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**HEC MONTRÉAL**

**[Mesure des réactions comportementales des utilisateurs aux  
recommandations d'un système d'aide à la prise de décision en supply chain]**

**par**

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**Sciences de la gestion**

**(Spécialisation Transformation Numérique des Organisations)**

*Mémoire présenté en vue de l'obtention  
du grade de maîtrise ès sciences en gestion  
(M. Sc.)*

[Avril] [2021]

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## CERTIFICAT D'APPROBATION ÉTHIQUE

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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**Projet # :** 2020-3866

**Titre du projet de recherche :** Mesure des réactions comportementales des utilisateurs aux recommandations d'un système d'aide à la prise de décision en supply chain

**Chercheur principal :**

Pierre-Majorique Léger  
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**Date d'approbation du projet :** 28 février 2020

**Date d'entrée en vigueur du certificat :** 28 février 2020

**Date d'échéance du certificat :** 01 février 2021

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Maurice Lemelin  
Président  
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## RENOUVELLEMENT DE L'APPROBATION ÉTHIQUE

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## Résumé

Les systèmes de recommandation sont des technologies visant à améliorer la qualité de la décision de leur utilisateur tout en réduisant les efforts liés à cette prise de décision en présentant des éléments d'information susceptibles d'intéresser son utilisateur. Ces systèmes ont fait leur apparition suite à la croissance exponentielle des données générées dans le monde, rendant leur traitement difficile pour les utilisateurs. Au fil des années, ces systèmes se sont largement démocratisés et nous pouvons les retrouver dans des contextes d'affaires.

Dans ce mémoire, nous étudions des facteurs de conception de message qui ont potentiellement un impact sur les perceptions et les attitudes des utilisateurs de systèmes de recommandation dans un contexte d'affaires. Une étude en laboratoire a été menée pour tester 4 facteurs de conception de messages identifiés dans la littérature. Les résultats de cette étude ont permis d'étendre la littérature existante en identifiant de nouveaux facteurs et en démontrant leur impact sur l'expérience de l'utilisateur. Concernant la pratique, cette étude donne aux concepteurs de message de recommandation une meilleure compréhension de l'impact des choix de conception sur les utilisateurs et sur la chance qu'ils acceptent les recommandations et utilisent leur système à nouveau.

Par la suite, une revue de littérature systématique a été conduite pour explorer les antécédents de la conception d'un système de recommandation efficace et proposer de futures recherches à mener pour étendre les connaissances de ce domaine. Cette revue de littérature a ainsi permis de faire un état des lieux des études menées et des connaissances en synthétisant les résultats des études pertinentes identifiées, d'informer les praticiens sur les effets des choix de conception des messages de recommandation sur l'expérience de l'utilisateur et de proposer de futures études à mener pour améliorer l'efficacité des messages de système de recommandation.

La logique de ce mémoire peut surprendre le lecteur par la présence d'une revue de littérature systématique après la présentation d'une étude pilote. Cela s'explique par le fait que l'article exposé dans le chapitre 1 a été présenté en premier lors d'une conférence *Neuro IS 2020*. Cette

présentation a ainsi permis à ses auteurs de recueillir de nombreuses réactions et perspectives de recherches démontrant le besoin de réaliser une revue de littérature systématique afin de combler les manques de la littérature sur les systèmes de recommandation.

**Mots clés :** [systèmes de recommandation; conception de message; acceptation et intention d'utilisation, prise de décision managériale]

## **Abstract**

Recommender Systems (RS) goal's is to improve the users' decision quality and reduce the cognitive effort related to this decision by presenting likely to be of interest for the users. Created in the early 2000s during the exponential growth of data on the internet, these systems have become popular over the years and are used in business and managerial contexts.

In this master thesis, we study message design factors' that potentially have an impact on perception and behavior RS users' in a managerial context. A laboratory study has been conducted in order to test 4 message design factors identified in the literature. Results extend the current literature by identifying new message design factors and demonstrating their impacts on the user experience. Thus, this study leads to a better comprehension of the impacts of the design choices on the users and the chance that they accept the recommendation and use the system again.

Next, a Systematic Literature Review (SLR) was conducted to explore the antecedents to effective RS message design. Thus, this SLR offers a contemporary mapping of studies related to user-RS interactions, extends the body of knowledge, informs the practitioners on the effect of message design choices on the user experience and presents opportunities for future research to improve recommendation message design.

The logic of this thesis may surprise the reader by the presence of a Systematic Literature Review after the presentation of a pilot study. This is explained by the fact that the pilot study was presented first at a Neuro IS 2020 conference. Thus, this presentation allowed its authors to gather many feedbacks demonstrating the need to carry out a systematic literature review.

**Keywords :** [Recommender System, Recommendation System Message, Message Design]

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Figure 1 - Proposed research model

## Liste des abréviations

RS : “*Recommender Systems*”

RA : “*Recommendation Agent*”

RA : “*Recommender Assistant*”

SLR : “*Systematic Literature Review*”

## **Avant-propos**

L'autorisation de rédiger ce mémoire sous la forme deux articles a été donnée par la direction administrative du programme de la Maîtrise des Sciences en gestion de HEC Montréal.

L'étude présentée dans le premier article a été permise grâce à l'approbation du comité d'éthique en recherche (CER) de HEC Montréal en février 2020.

Les articles ont été ajoutés au mémoire par le consentement écrit de ses coauteurs.

Le premier article présente les résultats d'une étude réalisée au sein du laboratoire du Tech3lab en mars 2020 évaluant l'impact de la conception des messages sur la probabilité que les utilisateurs acceptent les recommandations générées par le système de recommandations ainsi que sur leur intention d'utiliser le système.

Le deuxième article est une revue de littérature systématique des études et connaissances existantes sur les systèmes de recommandation et la conception des messages. Il est construit suivant le cadre méthodologique d'une revue de littérature systématique. Une présentation sur les systèmes de recommandation et les motivations de recherche sont proposées en introduction. L'approche méthodologique et les contributions attendues sont présentées par la suite. Enfin, les résultats de l'analyse des études et connaissances sont organisés en trois parties et des recherches futures pour poursuivre le travail sont proposées.

