengstler et al., 2016). Hence, users are known to prefer transparent recommendations to non-transparent recommendations (Sinha and Swearingen, 2002).

H4: Assortment planners will have a higher intention of adopting the RA throughout their decision-making process (i.e., RA used as a delegated agent or as a decision aid) when the RA's recommendations include explanations.

Furthermore, the important number of trade-offs made by the assortment planners during their decision-making process, trying to balance a great number of variables (e.g., past sales, retail trends, inventory, customers' needs, sales forecast), indicates that the product assortment created by an assortment planner will always vary from one assortment planner to another (Mantrala et al., 2009). Consequently, an optimal product assortment might not be fully optimal, which in turn diminishes the performance of the assortment planners. The cognitive load of gathering and processing information can negatively impact the quality of the decisions taken by users (Pereira, 2001). With the help of RAs, this cognitive load can be reduced through recommendations (Häubl and Trifts, 2000). However, in order to increase the quality of the decisions taken by the users, the RA's recommendations need to be considered (Pereira, 2001; Huseynov et al., 2016).

H5: When the RA's recommendations are complemented with easily accessible explanations, assortment planners will have a higher performance (i.e., decision quality).

3 Method

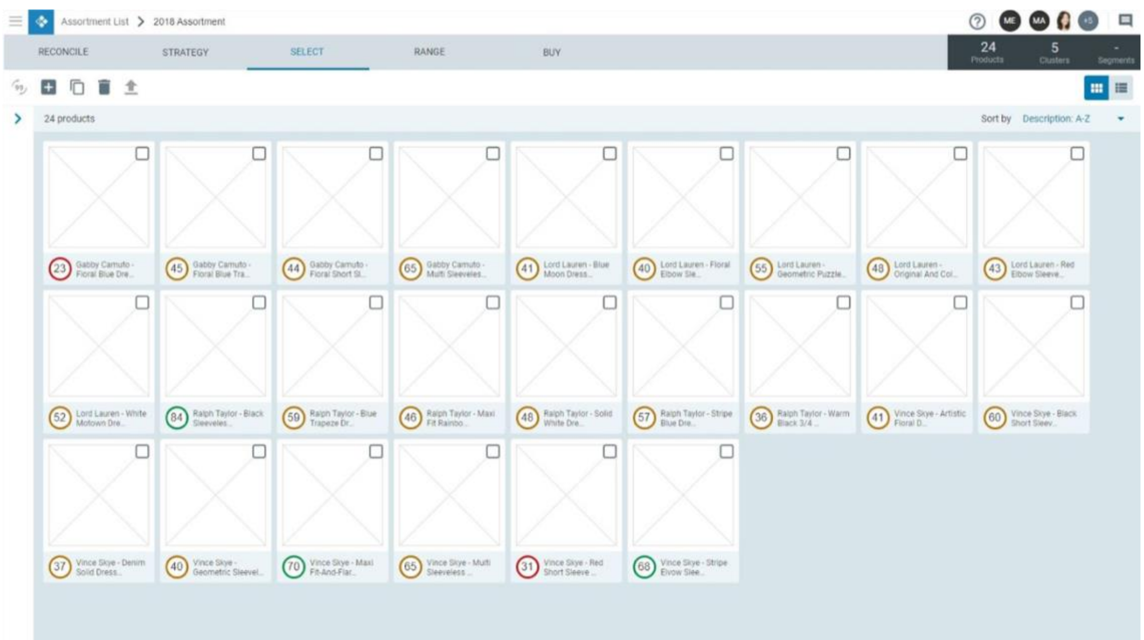
To test our hypotheses, a within-subject laboratory experiment was conducted. A total of twenty logistics and marketing professionals (M_{age} = 26, SD = 3.92; 9 women) participated in the study. During the experiment, participants used the experimental RA prototype for assortment planning developed by JDA Labs (Montreal, Canada). Overall, the experiment lasted two hours and each participant received a $30 gift card as a compensation. This project was approved by the Institutional Review Board (IRB) of our institution and each participant completed a consent form.

3.1 Experimental Design and Protocol

Participants had to make assortment decisions in six tasks and were allowed to take as much time as they needed for each task (about 5 minutes per task). These tasks were divided into two similar fictitious scenarios that were counterbalanced, three tasks per scenario. The three tasks of each scenario were counterbalanced and each task was exposing participants to a particular recommendation representation condition based on the two experimental factors (i.e., effort required to access information and information richness). Task 1 represented a low richness & low effort condition (T1), Task 2 reflected a high richness & low effort condition (T2), and Task 3 was a high richness & high effort condition (T3). Due to time constraints in the experiment and to avoid participant fatigue, the low richness & high effort condition was not included in the experiment. In order to familiarize participants with the assortment planning software, each scenario began with a practice task with no RA.

A total of 24 distinctive products per task were presented to participants for each scenario (24 products x 6 tasks). Participants were required to make an assortment decision by selecting the optimal assortment of products from the 24 displayed products (see Fig. 1). Each scenario specified the total number of products (ranging from 6 to 7) that needed to be selected for each task. Figure 1 represents the elements that were displayed for each product and in each condition to the participants. The product score, RA's recommendation, was generated using AI. This product score varied between 0 to 100 and was surrounded by a circle that changed colour depending on the score number (i.e., green > 66, 66 ≥ orange > 33, and red ≤ 33).

Figure 1 – For each task, 24 products were presented to the participants. Each product was presented with an image, its name including its brand, and its product score (i.e., RA's recommendation).



For T1 (low richness & low effort), the product score represented in Figure 1 was the only source of information made available to the participants. For T2 (high richness condition & low effort) and T3 (high richness & high effort), the product score was also made available to participants, however, participants could also acquire further product information by clicking on each product. Additional information included various product characteristics, e.g., attributes, past sales, margin and comparative products. The effort required to access additional information varied between T2 and T3. For T2, the information was made available through a modal window (see Fig. 2). As for T3, accessing the information necessitated additional navigation through a different page, thus requiring more effort from participants (see Fig. 3).

Figure 2 – For T2, each product had a modal window that was used to access the explanations of its product score (i.e., RA's recommendation).

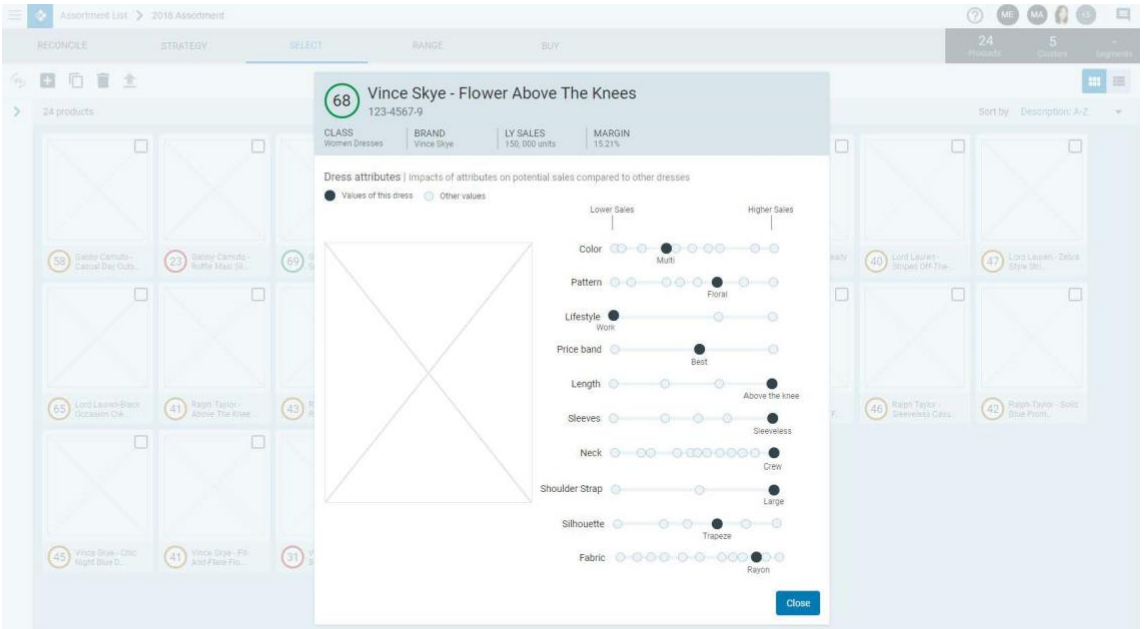
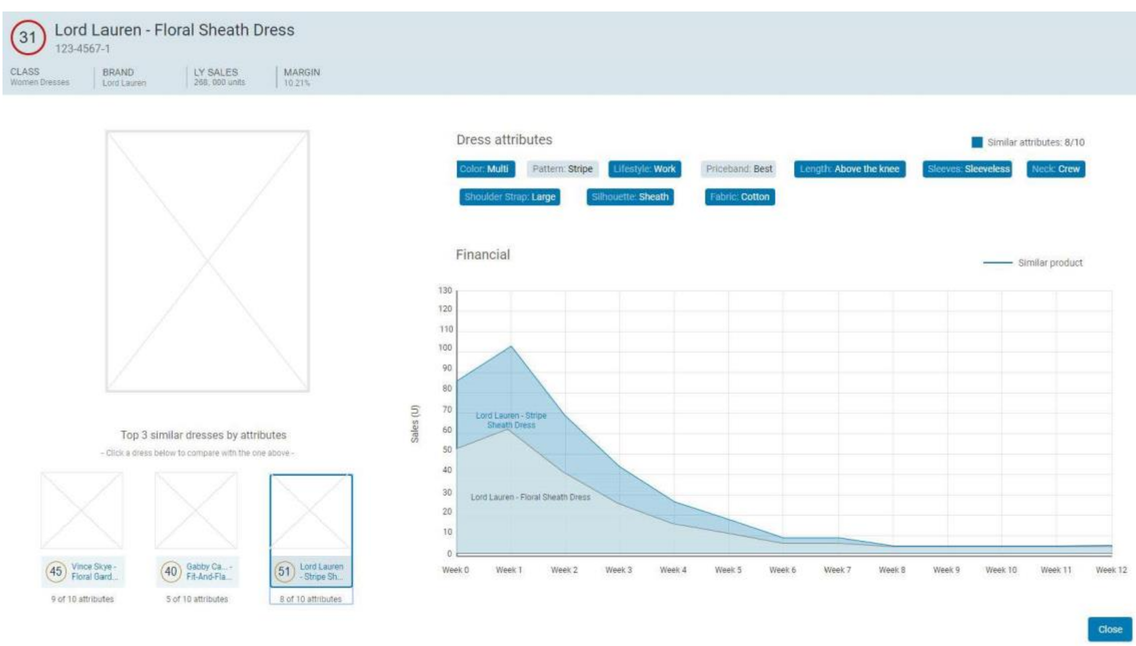


Figure 3 – For T3, each product had a new page presenting an additional layer of difficulty to access explanations of the RA's recommendation.



3.2 Apparatus and Measures

The experimental prototype for assortment planning by JDA Labs (Montreal, Canada) was made available to the participants through a 1680 x 1050 resolution monitor. This prototype was developed with Axure RP 8. All statistical analyses were performed with SAS 9.4.

Psychometric Measures. After each task, participants completed a questionnaire. This questionnaire used validated measurement scales to assess the participants' perceptions towards the RA regarding credibility (Ohanian, 1990), satisfaction (Sirdeshmukh et al., 2002), and type of future usage (i.e., RA used as a decision aid or as a delegated agent (Komiak and Benbasat, 2006)). Participants were also asked to rate their perceived task performance (from 1 to 10).

Performance measures. The performance of the participants was measured exclusively for the first scenario, because JDA Labs was only able to provide predetermined optimal assortments for this scenario. The guidelines of the first scenario, combined with all the additional information made available to the participants, led to a predetermined optimal assortment for each task. Each final assortment, for each task and each participant, was compared to the predetermined optimal assortment. When a product in the final assortment of the participant was also in the predetermined optimal assortment, one point was given. For each participant and each task, results were calculated as percentages. Thus, a performance score was created.

Behavioral measures. During each task, the visual attention of the participants was captured at a 60Hz sampling rate with a Smart Eye Pro system (Gothenburg, Sweden). A 9-point calibration grid was used. For each participant, calibration was repeated until sufficient accuracy was obtained (± 2 degrees of accuracy). The MAPPS 2016.1 software was used to analyse the eye tracking data. For each RA product score (see Fig. 1) and for each modal window or new page with additional information that was consulted by the participants, areas of interest (AOIs) were generated. The number and duration of ocular fixations, for each AOI, were collected. An ocular fixation was accepted at 200 milliseconds (Rayner, 1998).

Figure 4 – Experimental set-up.

4 Results and Analysis

H1 stipulates that the assortment planners' perceptions toward the RA regarding credibility (H1a), satisfaction (H1b), and performance (H1c) will be higher in the high richness & low effort condition. A linear regression with random intercept and a two-tailed level of significance adjusted for multiple comparisons was used to test the difference between the means of assortment planners' perceptions for each combination of conditions (see Table 1). First, results suggest that the perceptions of the participants toward the RA regarding credibility and satisfaction are positively affected when information on the different variables included in the calculations of the RA's recommendations is present (T2 and T3 greater than T1 with one-tailed level of significance, respectively 0.7055, $p \leq .0001$ and 0.6139, $p \leq .0001$; 0.6068, $p = .0027$ and 0.5103, $p = .0077$). However, no difference was found between the high richness conditions (T2 and T3) and the low richness condition (T1) for the participants' perceived performance toward the RA. Second, although results show that the assortment planners' perceptions toward the RA in terms of performance is impacted negatively by the effort required to access information (T2 greater than T3 with one-tailed level of significance, 0.4706, $p = .0474$), no difference between high richness & low effort (T2) and high richness & high effort (T3) was found on the perceptions of the participants toward the

RA regarding credibility and satisfaction. Hence, H1a, H1b, and H1c are partially supported.

Table 1 – Participants' Perceptions Results

	Hypothesis	Result	Estimate	p-value[1]
Credibility	H1a	T2 > T1	0.7055	< .0001
		T3 > T1	0.6139	< .0001
Satisfaction	H1b	T2 > T1	0.6068	0.0054
		T3 > T1	0.5103	0.0154
Performance	H1c	T2 > T3	0.4706	0.0948

[1] Two-tailed level of significance

In order to test H2, a Poisson regression with a mixed model adjusted for multiple comparisons with a two-tailed level of significance was performed. Thus, the difference between the least square means of the number of fixations for the AOIs of the different conditions was tested (i.e., the number of fixations on all the product scores of one condition versus another). Results revealed that participants, when in the high richness & high effort condition (T3), are consulting the product scores more frequently than when in the low richness & low effort and high richness & low effort conditions (T1 and T2), which provides strong support for H2 (T3 is greater than T1 and T2 with one-tailed level of significance, respectively 1.1617, $p = .0054$; 0.7471, $p = .0225$).

We also hypothesized that assortment planners, when in a high richness condition (i.e., high richness & low effort and high richness & high effort), will allocate their visual attention more towards the information explaining the different variables included in the product score (i.e., RA's recommendation) at the beginning of the decision-making process, rather than at the end (H3). To test H3, the difference between the first 25% and the last 25% of the number of fixations and the task duration for each AOI of each condition was compared by using a Wilcoxon signed rank test with a two-tailed level of significance. Results revealed no difference through time concerning frequency and the time spent by the participants on the RA's recommendations. In addition, results showed that participants, when in the high richness & low effort condition (T2), consulted more frequently and for a longer period of time the information on the different variables included in the calculations of the RA's recommendations at the beginning of the task ($p = .0137$ and $p = .0171$, respectively with a one-tailed level of significance). Furthermore, results also revealed that when in the high richness & high effort condition (T3), participants consulted this additional information for a longer period of time, but not more frequently, at the beginning of the task ($p = .0279$ with a one-tailed level of significance and $p = .1104$, respectively). These results were also in line with a similar test that was conducted to compare the difference between the first 40% and the last 40% of the number of fixations and the task duration for each AOI of each condition. Hence, these results partially confirm H3.

Moreover, the difference between the means of assortment planners perceived intention to adopt the RA throughout their decision-making process (i.e., RA used as a delegated agent or as a decision aid) for each combination of conditions was analyzed with a linear regression with random intercept and a two-tailed level of significance adjusted for multiple comparisons (see Table 2). Results show that, when in a high richness condition (i.e., high richness & low effort and high richness & high effort), participants had a higher intention of adopting the RA as a delegated agent and as a decision aid than when in the low richness & low effort condition (T2 and T3 are greater than T1 with one-tailed level of significance, respectively 0.8503, $p = .0001$; 0.5647, $p = .008$ and 1.0705, $p = .0001$; 0.9681, $p = .0002$). These results confirm H4.

Table 2 – Participants' Intention to Adopt the RA for Future Usage Results

	Hypothesis	Result	Estimate	p-value[1]
The Intention to Adopt the RA as a Delegated Agent	H4	T2 > T1	0.8503	0.0003
		T3 > T1	0.5647	0.016
The Intention to Adopt the RA as a Decision Aid		T2 > T1	1.0705	0.0002
		T3 > T1	0.9681	0.0005

[1] Two-tailed level of significance

To compare the difference between the intention to adopt the RA as a delegated agent and the intention to adopt the RA as a decision aid for each condition, a Wilcoxon signed rank test with a two-tailed level of significance was conducted. For all three conditions, results propose that participants are more inclined to adopt the RA as a decision aid than as a delegated agent (T1: $p \leq .0001$; T2: $p \leq .0001$; T3 $p \leq .0001$).

H5 specifies that the assortment planners' performance will be higher in the high richness & low effort condition compared to the other two conditions (i.e., low richness & low effort and high richness & high effort conditions). In order to test this hypothesis, a linear regression with a mixed model adjusted for multiple comparisons with a two-tailed level of significance was used. Results showed that participants had a higher performance in the high richness & low effort condition, which confirms H5 (T2 is greater than T1 and T3 with one-tailed level of significance, respectively 1.0500, $p = .0001$ and 0.2330, $p = .0001$). Furthermore, no difference between low richness & low effort (T1) and high richness & high effort was found (T3).