## Remerciements

Je tiens en premier lieu à remercier les co-directeurs de mon mémoire, les professeurs Pierre-Majorique Léger et Constantinos K. Coursaris pour leur mentorat sans faille. Votre disponibilité, vos conseils et votre écoute m'ont été d'une grande aide pour mener à bien ce projet. Intégrer le Tech3Lab a été une expérience très enrichissante, me permettant de développer de nombreuses connaissances et compétences fortes utiles pour ma vie professionnelle et mon développement personnel.

Je remercie également Blue Yonder et leur équipe de m'avoir donné l'opportunité de contribuer à leur projet de recherche et de leur précieuse collaboration sans qui le projet n'aurait pas eu lieu.

Je tiens aussi à remercier le Conseil de recherches en sciences naturelles et en génie du Canada et Prompt Innov (IRCPJ/514835-16, and 61\_Léger-Deloitte 2016.12, respectivement) pour sa contribution financière dans ce projet.

J'aimerais tout autant remercier les membres de l'équipe du Tech3Lab dont Ariel, Bertrand, Caroline, David, Elise, Emma, Frédérique, Julianne, Salima et Shang-Lin qui, dans des temps difficiles et particuliers, ont toujours su répondre présent et rester disponibles à chaque instant pour me venir en aide.

Je tiens également à remercier toutes les personnes que j'ai rencontrées au cours de ces 15 mois passés au Québec.

Finalement, je remercie Ludivine d'avoir toujours été à mes côtés, même dans des temps plus difficiles.

# Chapitre 1

## Introduction

### Mise en contexte de l'étude

Dans un contexte organisationnel, les salariés doivent prendre la meilleure décision face à une situation dans un temps minimal. Pour les aider dans ce processus et réduire les risques d'incertitude et d'erreur, certains employés, notamment les utilisateurs de tableau de bord, peuvent recourir à un système d'aide à la prise de décision basé sur l'intelligence artificielle (IA) appelé système de recommandation. Les systèmes de recommandation peuvent être définis comme étant "tout système qui produit des recommandations individualisées comme résultat ou qui a pour effet de guider l'utilisateur de manière personnalisée à des objets intéressants ou utiles dans un large espace d'options" [1]. La principale motivation des utilisateurs de recourir à de tels systèmes est d'améliorer la qualité de leur décision et de réduire les efforts cognitifs liés à cette prise de décision [2]. En effet, une personne utilisera une technologie de l'information s'il juge que celle-ci lui permet d'être plus performant dans sa tâche, il s'agit de la perception d'utilité [3, 4]. Cette technologie doit également être perçue comme facile d'utilisation, ce qui est défini comme le degré auquel une personne croit qu'utiliser un système particulier sera sans effort [3, 4]. Car si l'utilisation de cette technologie est trop contraignante pour son utilisateur, il ne l'utilisera pas malgré les bénéfices qu'il pourrait en tirer. Il a été démontré que la perception d'utilité et la perception de facilité d'utilisation d'un système informatique sont liées au comportement de l'utilisateur dans l'adoption et l'utilisation de ce système [4]. Un système perçu comme utile et facile d'utilisation augmentera la satisfaction et la confiance de son utilisateur envers le système et ses recommandations, ce qui mènera à une acceptation des recommandations et à une utilisation du système plus fréquente. Ainsi, si les entreprises veulent que leurs employés adoptent un système de recommandation pour les aider dans leur prise de décision, ce système doit répondre aux attentes et aux besoins de ces derniers.

Cependant, toutes les technologies de l'information ne sont pas identiques, et encore moins les systèmes de recommandation. Leur type et leurs caractéristiques, qui dépendent de leur fonction, processus et conception, font qu'ils n'auront pas le même effet sur leur utilisateur [2, 5, 6]. Parmi les systèmes de recommandation, nous pouvons distinguer les deux types de systèmes les plus

populaires, à savoir le *Content-based recommendation* et le *Collaborative recommendation*. Il existe également de plus en plus de *hybrid recommendation systems* qui combinent différents types de systèmes de recommandation. D'autres systèmes ont fait leur apparition au cours des années précédentes comme les *Demographic recommendation*, *Utility-based recommendation* et *Knowledge-based recommendation*, mais ils sont plus rares. Ce qui différencie ces systèmes de recommandation sont les techniques d'élicitation (i.e. la façon de collecter les données et les préférences des utilisateurs), l'algorithme de génération des recommandations et la présentation de la recommandation. Au vu de leur popularité et de leur diversité, de nombreuses études ont été menées sur les systèmes de recommandation afin de mieux comprendre l'interaction humain-machine.

Les algorithmes sont un sujet de recherche récurrent chez les chercheurs en systèmes de recommandation afin de les rendre plus performants. De meilleurs algorithmes mènent à une meilleure perception des recommandations par l'utilisateur ce qui conduit à une amélioration de l'expérience utilisateur en termes de satisfaction [7] et d'efficacité perçue du système [8]. La façon algorithmique dont les recommandations sont présentées affecte également les perceptions de l'utilisateur [9]. Par exemple, un algorithme K-nearest neighbors (KNN) d'apprentissage supervisé de base sera perçu comme moins facile d'utilisation qu'un algorithme conscient du contexte. Ainsi, les recommandations du deuxième algorithme sont perçues comme plus attractives et plus adaptées aux préférences de l'utilisateur. De plus, les utilisateurs utilisant un algorithme conscient du contexte acceptent plus facilement les recommandations qui leur sont présentées et expriment une plus forte intention d'utiliser à nouveau le système.

De nombreuses études ont été menées pour identifier d'autres influenceurs de l'expérience utilisateur que l'algorithme et les caractéristiques du système de recommandation, tel que la façon de communiquer et la personnalité du système [10], les aspects spécifiques du système [11], la présence d'explications de la recommandation [12, 13]. Ces études ont ainsi montré que le système n'est pas le seul à avoir une influence sur les perceptions des utilisateurs, mais également le contenu et le format des recommandations [2], ce qui a peu été étudié dans la littérature.