Table 3 – Participants' Performance Results

	Hypothesis	Result	Estimate	p-value[1]
Performance	H5	T2 > T1	1.0500	0.0002
		T2 > T3	0.2330	0.0002

[1]Two-tailed level of significance

To explore different AOIs which most attracted the visual attention of the high-performance and the low-performance participants, a Poisson regression with a mixed model, and a linear regression with a mixed model, both with a two-tailed level of significance adjusted for multiple comparisons, were performed. Thus, testing the difference between the least square means of the number of fixations and the duration of the AOIs for the different conditions for each level of performance. Results revealed that when in a high richness condition (T2 and T3), high-performance participants consulted the product scores more frequently but not for a longer period of time (T2 and T3 greater than T1, respectively 1.6405, $p \leq .0001$ and -0.5500, $p = 0.2052$; 1.6323, $p \leq .0001$ and -0.8942, $p = 0.1145$). In addition, no difference between high richness & low effort (T2) and high richness & high effort (T3) was found concerning the frequency, or the period of time in which the information explaining the different variables included in the product score was consulted. Compared to the high-performance participants, the low-performance participants spend the same amount of time and consulted the product scores as frequently throughout the different conditions. Moreover, a significant difference between high richness & low effort (T2) and high richness & high effort (T3) was found concerning the frequency but not the period of time in which the information explaining the different variables included in the product score was consulted (0.7539, $p = 0.005$ and 0.1535, $p = .7379$), thus indicating the effort required to access information impacted the low-performance participants.

5 Discussion and Concluding Comments

Results revealed that: (1) an RA providing rich information is perceived as more credible (H1a) and satisfactory (H1b); (2) users' perceived performance is negatively influenced by the effort required to access information (H1c); (3) the RA's recommendations are consulted more frequently by the assortment planners when the product scores are enhanced with difficult to access explanations (H2); (4) users are consulting consistently the product scores throughout their decision-making process; (5) when the RA provides additional information, planners are consulting this information more often at the beginning of their decision-making process (H3); (6) the intention to adopt the RA significantly increases with the richness of information, thus indicating that assortment planners seem to favor the recommendations of an RA when they are enhanced with additional information about the variables included in their calculations (H4); (7) users are more willing to adopt the RA as a decision aid than as a delegated agent; (8) the performance of the users is significantly higher when the RA provided rich information that was easily accessible (H5).

This paper's main theoretical implication is related to the advancement of RA adoption in B2B contexts. As AI is becoming more common in the workplace (Andrews et al., 2017), it is essential to understand how to best present AI-based recommendations in order to positively influence professionals' usage behavior and perceptions toward an RA. The findings in this study show the importance of RA's recommendations that are enhanced with easily accessible information. A RA providing rich information on the variables included in the calculations of its recommendations (i.e., product scores) increases assortment planners' perceptions toward the RA regarding credibility and satisfaction. These findings are in line with the literature focusing on the RA adoption of consumers (Heesacker et al., 1983; Xiao and Benbasat, 2007). Furthermore, the intention of the professionals to adopt this RA also increases with information richness. However, planners seem more willing to adopt the RA as a decision aid than as a delegated agent. Though in a consumer RA adoption context, this could be explained by the importance of a product purchase (Komiak and Benbasat, 2006). In a professional context, assortment planners could feel that following only the RA's recommendations in their decision-making process would diminish their performance, thus negatively affecting the quality of their assortment decisions (Spreitzer and Mishra, 1999). Moreover, the RA's recommendations, when enhanced with additional information that is accessible through an increased effort, are consulted more frequently by the users. This indicates the degree of importance that is given by the assortment planners to the product scores (Chen and Epps, 2013) when experiencing information overload (Aljukhadar et al., 2012). This could also explain why the planners perceived a higher performance when the additional information was easily accessible. In addition, the performance (i.e., decision quality) of the assortment planners increases with information richness and decreases with the effort to access this information.

This study also has implications for RA developers and UX designers. First, results show that professional users need to have access to information about the variables included in the calculations of the RA's recommendations in order to increase perceived credibility and satisfaction. That being said, the tremendous amount of data behind the AI-based recommendations needs to be brought forward to the users in a condensed intuitive form (Nilsson, 2014). Hence, a visual representation of this condensed form must be created by designers. Second, this additional information seems to be a key element in the adoption of an RA. Results revealed that assortment planners consulted the additional information that was easily accessible to them more frequently and for a longer period of time at the beginning of their decision-making process. This usage behavior indicates that the degree of importance (Chen and Epps, 2013) and cognitive engagement (Just and

Carpenter, 1976) toward this information decreases over time, emphasizing the importance of initial trust. Explaining the recommendation process increases professionals' initial trust towards the RA's recommendations, which then influences positively their continued usage of this RA (Pu and Chen, 2006; Wang and Benbasat, 2007). These insights can contribute to building best practices in UX design for AI.

Before applying these results, two limitations of this study need to be acknowledged. First, the low richness & high effort condition has not been tested in this experiment, due to time constraints and to avoid participant fatigue. Thus, future research should include this condition in order to extend the results of this study. Second, the two fictitious scenarios, in this experiment, informed participants that they were working for a fashion company which entailed that clothes were used as products (i.e., dresses and male upper body clothing). Hence, additional studies using a more complex category of products could help generalize the results of this study.

In conclusion, more research is needed to better understand the way RAs are used by professional users. For example, emotional and cognitive state at fixation on RA could be assessed using techniques proposed by Léger et al. (2014) and Courtemanche et al. (2017). These additional studies could provide further guidelines to RA developers and UX designers. Results of this study revealed that the usage of the assortment planners changed throughout their decision-making process, which confirms that user behavior changes over time (Knijnenburg et al., 2012; Sénécal et al., 2015). However, understanding how the user-RA relationship changes in terms of behaviors and perceptions over time could show that the explanations of the RA's recommendations become decreasingly significant and indeed unnecessary after a while, with the users then relying predominantly on the RA's recommendations to make decisions.

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Chapitre 4 : Troisième Article

Recommendation Agent Adoption: How Recommendation Presentation Influences Employees' Perceptions, Behaviors, and Decision Quality

Emilie Bigras[1], Marc-Antoine Jutras[1], Sylvain Sénécal[1], Pierre-Majorique Léger[1], Nicolas Robitaille[2], Karine Grande[2], and Christian Hudon[2]

[1] HEC Montréal, Montréal, Canada
[2] JDA Labs, Montréal, Canada

Abstract

Purpose – The purpose of this paper is to report the results of a laboratory experiment that investigated how assortment planners' perceptions, usage behavior and decision quality are influenced by the way recommendations of an artificial intelligence (AI)-based recommendation agent (RA) are presented.

Design/methodology/approach – A within-subject laboratory experiment was conducted with twenty subjects. Participants perceptions and usage behavior toward an RA while making decisions were assessed using validated measurement scales and eye-tracking technology.

Findings – The results of this study show the importance of a transparent RA demanding less cognitive effort to understand and access the explanations of a transparent RA on assortment planners' perceptions (i.e., source credibility, sense of control, decision quality, and satisfaction), usage behavior, and decision quality.

Research limitations/implications – This study contributes to filling the literature gap on RAs in organizational contexts, thus advancing knowledge in the human-computer interaction literature.

Practical implications – The findings of this study provide guidelines for RA developers and UX designers on how to best create and present an AI-based RA to employees.

Originality/value – Past research on RAs has mainly focused on the consumer context. This paper provides a comparative between consumers and employees perceptions, usage behavior, and decision quality toward RAs.

Keywords Recommendation agent, Artificial intelligence, Decision-making, Transparency, Cognitive effort, Perception, Behavior, Decision quality, Eye tracking

Paper Type Research paper

1 Introduction

Optimizing the composition and size of an inventory is critical for retailers to maximize their sales or gross margin (Mantrala et al., 2009). In order to create an optimal assortment of products, both consumers' needs and retailers' constraints must be respected (Handelsman and Munson, 1985; Amine and Cadenat, 2003). Assortment planners need to take into account qualitative and quantitative criteria, which include a great number of variables (e.g., past sales, retail trends, inventory, sales forecasts), while making assortment decisions for retailers (Brijs et al., 1999). In order to create the most optimal assortment of products, assortment planners must examine these variables thoroughly and compare them based on their level of importance which relies on the consumers' needs and retailers' constraints that must be respected. This important amount of information that needs to be considered by the assortment planners could negatively impact their decision quality (Lurie, 2004), thus negatively affecting the current and future sales of retailers (Mantrala et al., 2009).

To reduce the risk associated with information overload, employees' decision-making process can now be aided by artificial intelligence (AI)-based recommender systems (Andrews et al., 2017). Though AI-based recommendation agents (RAs) are now becoming more common in organizational contexts, past research on RAs has mainly focused on the online consumer context (e.g., Sénécal and Nantel, 2004; Wang and Benbasat, 2009).

In this paper, we answer the following research question: *How does the way recommendations of an AI-based RA are presented influence assortment planners' perceptions (i.e., source credibility, sense of control, decision quality, and satisfaction), usage behaviors, and decision quality?* Based on the literature on the consumer context, we expect that the perceptions, usage behavior, and decision quality of consumers and assortment planners will align even though their RA adoption process differs. This study contributes to filling the gap in the literature on RAs in organizational contexts and provides insights for RA developers and user experience (UX) designers on how to best present an AI-based RA to employees for them to consider and adopt its recommendations.

2 Literature Review

This study builds upon past research on RAs focusing on the online consumer context. We reviewed the literature on transparency and cognitive effort to then assess their impact on users' perceptions, usage behavior, and decision quality.