## Questions de recherche

Pour faire gagner du temps et réduire les efforts liés à la prise de décision, tout en minimisant les risques d'erreur et de mauvaises décisions qui pourraient leur porter préjudice, les entreprises ont la possibilité de mettre à disposition de leurs employés des systèmes de recommandation intégrés à leurs tableaux de bord managériaux. Afin de proposer le meilleur système, les développeurs utilisent les algorithmes les plus avancés et précis pour récolter les informations nécessaires au processus de recommandation et ainsi faire la recommandation la plus juste à l'utilisateur. Cependant, pour qu'un système de recommandation soit utilisé par des employés, il ne doit pas seulement être juste dans ses recommandations. Il doit également être facile d'utilisation et être perçu comme utile par ses utilisateurs pour qu'ensuite ils acceptent la recommandation et utilisent à nouveau le système. Les designers peuvent donc avoir recours à différents choix de présentation des messages de recommandations pour influencer les perceptions et le comportement des utilisateurs de systèmes de recommandation. Cependant, ces derniers ne disposent pas de lignes directrices expliquant clairement comment rédiger un message de recommandation de manière efficace.

Ce mémoire par article permettra dans un premier temps d'explorer de nouveaux composants de message de recommandation et de tester leur influence sur le comportement et la perception des utilisateurs du système utilisé et des recommandations qui leur sont proposées. Dans un second temps, ce mémoire permettra de faire un état des lieux des connaissances actuelles sur les antécédents des conceptions de message de système de recommandation efficace, de recenser des études présentant des résultats significatifs informant les praticiens des pratiques optimales de conception de message de recommandation et de proposer des opportunités de recherche futures pouvant révéler des lignes directrices. Ce mémoire tentera donc de répondre aux questions de recherche suivantes :

*De quoi se compose la littérature des messages de recommandation et quel est le format de présentation des messages de recommandations d'un système de recommandation le plus efficace concernant les perceptions et le comportement des utilisateurs de tels systèmes?*

*Dans quelle mesure les choix de présentation de message de recommandation influencent-ils les perceptions et le comportement des utilisateurs de systèmes de recommandation dans un contexte organisationnel managérial?*

### **Objectif de l'étude et contributions potentielles**

Ce mémoire possède deux objectifs. Premièrement, à travers une première étude en laboratoire il vise à identifier de nouveaux éléments de présentation de recommandation sous format de message texte qui influencent positivement les perceptions, les intentions et le comportement des utilisateurs d'un système de recommandation dans le but d'accepter la recommandation et d'utiliser à nouveau le système. Plus particulièrement, nous cherchons à identifier quels éléments de présentation des recommandations poussent les utilisateurs d'un tableau de bord à croire et accepter les recommandations générées par un système d'aide à la prise de décision, tout cela avec un minimum d'effort cognitif dans un minimum de temps requis. D'un point de vue théorique, cette étude contribue à combler le manque de recherche et de connaissance dans la littérature sur la conception des recommandations des systèmes de recommandations. D'un point de vue pratique, elle permet aux développeurs de systèmes de recommandation et aux designers en expérience utilisateur (UX) de confectionner des recommandations plus efficaces.

Le deuxième objectif de ce mémoire est d'explorer en profondeur les antécédents de la conception d'un système de recommandation efficace en développant les fondements théoriques de concepts connexes. Pour se faire, une revue de littérature systématique a été réalisée afin d'identifier les études possédant des résultats significatifs et pouvant informer la littérature ou donnant des pistes de recherche pour de futures études à mener. Il est attendu de cette revue de littérature systématique qu'elle produise des connaissances pour les praticiens (concepteur de systèmes de recommandation et chercheurs) sur l'impact des choix de conception d'un message de recommandation sur l'expérience utilisateur et qu'elle éclaire les chercheurs sur les futures recherches à mener dans ce domaine.

### **Informations sur les articles**

Avec le soutien d'une bourse de la Chaire de recherche industrielle CRSNG-Prompt en expérience utilisateur et sous la supervision de ses co-directeurs Pierre-Majorique Léger et Constantinos K.



Coursaris, l'auteur de ce mémoire a réalisé à l'hiver 2020 la phase de conception du design expérimental et les prétests de la première étude au sein du Tech3lab. La phase de conception du design expérimental et de la plateforme de test pour la deuxième étude a été réalisée en coopération avec Caroline Berger, stagiaire été au Tech3lab, pendant le printemps et l'été 2020. Les données de cette étude ont été collectées à l'été 2020 et ont servi à la rédaction de l'article situé en annexe 1, dont l'auteur du mémoire est co-auteur, correspondant à un approfondissement de la première étude menée à l'hiver 2020 par ce dernier. Au cours de l'automne 2020, une revue de littérature systématique sur la littérature existante des systèmes de recommandation et de la conception de message a été menée par l'auteur. Ainsi, le premier article permet de partager les résultats d'une étude menée sur des facteurs de conception de message de recommandation identifiées dans la littérature comme pouvant influencer l'expérience utilisateur dans le cadre de l'utilisation de systèmes de recommandation. L'article en annexe permet un second niveau d'analyse de ces facteurs avec un plus large panel de participants à l'étude en ligne et l'addition d'un nouveau facteur étudié. Le second article permet d'avoir une vision d'ensemble des connaissances de la conception des messages de recommandation des systèmes de recommandation et d'informer les praticiens des bonnes pratiques et des futures recherches à mener. Le premier article de ce mémoire a été présenté à la conférence scientifique *NeuroIS 2020 (Information Systems and Neuroscience - NeuroIS Retreat 2020)* en virtuel en juin 2020 [14]. L'article en annexe dont l'auteur est co-auteur a été présenté à la table ronde virtuelle du *SIGHCI workshop 2020* en décembre de la même année. Enfin, le second article présenté dans ce mémoire a été soumis et accepté pour être présenté à la conférence *HCI 2021* qui se déroulera en juillet 2021.