2.1 RA Transparency

Transparency of an intelligent agent is exposed when the logical reasoning behind its recommendations is explained to its users (Gregor and Benbasat, 1999). In a cooperative problem-solving context, where a system is present to support the decision-making process of a user (De Greef and Neerincx, 1995), explanations are crucial for users to consider the recommendations of a knowledge-based system to support their decisions (Gregor, 2001). In an organizational context, understanding the logical reasoning behind the recommendations of an intelligent agent is crucial for employees to justify their decisions to their superiors (Heitmann et al., 2007). Without perceiving the usefulness of these knowledgeable explanations, users will dismiss the recommendations presented to them through their decision-making process (Zanker, 2012). The details of the algorithm responsible for the recommendations of an RA can either be exposed completely or partially (Gedikli et al., 2014; Vig et al., 2009). Exposing a part of the algorithm responsible for the recommendations of an RA is usually done to protect the details of an algorithm or to diminish its complexity (Gedikli et al., 2014).

2.2 Cognitive Effort and RA Transparency

In the online consumer context, without the recommendations of an AI-based RA, users, throughout their decision-making process, must gather and consider all the decision relevant information (Pu and Chen, 2006). When this information load becomes too excessive for the user's limited capacity in processing information, cognitive fatigue and confusion emerge (Eppler and Meggis, 2004). Information overload is then reached, thus negatively affecting the efficiency and effectiveness of the users' decisions (Lurie, 2004). The users' perceived cognitive effort, required to process information while making a decision, has been shown to diminish with the usage of RAs (Bechwati and Xia, 2003). However, by adding explanations exposing the logical reasoning behind the recommendations of an RA, the cognitive effort of the users increases (Gregor, 2001). Hence, without these explanations, the recommendations of an RA would be ignored by the users throughout their decision-making process. Nonetheless, with these explanations, information overload could be reached by the users, thus negatively affecting their decision-making process. Consequently, the need for transparency and the cognitive effort needed to understand and access these explanations must be rightfully balanced.

2.3 Impact of transparency and cognitive effort on users' perceptions, usage behavior, and decision quality

Past research on RAs focusing on the online consumer context showed the impact of transparency and cognitive effort, when these two factors are not rightfully balanced, on users' perceptions (i.e., source credibility, sense of control, decision quality, and satisfaction), usage behavior, and decision quality.

Source credibility. To perceive the recommendations of an AI-based RA as credible, users need to recognize these suggestions as believable (Fogg et al., 2003). Multiple dimensions have been shown to influence source credibility (e.g., trustworthiness, expertise, attractiveness) (Ohanian, 1990). However, prior research on recommender systems' perceived credibility has mainly focused on two key dimensions: trustworthiness and expertise (Yoo and Gretzel, 2008; Yoo and Gretzel, 2011). The RA is perceived as trustworthy by the users when its recommendations are recognized as reliable and honest (Xiao and Benbasat, 2007). The RA is considered an expert when it is identified by the users as having the ability and the skills to recommend effectively (Senecal and Nantel, 2004; Xiao and Benbasat, 2007). Therefore, users perceived source credibility can increase with the help of transparency (Sinha and Swearingen, 2002). Explaining the logical reasoning behind the recommendations of an RA establishes users' trust and shows the expertise of these suggestions (Pu and Chen, 2006). Furthermore, according to the literature, users' trust also varies with the RA's perceived ease of use (PEOU) (Wang and

Benbasat, 2005). This RA's PEOU is negatively affected when the cognitive effort of the users increases (Xiao and Benbasat, 2007).

Sense of Control. In riskier contexts (e.g., car purchase), users that do not understand the recommendations of an RA have been shown to ignore these recommendations throughout their decision-making process (Herlocker et al., 2000). Hence, without perceiving a sense of control over the RA's recommendations, users will not consider these suggestions (Swearingen and Sinha, 2001). This feeling of control has been shown to be enhanced with transparency (Vig et al., 2009). Although a transparent RA increases cognitive effort, transparency is critical for users to feel a sense of control over the RA's recommendations (Konstan and Riedl, 2012). In addition, according to the literature, explaining the logical reasoning behind the recommendations of an RA partially, through simple explanations, is more effective on the users perceived sense of control than exposing the details of its algorithm completely (Herlocker et al., 2000; Vig et al., 2009).

Decision quality. Decision makers, in order to maximize the accuracy of their decisions (i.e., decision quality), must invest more cognitive effort (Xiao and Benbasat, 2007). However, decision makers are generally looking to maximize the accuracy of their decisions and minimize the cognitive effort invested (Payne et al., 1993). Evaluating all the available alternatives in depth, through a complex decision-making process, is normally impossible for users (Beach, 1993). Therefore, in order to reduce cognitive effort, decision makers will be willing to settle for a non-optimal choice (Johnson and Payne, 1985). Hence, users will adapt their decision-making strategies to their environment (Payne, 1982). For instance, in an online context, shoppers could first begin their decision-making process by screening the available products (i.e., initial screening stage) (Häubl and Trifts, 2000). They could then select the most relevant items and compare them in depth (Häubl and Trifts, 2000). This could finally lead to the purchase of a product (Häubl and Trifts, 2000). By including a decision aid (e.g., RA) throughout this decision-making process, users could be able to make more accurate decisions more easily (Dellaert and Häubl, 2012).

When used in a decision-making process, RAs have been shown to increase decision quality and reduce cognitive effort (Pereira, 2001; Huseynov et al., 2016). Previous research on decision aids confirmed that decision makers can increase the depth of their evaluation, between the available alternatives, by consulting the recommendations of a decision aid, thus positively affecting decision quality (Hoch and Schkade, 1996). With a transparent RA, users are able to perceive the usefulness of its recommendations through their decision-making process (Zanker, 2012). By considering these recommendations, both subjective and objective decision quality (i.e., the user's perceived and actual performance) increases (Pereira, 2001). However, the cognitive effort associated with understanding the logical reasoning behind these recommendations (i.e., the increase in cognitive load) will negatively impact the user's subjective and objective decision quality (Pereira, 2001).

Satisfaction. User satisfaction with a decision-making process is perceived when expectations are confirmed (Kim et al., 2009). Therefore, the users' actual performance with an RA must be in line with or exceed their expectations (Xiao and Benbasat, 2007). Prior research on decision support systems has shown the importance of information quality on users' decision-making satisfaction (DeLone and McLean, 2003; Bharati and Chandhury, 2004). Information quality is composed of multiple dimensions (e.g., information accuracy, information completeness, information relevance) (Bailey and Pearson, 1983). Thus, understanding the logical reasoning behind the recommendations of an AI-based RA, through knowledgeable explanations, is essential for users to perceive the quality of these suggestions. Furthermore, these recommendations, when perceived as useful, have been demonstrated to positively influence user satisfaction with the RA and the decision-making process with the RA (Xiao and Benbasat, 2007). However, a transparent RA (i.e., increase in cognitive load) will decrease user satisfaction (Pereira, 2001; Bechwati and Xia, 2003; DeLone and McLean, 2003; Xiao and Benbasat, 2007).

RA adoption and usage. To consider the recommendations of an AI-based RA in an online context, shoppers must perceive its suggestions as accurate, easy to use, satisfactory, trustworthy, and useful (Pereira, 2001; Wang and Benbasat, 2005; Komiak and Benbasat, 2006; Xiao and Benbasat, 2007). Thus, the first interaction of a user with an RA (i.e., pre-adoption) is crucial in influencing its adoption and usage (Wang and Benbasat, 2007; Hengstler et al., 2016). A transparent RA is then essential for users to accept these recommendations throughout their decision-making process (Sinha and Swearingen, 2002; Swearingen and Sinha, 2002). However, in an organizational context, employees have no choice in adopting their employer's information system (Karahanna et al., 1999). Nevertheless, the continued usage of that system mainly depends on its perceived usefulness and ease of use (Davis et al., 1989).

In the context of a transparent RA, a user experiencing information overload while consulting its knowledgeable explanations is expected to accept the RA's recommendations (Aljukhadar et al., 2012). Therefore, as a result of cognitive fatigue or confusion, a user would accept the RA's recommendations without understanding the logical reasoning behind them (Eppler and Mengis, 2004). The RA's recommendations would then be consulted more frequently by the user due to their increased importance in the user's decision-making process (Chen and Epps, 2013; Lai et al., 2013).

3 Hypotheses

The preceding literature review clearly shows a gap in the existing research into RAs. Compared to the consumers' perceptions, usage behavior, and decision quality toward RAs in an online context, the employees' perceptions, usage behavior, and decision quality toward RAs in an organizational context has not been studied in depth. Building upon the preceding literature review that mostly characterized the user as a consumer, we postulate that the perceptions, usage behavior, and decision quality of a consumer and an employee should align even though their RA adoption process differs. Hence, the way recommendations are presented should influence, similarly to a consumer, the perceptions, usage behavior, and decision quality of an assortment planner.

In order to create an optimal assortment of products, assortment planners must maximize their cognitive effort invested (Brijs et al., 1999; Lurie, 2004). However, past research has shown that decision makers want to maximize the accuracy of their decisions and minimize their cognitive effort invested (Payne et al., 1993). Therefore, by considering the recommendations of an AI-based RA throughout their decision-making process, assortment planners could diminish their cognitive effort invested and maximize their decision accuracy (Aljukhadar et al., 2012). Unfortunately, without understanding the logical reasoning behind these recommendations, assortment planners should dismiss these suggestions (Gregor, 2001; Zanker, 2012). A transparent RA is then crucial for assortment planners to justify their assortment decisions to their superiors (Heitmann et al., 2012). Due to the cognitive effort needed by the assortment planners to access and understand the explanations of a transparent RA, the accuracy of their decisions could be diminished (Gregor, 2001). Hence, a transparent RA demanding less cognitive effort seems to be the most suitable balance between transparency and cognitive effort.