### **Résumé du premier article**

Les systèmes de recommandation se sont fortement popularisés au sein des entreprises au cours de la dernière décennie. De nombreuses études ont été menées au niveau du système afin de définir l'algorithme le plus performant à utiliser et la technique la plus efficace de collecter les préférences des utilisateurs pour fournir les recommandations les plus justes. D'autres études ont été dirigées au niveau du design du système afin d'évaluer la conception qui influence le plus positivement le comportement et la perception des utilisateurs afin qu'ils acceptent les recommandations et utilisent à nouveau le système. Ces études ont permis de montrer l'importance de la perception d'utilité et de facilité d'utilisation dans l'interaction humain-machine, ainsi que le rôle de la

satisfaction et de la confiance de l'utilisateur envers le système. Cependant, peu d'études se sont intéressées à la conception des messages de recommandation. Ainsi, cette étude examine des composants de message de recommandation pouvant influencer la perception et le comportement des utilisateurs de système de recommandation afin de réduire les efforts cognitifs liés à cette prise de décision et augmenter les chances qu'ils acceptent la recommandation et utilisent à nouveau le système. Une étude en laboratoire a été menée auprès de six (6) participants afin de tester la validité des facteurs identifiés dans la littérature. Les résultats montrent que la spécificité de l'information (c.-à.-d. si le message contient des précisions sur la solution et/ou le problème) et la séquence de l'information (c.-à.-d. l'ordre de présentation du problème et de la solution) influencent le comportement et l'attitude des utilisateurs envers le système et ses recommandations. De plus, les réponses cognitives des participants face aux recommandations ont été influencées par les composants de message étudiés, notamment le suivi du regard qui est plus court dans le sens de lecture problème-solution. En plus de contribuer à la littérature sur la conception des messages de recommandation, les résultats ont des implications pour la conception de systèmes de recommandation plus efficaces.

### **Résumé du deuxième article**

Cet article rapporte les résultats d'une revue de littérature systématique de la littérature existante sur les systèmes de recommandation et la conception de message. Par l'identification, l'analyse et la synthèse d'études pertinentes sur le sujet, cette revue de littérature permet d'étendre les connaissances sur l'efficacité des messages de recommandation, d'informer les praticiens de l'effet de leurs choix de conception des messages de recommandation sur l'expérience utilisateur et de motiver les chercheurs pour la conduite de recherches futures sur de nouveaux composants de message de système de recommandation identifiés dans la littérature. Pour se faire, 132 articles ont été collectés à la suite de recherches menées dans diverses bases de données scientifiques. Parmi ces articles, 41 ont été conservés suite à l'évaluation de leur pertinence et de leur qualité. Ils ont ensuite été classés, interprétés et synthétisés selon une méthode stricte afin de répondre aux objectifs de recherche. Pour faciliter la lecture des résultats, ceux-ci ont été regroupés dans trois tableaux distincts prenant la forme de matrice-concept. Chacun correspond à la question de recherche à laquelle il répond et comprend le nom de l'article et de ses auteurs, l'étude menée et les résultats trouvés.

## Contribution de l'auteur

Afin de comprendre la contribution de l'auteur de ce mémoire dans la rédaction des articles qui le composent, un tableau descriptif de sa contribution dans l'article 1 est proposé ci-dessous (voir Tableau 1). Ce dernier présente la contribution en pourcentage de l'auteur de ce mémoire à chaque étape du processus de recherche. Concernant l'article 2, l'auteur est l'entier rédacteur de celui-ci. Les co-auteurs, à savoir Wietske Van Osch, Joerg Beringer, Pierre-Majorique Léger et Constantinos K. Coursaris, ont contribué à la rédaction de cet article sous la forme de recommandations pour l'améliorer.

**Tableau 1** - Contribution de l'auteur dans la rédaction de l'article 1

| <b>Étapes du processus</b>           | <b>Contribution de l'auteur</b>  |
|--------------------------------------|--|
| Définition des besoins du partenaire | Identification des besoins d'affaires du partenaire et transcription des besoins en questions de recherche scientifique - 60%.<br><ul style="list-style-type: none"><li>● Pierre-Majorique Léger et Constantinos K. Coursaris, co-auteurs de l'article, ont également contribué à cette tâche.</li></ul>   |
| Revue de la littérature              | Élaboration et rédaction de la revue de littérature pour identifier les facteurs de conception de message de recommandation observés dans les études antérieures et définir les nouveaux construits à observer durant l'étude - 100%.<br><br>Définition des outils de mesures à utiliser selon les construits du modèle de recherche de l'étude - 70%.<br><ul style="list-style-type: none"><li>● L'équipe de recherche s'est assurée que les outils sélectionnés permettaient de mesurer les construits</li></ul><br>Communication avec le partenaire pour la conception des stimuli - 80%.<br><ul style="list-style-type: none"><li>● Rédaction des stimuli au format texte et conception des stimuli sous format .jpeg.</li><li>● Constantinos K. Coursaris, co-auteur de l'article, a aidé à la rédaction des stimuli.</li></ul> |

|  |   |
|--|---|
|  |   |
| Conception du design expérimental        | <p>Rédaction de la demande au CER et des modifications de projet par la suite - 100%.</p> <ul style="list-style-type: none"> <li>• Le reste de l'équipe de recherche s'est assurée que toutes les demandes envoyées au CER étaient conformes.</li> </ul> <p>Implémentation des stimuli dans Tobii X pro - 100%.</p> <p>Organisation de la salle de collecte - 100%.</p> |
| Recrutement des participants             | <p>Rédaction du questionnaire de recrutement - 100%.</p> <p>Recrutement et gestion des participants - 100%.</p> <p>Administration des récompenses - 100%.</p>   |
| Prétest et collecte de données           | <p>En charge des opérations lors de la collecte de données - 50%.</p> <ul style="list-style-type: none"> <li>• Un assistant de recherche était présent à chaque collecte de données.</li> </ul>   |
| Extraction et transformation des données | <p>Extraction et mise en forme des données en préparation de l'analyse - 100%.</p>  |
| Analyse des données                      | <p>Interprétation statistique des données - 80%.</p> <ul style="list-style-type: none"> <li>• Shang Lin Chen, co-auteur de l'article, a effectué les tests statistiques .</li> </ul>  |
| Rédaction des articles                   | <p>Contribution à l'écriture des articles du mémoire - 100%.</p> <ul style="list-style-type: none"> <li>• L'article a été amélioré selon les recommandations de ses co-auteurs.</li> </ul>  |