Based on the preceding literature review, we postulate that a transparent RA demanding less cognitive effort to access and understand its explanations (i.e., a transparent RA together with low cognitive effort) will have a greater positive influence on assortment planners' perception regarding source credibility (Sinha and Swearingen, 2002; Wang and Benbasat, 2005), control (Vig et al., 2009), decision quality (Pereira, 2001; Zanker, 2012), and satisfaction (Pereira, 2001; Bechwati and Xia, 2003; DeLone and McLean, 2003; Xiao and Benbasat, 2007) than other RAs (i.e., a non-transparent RA together with low cognitive effort and a transparent RA together with high cognitive effort). We thus formulate the following hypothesis.

H1. A transparent RA demanding low cognitive effort will have a greater positive impact on assortment planners' perception towards the RA's credibility (H1a), their perceived sense of control (H1b) their decision quality (H1c), and their satisfaction regarding the RA (H1d) than other RAs.

In addition, we suggest, based on the literature review, that a transparent RA together with low cognitive effort will have a greater positive influence on assortment planners' objective decision quality than other RAs (i.e., a non-transparent RA together with low cognitive effort and a transparent RA together with high cognitive effort) (Pereira, 2001). We thus postulate the following hypothesis.

H2. A transparent RA demanding low cognitive effort will have a greater positive impact on assortment planners' decision quality than other RAs.

Furthermore, based on Eppler and Mengis (2004), Aljukhadar et al. (2012), and Chen and Epps (2013) we postulate that assortment planners, throughout their decision-making process, will consult more frequently the recommendations of a transparent RA demanding more cognitive effort to access and understand its explanations (i.e., a transparent RA together with high cognitive effort) compared to other RAs (i.e., a non-transparent RA together with low cognitive effort and a transparent RA together with low cognitive effort). We therefore postulate the following hypothesis.

H3. Assortment planners will consult more frequently throughout their decision-making process the recommendations of a transparent RA coupled with high cognitive effort compared to other RAs.

Moreover, based on the preceding literature review which stipulated that the first interaction of a user with an RA will determine its adoption and usage (Wang and Benbasat, 2007; Hengstler et al., 2016), we postulate that assortment planners will consult more frequently and for a longer period of time the explanations of a transparent RA at the beginning of their decision-making process, rather than at the end (Sinha and Swearingen, 2002; Swearingen and Sinha, 2002). We thus put forward the following hypothesis.

H4. Assortment planners will consult more frequently (H4a) and for a longer period (H4b) of time the explanations of a transparent RA at the beginning of their decision-making process, rather than at the end.

Finally, based on Karahanna et al. (1999) and Davis et al. (1989), we suggest that explaining the logical reasoning behind the recommendations of an RA (i.e., a transparent RA) will have a greater positive influence on assortment planners' intention to adopt and use an RA throughout their decision-making process compared to a non-transparent RA. We thus postulate the following hypothesis.

H5. A transparent RA will have a greater positive impact on assortment planners' intention of adopting and using an RA throughout their decision-making process compared to a non-transparent RA.

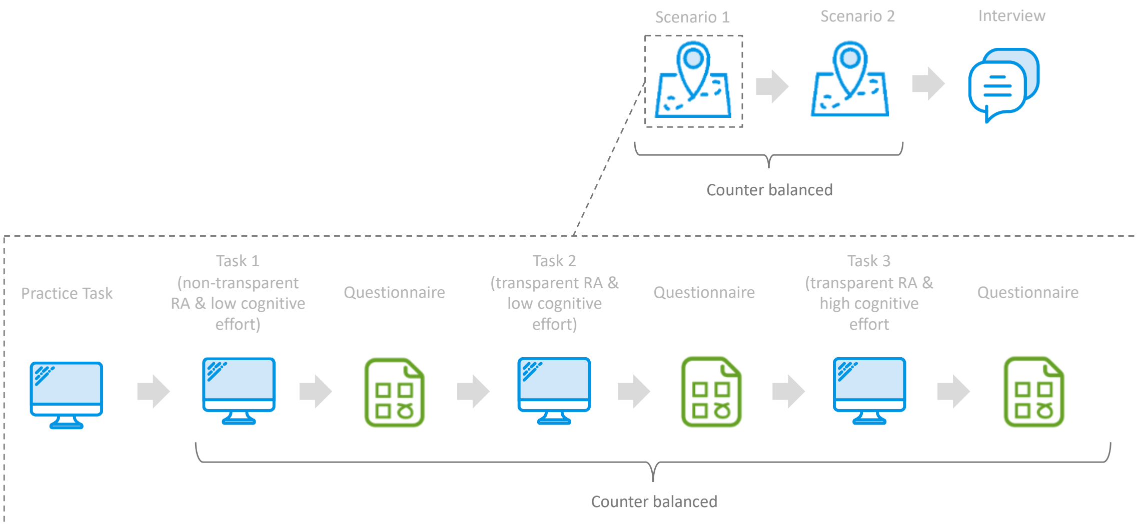
4 Methodology

4.1 Experimental setting

A within-subject laboratory experiment was performed with subjects who had to make assortment decisions by using an experimental RA prototype for assortment planning developed by JDA Labs (Montreal, Canada). This prototype was developed with Axure RP 8 and was made available, to the participants, through a 1680 x 1050 resolution monitor. A total of twenty logistics and marketing professionals (11 men and nine women) participated in the study. The average age of this sample was 26 years old with a standard deviation of 3.92 years. Each participant completed a consent form and received a $30 gift card as a compensation. This project was approved by the Institutional Review Board (IRB) of our institution.

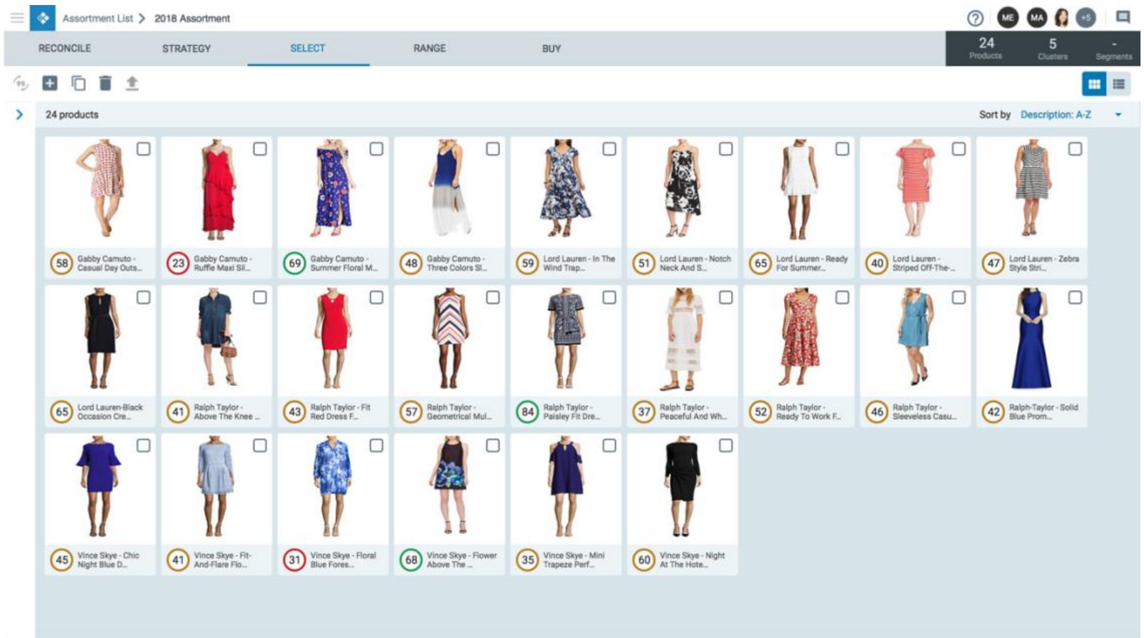
As illustrated in Figure 1, participants had to make assortment decisions for two similar fictitious scenarios that were counterbalanced. The context of these scenarios was the retail clothing industry (i.e., dresses (Scenario 1) and male upper body clothing (Scenario 2). Each scenario began with a practice task that did not include an RA to familiarize participants with the assortment planning software. This practice task was followed for each scenario by three distinct conditions in a counterbalanced order. Each condition displayed a particular recommendation representation that was designed based on the two experimental factors (i.e., transparency and cognitive effort). Task 1 reflected a non-transparent RA & low cognitive effort condition (T1), Task 2 represented a transparent RA & low cognitive effort condition (T2), and Task 3 was a transparent RA & high cognitive effort condition (T3). The non-transparent RA & high cognitive effort condition was not part of the experiment since it is a type of RA that neither organizations nor employees would realistically use. This experiment lasted on average two hours and no time constraint was imposed for each task (about 5 minutes per task).

Figure 1 – Experimental protocol.



For each task (3 tasks) of each scenario (2 scenarios), 24 different products were displayed (see Figure 2). From these 24 distinctive products, participants needed to select a fixed number of products (ranging from 6 to 7) to create an optimal assortment of products. The total number of products that needed to be selected by the participants for each condition was stated in both scenarios. Furthermore, the products of each task were similarly presented to the participants with an image, its name including its brand, and its product score (i.e., RA’s recommendation). The RA’s recommendation of each product was generated using AI and varied between 0 and 100. Depending on its score number, each RA recommendation was surrounded by a specific color (i.e., green > 66, 66 ≥ orange > 33, and red ≤ 33).