### Structure du mémoire

Les deux prochains chapitres présentent les résultats de l'étude menée dans ce mémoire. Plus précisément, le chapitre 2 correspond au premier article qui a été publié à la conférence scientifique *NeuroIS 2020*. Ensuite, le chapitre 3 présente le deuxième article qui a été approuvé pour la

conférence scientifique *HCI 2021* qui sera publié prochainement et présenté en juillet 2021. Le dernier chapitre qui conclut ce mémoire rappelle les résultats trouvés lors des deux articles ainsi que leur complémentarité. Il montre également comment ces résultats répondent aux questions de recherche présentées en début de mémoire et contribuent à l'avancement de la recherche scientifique et de la pratique. Pour finir, ce chapitre évoque les limites de cette étude et les futures recherches à mener pour poursuivre ce travail.

## **Chapitre 2**

# **Beyond System Design: The Impact of Message Design on Recommendation Acceptance**

### **Abstract**

The current paper reports on the results of a pilot study to explore the impact of message design on users' likelihood to accept system-generated recommendations as well as their intention to use the recommendation system (RS). We aim to extend the RS literature, which has hitherto focused on system design elements, but has generally overlooked the importance of message design, a key element in facilitating effective attention and information processing, particularly in the context of managerial decision-making.

**Keywords:** Managerial Decision-Making, Recommendation Systems, Message Design, Acceptance and Use Intention, Eye Tracking.

### **1 Introduction**

Recommendation systems (RS) are increasingly popular tools for augmenting the human process of decision-making. Studies of RS have focused largely on design implications at the system level [10,8], with limited research on RS interface design [1]. During these studies, interaction data from a user's interaction with the recommendations are collected and subsequently juxtaposed against attributes of artifacts stored in large repositories to subsequently produce and present recommendations. To date, however, there has been no research exploring the impact of the recommendation message's design on the user's interaction with and behavior toward the recommendation, such as accepting it (e.g., for web-based resource recommendations, clicking on the linked recommendation; for behavioral recommendations, clicking on an 'accept' button), rejecting/ignoring it, or requesting additional information in support of the recommendation.

Particularly in the context of managerial decision-making, it is not the system alone, but also the nature of the message content that will drive the manager's perceptions of trust and likelihood to accept a decision recommendation [7]. In this context, as information processing of recommendations would be done on the basis of both content elements (Areas of Interest or AOIs) and interaction elements (e.g., buttons), a granular analysis of both design elements simultaneously

is warranted. Hence, this study sets out to explore what would make users of a management dashboard trust and accept decision recommendations generated by the built-in decision support system with minimal cognitive effort and time required. Specifically, we will explore what the effects of design (choices) of message components are on the:

RQ1. Implicit (e.g. neurophysiological) and explicit (e.g. self-perceived) cognitive and emotional responses during the interaction with RS ;

RQ2. Behaviors (i.e., proportion of accepted recommendations) ;

RQ3. Attitudes (e.g., confidence) toward the recommendation and the system.

## **2 Related work**

### **2.1 Previous Work on Recommender Systems**

Extant research on RS has provided extensive support regarding the effects of the use of Recommendation Agents (RAs) on user perceptions of ease of use, control, trust and system effectiveness [10] and has shown that these four user evaluation outcomes have an impact on intentions for future use. Furthermore, prior work demonstrated that RA type and RA use influence users' decision-making effort and quality; it also showed that recommendation content influences users' evaluations of the RAs and subsequent decision-making; however, the effects of the nature of the content on the user's perceptions of both the recommendation and the system as well as the subsequent intention to accept future recommendations and adopt (use) the system is unknown.

Finally, only limited empirical research has begun to explore the effects of RS use on adoption intentions [8] and having used psychometric methods for additional validation. In this research, we aim to build on their [8] validated model and extend it by exploring the effects of message design using mixed-methods.

### **2.2 Message Design Components**

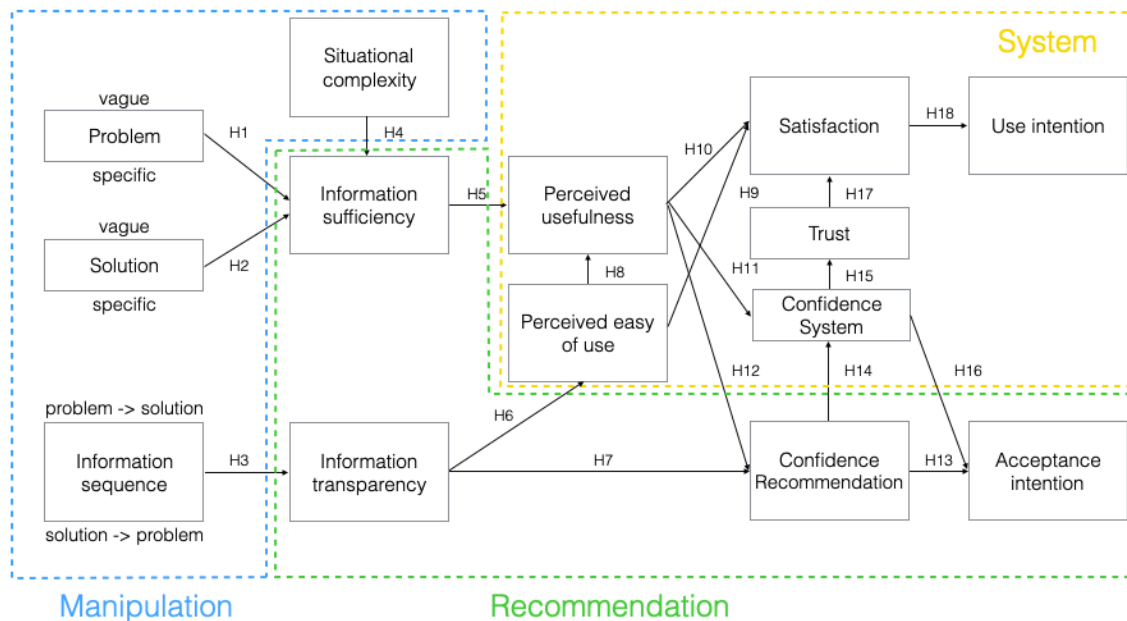
The importance of message design is well-understood in domains ranging from advertising to health information. Indeed, the domain of message design is highly inter-disciplinary and existing research on message design shows the complexity of such design [7]. Underpinning message design are four groups of design principles, namely functional (e.g., problem definition),

administrative (e.g., information access or cost), aesthetic (e.g., harmony), and cognitive principles (e.g., facilitating attention) [7].

In this study, given our focus on managerial decision-making, we focus on four message components that emerge from two groups of design principles, namely functional and cognitive. Functional principles deal with providing requisite information (e.g., about the problem or solution) and do so in a clear manner, as complicated language in message design is known to impair understanding [7]. Cognitive principles concern message design so as to facilitate attention and effective information processing [7]. The structure of messaging—i.e., the sequence in which information is presented is also part of these cognitive principles [7]. We manipulate three aspects of message design associated with the above functional and cognitive principles of providing information clarity, and facilitating attention and information processing, namely: the (lack of) specificity of the problem and/or description, and the sequencing of information (presenting problem or solution first). We also manipulate decision-making complexity given its importance in creating understandable language [6, p. 169].

### 2.3 Research Model and Hypotheses

Based on an integration of the RS and message design literatures discussed above, we propose 18 hypotheses reflected in Figure 1 below.





**Fig. 1.** Proposed research model

### **3 Methodology**

**Experimental design:** A four-factor, each with two levels (i.e., 2x2x2x2), between-within research design was employed in this study. Factors involved (i) Information Sequence (Problem-to-Solution or reverse); Information Specificity comprised of (ii) Problem Specificity (Vague vs. Specific) and (iii) Solution Specificity (Vague vs. Specific); and (iv) Decision Complexity (Simple Decision vs. Complex Decision). Participants were presented with 3 stimuli per treatment condition, for a total of 48 stimuli.

**Participants:** The pilot study gender-balanced sample involved six (6) participants, with ages between 23 and 26 years old ( $M = 24.33$  years), all attending a large Business School in North America. They had normal or corrected-to-normal vision without glasses, and had never been diagnosed with epilepsy, or other health, neurological and psychiatric conditions. Participants were offered a \$20 gift card as compensation.

**Experimental Procedure and Stimuli:** Using a scenario where participants acted as a restaurant manager, decisions related to inventory or order delivery situations had to be made on the basis of system recommendations. Decision-making varied in terms of the construction of the recommendation message in relation to its information sequence and specificity, but also in terms of the situation's complexity. Successive screenshots ( $n=48$ ) showing situations (i.e., a problem and a solution recommended by the recommender system) in text were used as stimuli. Two buttons (« CONFIRM » and « DETAILS ») corresponding to the two decision options available were shown below each recommendation. Participants had to either Confirm the recommendation as-is or request additional Details if unsure. The Details themselves would not be shown to the participant (something they were aware of during the briefing stage).

**Apparatus and Measures:** A comprehensive approach in the collection of neuro-physiological data was enabled by a sophisticated, integrated multi-system setup [4, 5]. Tobii x60 (Tobii AB, Danderyd, Sweden) was used to capture the participants' USB- keyboard-entered responses to each decision-making situation and the associated eye- tracking providing gaze and pupil dilation data as a proxy for cognitive load. Facereader (Noldus, Wageningen, the Netherlands) and a desktop-based built-in webcam were used to record the emotional valence based facial expressions

of participants throughout the experiment. Arousal was inferred from electrodermal activity (EDA) collected via a MP-150 Biopac Bionomadic (Santa Barbara, California). Participant responses to self-reported measures were collected via a Qualtrics (Provo, Utah, United States) web-based survey administered on the same desktop computer as the presented stimuli and in sequence with the stimuli. Constructs were measured with single items.

**Survey and Instrument Validation:** The questionnaire used in this study consists of previously validated scales [2, 8] measuring constructs shown in the research model.

#### **4 Preliminary Results and Ongoing Work**

Responding RQ1, preliminary analysis of three sets of neurophysiological data is presented below. First, valence was positively associated with Information Sufficiency ( $b=.007$ ,  $p<.0001$ ), solution specificity ( $b = .008$ ,  $p<.0001$ ), and usefulness ( $b=.007$ ,  $p<.0001$ ); similarly, arousal was negatively related to transparency ( $b=-.052$ ,  $p<.05$ ). Cognitive load was greater for vague rather than specific problems ( $b=-.035$ ,  $p<.0001$ ) and for vague rather than specific solutions ( $b=-.029$ ,  $p<.0001$ ). Also, the arousal slope associated with simple decisions was roughly one-half of the arousal slope for complex decisions; hence, an additive effect on arousal may be experienced in complex decision situations. Lastly, gaze tracking visualizations show users re-reading the solution when information is sequenced in the solution-to-problem format.

Regarding RQ2, Information Specificity was found to drive users to accept the recommendation significantly more so for messages providing problem specificity (H4:  $b=1.3157$ ,  $p<0.0001$ ) and solution specificity (H4:  $b=1.8626$ ,  $p<0.0001$ ).