Figure 2 – 24 products displayed per task.



For T1 (non-transparent RA & low cognitive effort), the RA's recommendations were the only information made available to the participants. For T2 (transparent RA & low cognitive effort) and T3 (transparent RA & high cognitive effort), the RA's recommendations were also made available to the participants, however, participants could also have access to the partially exposed details of the algorithm responsible for the RA's recommendations (i.e., explanations). By clicking on each product, participants could consult further product information (e.g., attributes, past sales, margin and comparative products) which was included in the algorithm responsible for each RA recommendation. The cognitive effort necessary to access and understand these explanations differed between T2 and T3. For T2, the additional product information was made available through a modal window (see Figure 3). As for T3, the explanations of each product score were made available through a different page which required additional navigation and cognitive effort from the participants (see Figure 4).

Figure 3 – Modal window for each product of T2.

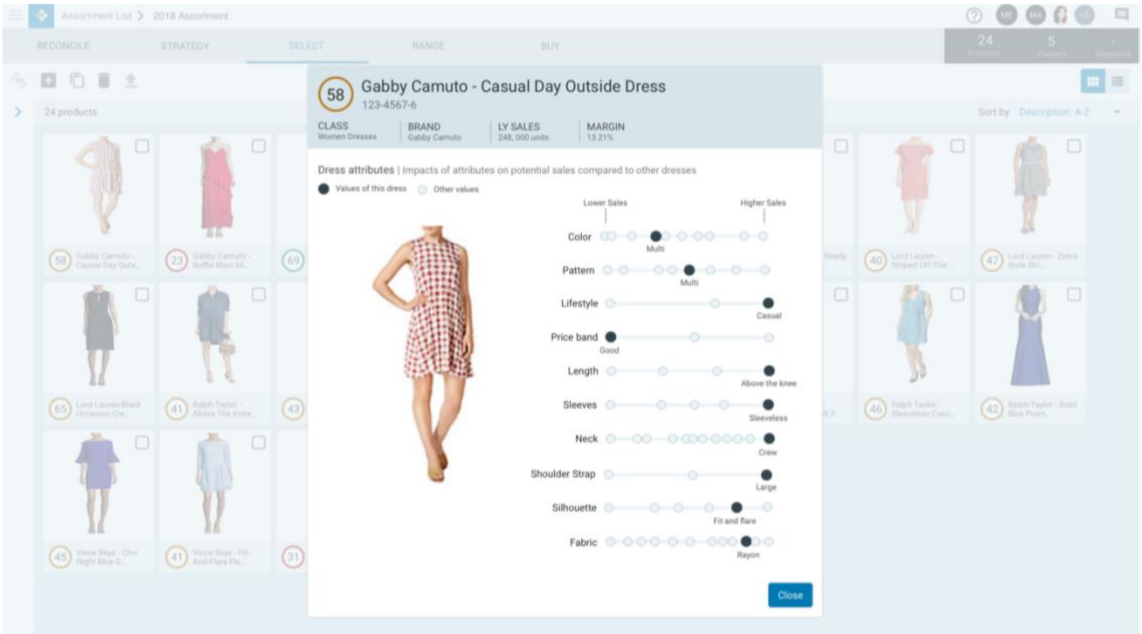


Figure 4 – New page for each product of T3.

At the end of the experiment, a semi-structured interview was conducted (about 15 minutes). Throughout this interview, participants were asked to discuss their decision-making process. Two main subjects were addressed. The first subject focused on the strategies used by the participants to make an assortment decision. The second topic examined the participants understanding of the RA's recommendations. All interviews were recorded and transcribed.

4.2 Measures

Self-reported measures. After each task, participants completed a questionnaire. This questionnaire measured participants' perception towards the RA in terms of source credibility (i.e., 10 items on a 7-point semantic differential scale to measure perceived trustworthiness (Cronbach's $\alpha =$ .93) and expertise (Cronbach's $\alpha =$ .94) (Ohanian,1990)), control (i.e., 5-point SAM Scale to measure perceived dominance (Bradley and Land, 1994)), satisfaction (i.e., 3 items on a 10-point semantic differential scale to measure perceived satisfaction (Cronbach's $\alpha =$ .97) (Sirdeshmukh et al., 2002)), and future usage as an aid (i.e., 3 items on a 7-point likert scale to measure the intention to adopt and use the RA as a decision aid (Cronbach's $\alpha =$ .94) (Komiak and Benbasat, 2006)). The measurement scales were all adapted to the context of this study. Furthermore, the questionnaire also asked participants to rate their perceived task decision quality from 1 to 10.

Decision quality measures. The decision quality of the participants was only measured for one scenario (i.e., the first scenario). A predetermined optimal assortment was provided by JDA Labs for each condition of this scenario. JDA Labs was not able to provide predetermined optimal assortments for both scenarios. Therefore, participants, with the help of the scenario's guidelines and all the information made available to them, were led, for each task, to a predetermined optimal assortment of products. The assortment of products selected by each participant for each condition was compared to the predetermined optimal assortment, thus evaluating the decision accuracy (i.e., decision quality) of the participants. A decision quality score was then created, for each task and each participant, by awarding one point per selected product included in the predetermined optimal assortment. This decision quality score was then transformed in a percentage for each task and each participant.

Behavioral measures. The behavioral intentions of a user in adopting and using the recommendations of an AI-based RA throughout a decision-making process can be investigated with the help of questionnaires (Karahanna et al., 1999; Wang and Benbasat, 2005; Komiak and Benbasat, 2006). While questionnaires are helpful in capturing self-report measures, they do not capture the actual conscious and unconscious behavior of a user throughout a decision-making task (Ortiz de Guinea and Webster, 2013). For example, with the help of eye-tracking technology, the eye movements of a user can be monitored, thus capturing the user's actual behavior (i.e., visual attention) throughout a decision-making process (Vayre et al., 2006; Chae and Lee, 2013). The objective adoption and usage of an RA can be determined by knowing where and what a user is looking at any given time (i.e., fixation), (Vayre et al., 2006; Chae and Lee, 2013). The duration of an ocular fixation (i.e., gaze duration (Lai et al., 2013)) can be associated with the cognitive effort needed by a user in processing the information consulted (Just and Carpenter, 1976). When a specific element is frequently consulted by a user (i.e., total fixation count (Lai et al., 2013)), it can be characterized as important to the user (Chen and Epps, 2013). Hence, the eye-tracking technology was used in this study to capture the total fixation count and gaze duration of the participants on specific elements throughout each decision-making process.

The eye movements of the participants were monitored at a 60Hz sampling rate with a Smart Eye Pro System (Gothenburg, Sweden). For each participant, a gaze calibration was performed using a 9-point calibration grid. This process was repeated until sufficient accuracy was obtained (± 2 degrees of accuracy). The eye-tracking data analysis was conducted with the MAPPS 2016.1 software. Predetermined areas of interest (AOIs) were created to collect the gaze duration and the total fixation count of each AOI. These AOIs were generated for each RA recommendation and for each modal window or new page examined by the participants. An ocular fixation was characterized as satisfactory at 200 milliseconds and above (Rayner, 1998).

Data analysis. All statistical analyses were performed with SAS 9.4 and considered the within-subject design of this study. The psychometric and eye-tracking data collected for each condition of the two similar scenarios were aggregated in the analysis.

5 Results

H1 suggested that a transparent RA together with low cognitive effort (T2) will have a greater positive impact on participants' perception regarding source credibility (H1a), control (H1b), decision quality (H1c), and satisfaction (H1d) than other conditions (T1 and T3). A linear regression with random intercept and a one-tailed level of significance adjusted for multiple comparisons was performed to test the difference between the means of participants' perceptions for each combination of tasks (see Table 1). The results provided strong support for H1b (T2 is greater than T1 and T3, respectively 0.3500, $p = .0185$; 0.3000, $p = .0365$). However, as illustrated in Table 1, H1a, H1c, and H1d were partially confirmed. The results showed that exposing the logical reasoning behind the RA (i.e., a transparent RA) had a significant effect on the assortment planners' perception towards the RA regarding source credibility (H1a), decision quality (H1c), and satisfaction (H1d) (T2 greater than T1, respectively 0.7055, $p \leq .0001$; 0.4706, $p = .0474$; 0.6068, $p = .0027$). Furthermore, the increased cognitive effort necessary to access and process the explanations of a transparent RA had no impact on the assortment planners' perception towards the RA regarding source credibility (H1a), decision quality (H1c), and satisfaction (H1d) (i.e., the difference between transparent RA & low cognitive effort (T2) and transparent RA & high cognitive effort (T3) was not statistically significant).

Table 1 – Participants' Perceptions Results

	Hypothesis	Result	Estimate	p-value
Source credibility	H1a (T2 > T1 & T2 > T3)	T2 > T1	0.7055	< .0001
		T2 > T3	0.0916	0.2554
Control	H1b (T2 > T1 & T2 > T3)	T2 > T1	0.3500	0.0185
		T2 > T3	0.3000	0.0365
Decision quality	H1c (T2 > T1 & T2 > T3)	T2 > T1	0.4706	0.0474
		T2 > T3	0.2991	0.0678
Satisfaction	H1d (T2 > T1 & T2 > T3)	T2 > T1	0.6068	0.0027
		T2 > T3	0.0964	0.3052

Note: One-tailed level of significance

H2 stipulated that a transparent RA together with low cognitive effort (T2) will have a greater positive impact on the assortment planners' objective decision quality than other conditions (T1 and T3). A linear regression with a mixed model adjusted for multiple comparisons with a one-tailed level of significance was performed to test the difference between the means of participants' objective decision quality for each combination of conditions. As illustrated in Table 2, the results provided strong support for H2 (T2 is greater than T1 and T3, respectively 1.0500, p = .0001 and 0.2330, p = .0001).

Table 2 – Participants' Decision Quality Results

	Hypothesis	Result	Estimate	p-value
Decision quality	H2	T2 > T1	1.0500	0.0001
	(T2 > T1 & T2 > T3)	T2 > T3	0.2330	0.0001

Note: One-tailed level of significance

H3 suggested that assortment planners will consult throughout their decision-making process the recommendations of a transparent RA coupled with high cognitive effort (T3) more frequently than when exposed to other conditions (T1 and T2). A Poisson regression with a mixed model adjusted for multiple comparisons with a one-tailed level of significance was performed to test the difference between the least square means of the RA's recommendations total fixation count of each condition. In support of H3, the results showed that participants exposed to the transparent RA & high cognitive effort condition (T3) were consulting more frequently the RA's recommendations throughout their decision-making process than when exposed to the two other conditions (i.e., the non-transparent RA & low cognitive effort (T1) and transparent RA & low cognitive effort (T2) conditions) (T3 is greater than T1 and T2, respectively 1.1617, p = .0054; 0.7471, p = 0.0225).

H4 stipulated that assortment planners will consult more frequently (H4a) and for a longer period of time (H4b) the explanations of a transparent RA (T2 and T3) at the beginning of their decision-making process, rather than at the end. A Wilcoxon signed rank test with a one-tailed level of significance was performed to compare the difference between the first 25% and the last 25% of the frequency (i.e., total fixation count) and the period of time (i.e., gaze duration) with which the explanations of a transparent RA were consulted for each condition (T2 and T3). The results showed that the explanations of a transparent RA coupled with low cognitive effort (T2) were consulted more frequently (H4a) and for a longer period of time (H4b) at the beginning of the participants' decision-making process, rather than at the end (respectively, p = .0137 and p = .0171). However, the explanations of a transparent RA associated with high cognitive effort (T3) were consulted more frequently (H4a), but not for a longer period of time (H4b), at the beginning of the participants' decision-making process, rather than at the end (respectively, p = .0279 and p = .0552). Furthermore, a similar test comparing the difference between the first 40% and the last 40% of the frequency (i.e., total fixation count) and the period of time (i.e., gaze duration) with which the explanations of a transparent RA were consulted for each condition (T2 and T3) was performed and confirmed these results. Hence, H4a was supported and H4b was partially supported.

H5 suggested that a transparent RA (T2 and T3) compared to a non-transparent RA (T1) will have a greater positive impact on the assortment planners' intention of adopting an RA as an aid throughout their decision-making process. In order to test this hypothesis, a linear regression with random intercept and a one-tailed level of significance adjusted for multiple comparisons was performed, thus comparing the difference between the means of assortment planners perceived intention of adopting an RA throughout their decision-making process for each combination of tasks. As illustrated in Table 3, the results reported that the assortment planners' intention of adopting an RA as an aid is positively increased when the logical reasoning behind the RA is partially exposed (i.e., a transparent RA) (T2 and T3 are greater than T1, respectively 1.0705, p = .0001; 0.9681, p = .0002). Therefore, H5 was supported.

Table 3 – Participants' Intention to Adopt the RA for Future Usage Results

	Hypothesis	Result	Estimate	p-value
The Intention to Adopt the RA as a Decision Aid	H5 (T2 > T1 & T3 > T1)	T2 > T1	1.0705	0.0001
		T3 > T1	0.9681	0.0002

Note: One-tailed level of significance

6 Discussion and Concluding Comments

The analysis of our results revealed that a transparent RA together with low cognitive effort had a greater positive impact on the participants perceived sense of control than the other RAs (i.e., the non-transparent RA & low cognitive effort and transparent RA & high cognitive effort conditions) (H1b). In addition, the results showed that the participants perceived RA credibility (H1a), decision quality (H1c), and satisfaction (H1d) were positively affected by a transparent RA and were not impacted by the cognitive effort needed to access and understand the explanations of a transparent RA (i.e., low cognitive effort versus high cognitive effort). Compared to the participants perceived decision quality, their objective decision quality was significantly higher when they were exposed to a transparent RA demanding less cognitive effort (i.e., the transparent RA & low cognitive effort condition) (H2). Furthermore, the recommendations of a transparent RA demanding more cognitive effort (i.e., the transparent RA & high cognitive effort condition) were consulted more frequently by the participants compared to the recommendations of the other conditions (i.e., the non-transparent RA & low cognitive effort and transparent RA & low cognitive effort conditions) (H3). Moreover, the explanations of a transparent RA demanding less (more) cognitive effort were consulted more frequently (H4a) and (but not) for a longer period of time (H4b) at the beginning of the participants' decision-making process, rather than at the end. When exposed to a transparent RA, the participants' intention of adopting an RA throughout their decision-making process also increased (H5).

These findings contribute to filling the literature gap on RAs in organizational contexts, thus advancing knowledge in the human-computer interaction (HCI) literature. For example, past research on RAs in the online context showed that the perceived usefulness, through transparency is crucial for the adoption and continuous usage of an RA by consumers (Zanker, 2012). The results of this study showed that the participants' intention to adopt an RA throughout their decision-making process was significantly higher when they were exposed to a transparent RA, thus aligning with the findings of the online consumer context. In an organizational context, employees must adopt their employer's information system (Karahanna et al., 1999). However, their decisions also need to be justified to their superiors (Heitmann et al., 2007). Hence, this paper validates how the perceptions and usage behaviors of assortment planners are influenced by the way recommendations of an AI-based RA are presented.

The results of this study provide insights for RA developers and UX designers on how to best present AI-based recommendations to employees for them to consider and adopt these recommendations. The recommendations of an AI-based RA are based on an overwhelming amount of data (Dellaert and Häubl, 2012). Consequently, based on our findings, exposing partially the logical reasoning behind the recommendations of an RA through easily accessible explanations seems to be key. Such findings can contribute to the creation of best practices in UX design. However, the way to best present these explanations is a challenge for UX designers. A condensed visual representation, rightfully balancing transparency and cognitive effort, must be created by designers (Nilsson, 2014). In addition, after the experiments, participants shared insights on the strategies they used while making assortment decisions and their understanding of the RA's recommendations. These interviews brought forward the concept of a customized RA (9 of 20 participants) which could be considered by RA developers to enhance employees' RA adoption and continuous usage.

This paper has several limitations that must be acknowledged. The organizational context of this study was based on the retail clothing industry. To generalize the results of this study, future research should focus on a different industry. Furthermore, the significant results of this study were based on twenty logistics and marketing professionals who could be characterised has a small sample size even though this is a typical sample size for a NeuroIS research (Riedl end Léger, 2016). Hence, future research should replicate this study with a larger sample size to confirm our findings.

When the decision-making process of an employee is aided by an AI-based RA, the risk associated with information overload decreases both for the employee and its employer (Mantrala et al., 2009; Hengstler et al., 2016; Andrews et al., 2017). More research is then needed to fully understand how RAs are used by employees and how employees are affected by RAs in an organizational context, thus providing additional guidelines to RA developers and UX designers. For example, the techniques proposed by Léger et al. (2014) and Courtemanche et al. (2017) could be used to understand the emotional and cognitive state of an employee at the time of fixation on the recommendations of an RA.

Acknowledgements

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Appendix

Measurement items

Source credibility (seven-point scale (Ohanian, 1990))

According to you, the recommendation agent (RA) is …

“Dependable”/ “undependable.”

“Honest”/ “dishonest.”

“Reliable”/ “unreliable.”

“Sincere”/ “insincere.”

“Trustworthy”/ “untrustworthy.”

“Expert”/ “not an expert.”

“Experience”/ “inexperienced.”

“Knowledgeable”/ “unknowledgeable.”

“Qualified”/ “unqualified.”

“Skilled”/ “unskilled.”

Control (five-point scale (Bradley and Land, 1994))

Using the following scale, select the number that matches what you felt in relation to the task you just experienced.

“Submissive”/ “in control.”

Satisfaction (ten-point scale (Sirdeshmukh et al., 2002))

What is your level of satisfaction with your last experience …

“Highly unsatisfactory”/ “highly satisfactory.”

“Very unpleasant”/ “very pleasant.”

“Terrible”/ “delightful.”

Future usage as an aid (seven-point scale, “strongly disagree”/ “strongly agree” (Komiak and Benbasat, 2006))

“I am willing to use this recommendation agent (RA) as an aid to help with my decision about which products to buy.”

“I am willing to let this RA assist me in deciding which products to buy.”

"I am willing to use this RA as a tool that suggest to me a number of products from with I can chose."

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Conclusion

L’objectif de ce mémoire est d’identifier le format de présentation des recommandations d’un AR basées sur l’IA qui est préférable pour les planificateurs d’assortiment en ce qui concerne leurs perceptions, leur comportement d’utilisation et la qualité de leurs décisions. Plus précisément, ce mémoire a permis d’obtenir une meilleure compréhension de l’impact de la représentation visuelle des recommandations d’un AR, ainsi que de leur contenu, sur les perceptions, le comportement d’utilisation et la qualité de décision des planificateurs d’assortiment.