Answering RQ3, all hypothesized relationships received strong statistical support (Hypotheses 1 through 18) and are presented in three sets of results below. First, information specificity (i.e., problem and solution specificity) impacted information sufficiency (respectively, H1:  $b=.895$ ,  $p<.001$ ; H2:  $b=1.423$ ,  $p<.001$ ). Situational complexity and information sequence, respectively, negatively affected information sufficiency (H4:  $b=-.548$ ,  $p<0.001$ ) and information transparency (H3:  $b = -.687$ ,  $p<.001$ ). Second, effects were shown for: information sufficiency on usefulness (H5:  $b=.808$ ,  $p<.001$ ); information transparency on ease of use (H6:  $b=.458$ ,  $p<.001$ ) and recommendation confidence (H7:  $b=.934$ ,  $p<.001$ ); and recommendation confidence on intention to accept the recommendation (H13:  $b=.891$ ,  $p<.001$ ), which was also affected by confidence in

the system (H16:  $b=.935$ ,  $p<.001$ ). Third, ease of use impacted usefulness (H8:  $b=.634$ ,  $p<.001$ ) and satisfaction (H9:  $b=.792$ ,  $p<.001$ ). Usefulness influenced recommendation confidence (H12:  $b=.780$ ,  $p<.001$ ), system confidence (H11:  $b=.843$ ,  $p<.001$ ), and system satisfaction (H10:  $b=.810$ ,  $p<.001$ ). Recommendation confidence affected system confidence (H14:  $b=.833$ ,  $p<.001$ ), in turn, system trust (H15:  $b=.77$ ,  $p<.001$ ), and ultimately satisfaction (H17:  $b=.873$ ,  $p<.001$ ). Lastly, satisfaction affected the intention to use the RS (H18:  $b=.949$ ,  $p<.001$ ).

## 5 Conclusion

This paper reports the results of a pilot exploring the effects of three message design components—specificity of problem and solution descriptions and information sequence—on users’ perceptions and attitudes towards the recommendation and the RS as a whole. Despite limitations in terms of sample size and research design (lack of counterbalancing), findings offer strong support of the importance of message design as a critical element in facilitating information processing, particularly in the context of managerial decision-making. Findings help extend RS literature by shifting the focus from system to message design. It underscores the importance of this overlooked design aspect, which is not just a critical antecedent of users’ recommendation acceptance rather also of their attitude toward and intention to use the system. A complete neuro- physiological data analysis from the study will be presented at the conference.

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# Chapitre 3

## Improving user experience through recommendation message design: A Systematic Literature Review of extant literature on Recommender Systems and message design

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**Abstract.** This paper reports the findings of a Systematic Literature Review of extant literature on Recommender Systems (RS) and message design. By identifying, analyzing and synthesizing relevant studies, we aim to generate a contemporary mapping of studies related to user-RS interaction, extend the body of knowledge regarding effective recommendation messages, inform practitioners about the effect of recommendation message design choices on the user's experience, and motivate researchers to conduct related future research on new RS message factors identified in the literature. To conduct this SLR, 132 papers were collected and analyzed after assessing their relevance and quality, 41 papers were selected, classified, interpreted and synthesized under a strict methodology producing the results reported in this paper, and concluding with a concept matrix outlining opportunities for future research on how to optimize the design of RS in support of a managerial decision-making context.

**Keywords:** User Experience, Recommender Systems, Message Design. Systematic Literature Review.

### 1 Introduction

To help businesses, employees, and customers improve their decision-making quality while reducing their decision-making effort, Recommender Systems (RSs) have been used in many domains since the mid-1990s (e.g., e-commerce, management, education, healthcare, government) [1, 2, 3, 4]. For example, Amazon.com, a well-known e-commerce vendor, recommends products

to its customers through an RS. Another example, Netflix uses an RS to offer its users movies according to their preferences.

Due to this growing use and importance of RSs, researchers have studied their performance [5], algorithmic accuracy [6, 7, 8, 9], elicitation recommendation methods [10, 11, 12, 9] and explanations [13, 14, 15, 16] and demonstrated the system design's effects on user experience. Studies have shown that the recommendation's nature (i.e. the message's content and format) will impact users' beliefs, attitudes and behavioral intentions, particularly in the context of managerial decision-making [17, 18]; however, these past studies were mostly focused on system-level (e.g. interface) design implications [19]. Also, given that recommendation explanations can improve user experience [20, 21], there is a need for future research to understand how the recommendation message format and content could be improved to further improve users' decision-making [22, 23, 24].

Whereas knowledge on the impact of message design choices on the reader's perceptions and behaviors are more developed in other areas [25, 26, 27, 28, 29, 30], limited research exists on what would optimize the design of recommendation messages [31]. Building on the work by [32], this paper aims to further explore the antecedents to effective recommender system design by developing the theoretical grounding of related concepts.

The aim of this study is to carry out a systematic literature review of relevant studies in order to: 1) Generate a contemporary mapping of studies related to user-RS interactions; 2) Extend the body of knowledge by synthesizing the retrieved studies' findings into a framework describing the design factors that impact the effectiveness of recommendation messages and inform practitioners including system designers about the effects of recommendation message design choices on the user's experience; 3) Propose new RS message factors to study and motivate researchers to conduct related future research to deepen our understanding. Hence, this study is guided by the following research questions:

RQ1 What comprises the current knowledge base of the antecedents to effective RS message design?

RQ2 What statistically significant results from past research can inform current scholars and practitioners of optimal RS message design practices?

RQ3 What are the opportunities for future research subsequently potentially revealing guidelines on how to optimize RS message design in a managerial decision-making context?

This article is presented as follows. First, we describe the research methodology by presenting the protocol we followed to conduct this Systematic Literature Review. Next, we present the analysis and results of our review by answering our three research questions. Finally, we conclude the paper by a discussion of our work, what it brings to the scientific and practical fields, and opportunities for future research.

## **2 Research Methodology**

This paper is a Systematic Literature Review of extant literature concerning RS and message design [33]. A review protocol was defined in order to conduct the literature review and consists of the four stages below: i) searching for literature in scientific databases, ii) reviewing and assessing the search results, iii) analyzing and synthesizing the results, and iv) reporting the review findings.

To find the appropriate studies, queries with relevant search terms were carried out in international databases of authoritative academic resources and publishers, international journals and selected conference proceedings. Details on the search queries are presented in Table 1.