Une expérience en laboratoire intra-sujet a été réalisée à l’automne 2017 avec un total de 20 participants. Ceux-ci devaient prendre des décisions d’assortiment en utilisant un prototype expérimental incluant un AR pour la planification d’assortiment développé par JDA Labs (Montréal, Canada). Chaque participant a été rémunéré à l’aide d’un coupon COOP HEC de 30$. Les perceptions des participants et leur comportement d’usage envers un AR lors de leur processus de prise de décision d’assortiment ont été collectés par des questionnaires, un oculomètre et des entrevues. La qualité de décision des participants a été observée en comparant chaque assortiment optimal de produits créé par ceux-ci à l’assortiment optimal de produits préétabli par le partenaire. Cette collecte de données a permis à l’étudiante de ce mémoire de rédiger trois articles complémentaires.

Ce chapitre rappelle les questions de recherche de ce mémoire et présente les principaux résultats complémentaires des trois articles. Les contributions théoriques et pratiques de ce mémoire, ainsi que les limites de cette étude et les futures avenues de recherche sont également abordées.

Rappel des questions de recherche et principaux résultats

Les résultats de ces trois articles ont permis de répondre aux deux questions de recherche de ce mémoire, soit :

Dans quelle mesure le format de présentation des recommandations d'un AR basées sur l'IA influence les perceptions, le comportement d'utilisation et la qualité de décision des planificateurs d'assortiment envers cet AR ?

Quel format de présentation des recommandations d'un AR basées sur l'IA est considéré comme étant préférable en ce qui concerne les perceptions, le comportement d'utilisation et la qualité de décision des planificateurs d'assortiment envers cet AR ?

Plus précisément, cinq hypothèses compilées des trois articles ont été formulées en se basant sur la littérature des ARs en commerce de détail du point de vue des consommateurs pour tenter de répondre à ces questions de recherche.

Tout d'abord, H1 postulait qu'un AR incluant des explications sur ses recommandations et demandant moins d'effort cognitif pour accéder et comprendre ces explications aurait un impact positif plus important sur la perception des planificateurs d'assortiment concernant la crédibilité de l'AR (H1a), le sentiment de contrôle envers l'AR (H1b), la qualité de leur décision (H1c) et la satisfaction des recommandations de l'AR (H1d) que les autres formats de présentation d'un AR (c.-à-d., AR sans explication & effort cognitif investi faible et AR avec des explications & effort cognitif investi élevé). Les résultats de cette étude ont partiellement supporté cette hypothèse. En effet, les résultats ont montré qu'un AR incluant des explications et demandant un effort cognitif investi plus faible avait un impact positif plus important sur la perception des participants concernant le sentiment de contrôle envers l'AR que les autres formats de présentation d'un AR (c.-à-d., AR sans explication & effort cognitif investi faible et AR avec des explications & effort cognitif investi élevé) (H1b). Par contre, la perception des participants concernant la crédibilité de l'AR (H1a), la qualité de leur décision (H1c) et la satisfaction des recommandations de l'AR (H1d) était affectées positivement par un AR incluant des explications et non par l'effort cognitif investi pour accéder et comprendre ces explications.

De plus, H2 énonçait qu'un AR incluant des explications sur ses recommandations et demandant moins d'effort cognitif pour accéder et comprendre ces explications aurait un impact positif plus important sur la qualité objective des décisions prises par les planificateurs d’assortiment que les autres formats de présentation d’un AR (c.-à-d., AR sans explication & effort cognitif investi faible et AR avec des explications & effort cognitif investi élevé). Les résultats de cette étude ont montré que la qualité objective des décisions prises par les participants était significativement plus élevée lorsque ceux-ci étaient exposés à un AR incluant des explications sur ses recommandations et demandant moins d’effort pour accéder et comprendre ces explications (c.-à-d., AR avec des explications & effort cognitif investi faible). Ces résultats supportent donc fortement H2.

Pour ce qui est de la troisième hypothèse (H3), celle-ci affirmait que les planificateurs d’assortiment consulteraient plus fréquemment, lors de leur processus de prise de décision, les recommandations d’un AR avec des explications demandant un effort cognitif plus élevé à accéder et à comprendre comparativement aux autres formats de présentation d’un AR (c.-à-d., AR sans explication & effort cognitif investi faible et AR avec des explications & effort cognitif investi faible). Les résultats de cette étude ont permis de confirmer H3.

La quatrième hypothèse postulait que les planificateurs d’assortiment consulteraient plus fréquemment (H4a) et pour une période de temps plus longue (H4b) les explications sur les recommandations d’un AR au début de leur processus de prise de décision, plutôt qu’à la fin. Les résultats de cette étude ont montré que les explications sur les recommandations d’un AR demandant un effort cognitif investi faible (c.-à-d., AR avec des explications & effort cognitif investi faible) étaient consultées par les participants plus fréquemment (H4a) et pour une période de temps plus longue (H4b) au début de leur processus de prise de décision, plutôt qu’à la fin. Pour ce qui est du format de présentation d’un AR avec des explications & effort cognitif investi élevé, les résultats ont démontré que les participants ont consulté ces explications plus fréquemment (H4a), mais pas pour une période de temps plus longue (H4b), au début de leur processus de prise de décision, plutôt qu’à la fin. Ainsi, les résultats de cette étude ont supporté H4a et ont partiellement supporté H4b.

Enfin, H5 posait comme hypothèse qu’un AR incluant des explications sur ses recommandations aurait un impact positif plus important sur l’intention des planificateurs d’assortiment d’adopter et d’utiliser cet AR durant leur processus de prise de décision comparée à un AR sans explication. Cette hypothèse a été fortement supportée par les résultats de cette étude.

Contributions

D'un point de vue théorique, les résultats de ce mémoire contribuent à combler le manque dans la littérature sur les ARs dans des contextes organisationnels. Ceux-ci permettent donc d'ajouter aux connaissances existantes de la littérature sur l'interaction humain-machine. Étant donné l'intégration de plus en plus courante de l'IA dans des contextes organisationnels (Andrews et al., 2017), comprendre l'impact de la représentation visuelle des recommandations d'un AR, ainsi que de leur contenu, sur les perceptions, le comportement d'utilisation et la qualité de décision des professionnels est crucial. Les résultats principaux de ce mémoire mettent de l'avant l'importance, sur les perceptions, le comportement d'utilisation et la qualité de décision des planificateurs d'assortiment, d'un AR incluant des explications sur ses recommandations et demandant moins d'effort cognitif pour accéder et comprendre ces explications. Ces résultats concordent aux conclusions des études antérieures sur les ARs dans un contexte en ligne. En effet, les études antérieures ont montré l'importance de l'utilité perçue et de la facilité d'utilisation d'un AR pour son utilisation et son adoption continue par les consommateurs (p. ex., Wang et Benbasat, 2005; Zanker, 2012).

D'un point de vue pratique, les résultats de ce mémoire, permettent aux développeurs d'AR et aux designers en UX d'obtenir une meilleure compréhension de l'impact du format de présentation des recommandations d'un AR basées sur l'IA sur les perceptions, le comportement d'utilisation et la qualité de décision des employés. Les recommandations d'un AR basées sur l'IA considèrent une quantité importante d'informations qui pourrait surcharger cognitivement les employés (Dellaert et Häubl, 2012). En se basant sur les résultats de cette étude, les développeurs d'AR et les designers en UX pourraient générer des ARs influençant positivement l'adoption et l'utilisation continue des employés. Les résultats de ce mémoire peuvent donc contribuer à définir des lignes directrices pour les développeurs d'AR et les designers en UX, telles que l'importance d'explications sur les recommandations d'un AR au début d'un processus de prise de décision. Cependant, le format de présentation des explications des recommandations d’un AR reste un défi pour les designers en UX. En effet, un visuel considérant l’équilibre adéquat entre le besoin d’explications et l’effort cognitif investi pour accéder et comprendre ces explications doit être créé par les designers en UX (Nilsson, 2014). Selon les résultats de ce mémoire, cet équilibre serait un AR avec des explications sur ses recommandations et demandant un effort cognitif investi faible pour accéder et comprendre ces explications.

Limites et recherches futures

Pour contextualiser les résultats de ce mémoire, quelques limitations doivent être mises de l’avant. Premièrement, le contexte organisationnel de cette étude s’est concentré sur l’industrie du commerce de détail, soit plus précisément les biens modes. En effet, les deux scénarios de cette étude mentionnaient aux participants qu’ils étaient des planificateurs d’assortiment pour un détaillant de vêtements. Ainsi, les recherches futures devraient se concentrer sur des contextes organisationnels différents pour généraliser cette étude. Deuxièmement, un total de 20 participants a contribué aux résultats significatifs de ce mémoire ce qui pourrait être caractérisé comme un petit échantillon. Cependant, ceci est un échantillon typique pour la recherche en *NeuroIS* (Riedl en Léger, 2016). Les futures recherches pourraient tout de même répliquer cette étude en augmentant la taille de l’échantillon pour confirmer les résultats de celle-ci.

Pour conclure, un plus grand nombre de recherches sur les ARs en contextes organisationnels doit être réalisé pour obtenir une meilleure compréhension de l’adoption et l’utilisation continue des ARs par les employés. Par exemple, pour comprendre davantage l’impact émotionnel et cognitif des ARs sur les employés dans des contextes organisationnels, les techniques proposées par Léger et al. (2014) et Courtemanche et al. (2017) pourraient être utilisées. Ceci permettra donc de contribuer davantage à la création de lignes directrices pour les développeurs d’AR et les designers en UX.

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