**Table 1.** List of search keywords and scientific databases used to identify papers.

| Search keywords  | Scientific databases   |
|--|--|
| <ul style="list-style-type: none"> <li>· “Recommender System”</li> <li>· “Recommendation System”</li> <li>· “Recommender System message”</li> <li>· “Recommendation System message”</li> <li>· “Recommender System message design”</li> <li>· “Recommendation System message design”</li> <li>· “Recommender System user acceptance”</li> <li>· “Recommendation System user acceptance”</li> <li>· “Recommendation message design”</li> <li>· “Message design”</li> <li>· “Message design acceptance”</li> <li>· “Message design guidelines”</li> <li>· “Warning message design”</li> <li>· “Persuasive message design”</li> <li>· “Information Systems message design”</li> <li>· “Trust in Recommender System”</li> <li>· “Trust in Recommendation System”</li> <li>· “Explanation in Recommender System”</li> <li>· “Explanation in Recommendation System”</li> </ul> | <ul style="list-style-type: none"> <li>· Google Scholar</li> <li>· ACM Digital Library</li> <li>· ABI/INFORM collection (Proquest)</li> <li>· IEEE Xplore</li> <li>· SpringerLink</li> <li>· ScienceDirect</li> <li>· Journal of the Association for Information Systems</li> <li>· Information Systems Journal</li> <li>· Information Systems Research</li> <li>· Journal of Information technology</li> <li>· Association for Information Systems Transactions on Human-Computer Interaction</li> <li>· Management Information Systems Quarterly</li> <li>· Journal of Management Information Systems</li> </ul> |

The timeframe of the research was specified to the last decade (2010-2020), during which researchers conducted numerous user-centric studies and the importance of recommendation presentation emerged.

When all papers had been identified, we subsequently proceeded to assess their applicability to this literature review applying two filtering stages, focused on relevance and quality respectively. In the first filtering stage, we applied a set of inclusion and exclusion criteria to assess the relevance of the article to the purposes of this literature review, as defined in Table 2.

**Table 2.** Inclusion and exclusion criteria used to filter the 132 identified papers.

| Include papers about or published in...  | Exclude papers...   |
|--|---|
| <ul style="list-style-type: none"> <li>· RS user acceptance</li> <li>· RSs user-centric studies</li> <li>· Message design</li> <li>· Peer-reviewed conferences, workshops, and journals</li> <li>· English</li> <li>· Between from 2010 to 2020</li> </ul> | <ul style="list-style-type: none"> <li>· Not addressing RS or message design</li> <li>· Papers addressing RSs but centered on methods and techniques (algorithm, elicitation recommendation, RS types, data mining etc.)</li> <li>· Without empirical evidence</li> </ul> |



Applying these inclusion and exclusion criteria, 132 papers corresponding to the search terms and criteria were collected, which were subsequently subjected to a quality review.

After identifying and collecting the papers, they were analyzed in order to assess the quality of their content according to the following criteria: 1) Citations (numerous and varied); 2) Clear and detailed presentation of the results and their implication and contribution to the field; 3) Brings new knowledge and/or proposes relevant future research to be carried out.

Applying these quality criteria to the remaining 132 papers, 91 papers were removed. Then, the remaining 41 papers were classified according to the research discipline and results. Finally, non-statistical methods were used to evaluate and interpret findings of the collected papers and conduct the synthesis of this review.

### **3 Analysis and Results**

#### **3.1 RQ1 What comprises the current knowledge base of the antecedents to effective RS message design?**

In the following, the current knowledge base of the antecedents to effective RS message design are summarized. Given the similarity of identified topics, we grouped existing findings into four (4) major groups of knowledge: (1) users' perceptions and behaviors, (2) information design, (3) recommendation message format and content and (4) explanations in recommendation messages.

##### **User's perceptions and behaviors**

Based on [18], [17] developed a user-centric evaluation framework for recommender systems named *ResQue* in order to determine the essential qualities of an effective and satisfying RS and the key determinants motivating users to adopt a recommender technology. The model shows that RS transparency and perceived usefulness influence the user's trust and confidence in the RS, which are linked to the intention to use and/or purchase. In their turn, control, perceived usefulness, and perceived ease of use of the RS affect the overall satisfaction of the user, which is also linked to users' use intentions of the RS. The authors also explain that to create a transparent system, the recommendation must be accurate and contain explanations. The user feels control over the RS if the interaction is adequate. Also, the RS is perceived as easy to use due to an adequate interface

and perceived as useful if the recommendations are accurate, novel, diverse and contain sufficient information.

### **Information design**

Information design is a concept whose main goal is the clarity of communication. So, its principles are beneficial to any context where the aim is to provide information to someone, e.g. via a recommendation system message. [34, 25, 35] have studied information design and gathered theories and guidelines for message designers. Based on the observation that several authors have pointed out that the message's form follows function, authors argue that the message's content is more important than its actual execution [34, 35]. Thus, the information in each message will have to be structured and adapted to the needs of the intended receivers. Also, because the intended receivers must have easy access to facts and information when they need it, information should be conveyed in a clear manner from the sender (i.e., recommender system) to the receiver (i.e., recommender system's user). Thus, complicated language which will impair the understanding of the recommendation system message should be avoided.

### **Recommendation message format and content**

The procedure of the recommendation's presentation depends on the implemented algorithms. Depending on the algorithm chosen by the designers, recommendations will vary. However, no matter the algorithm chosen, the recommendation message itself, and more specifically its design, will have a significant influence on the user experience, their perceptions and behavior.

Effectively, information sufficiency, defined by [36] as "the content presented to the user that should be enough for him/her to understand the situation and to act on it while saving time and effort if he or she do not have this information or in a different form", is a characteristic of an effective recommendation message; similarly important characteristics include transparency, flexibility, and accessibility because "the recommendation should allow the shopper to easily navigate through" [36]. Moreover, [37] recommend to RS designers to pay attention to the display format of the recommendations by using navigational efficacy, design familiarity, and attractiveness. Also, these same authors identified in the literature that the user's perceived credibility of the system influences the user's attitudes and behaviors.

Like [17], [38] consider that the accuracy of the recommendations is an important factor in the decision-making process preceding the uptake of the recommendations, but their potential value for the user are also important. On their side, [39] argue that the degree of trust users put in the system plays an important role in the acceptance of a recommendation. In addition to transparency and perceived usefulness, explanations contribute to user trust in RS [40, 41, 42]. Furthermore, these factors can affect each other. For example, the accuracy and the diversity of recommendations positively affect user trust and lead to an increased adoption rate of recommendations [43].

Thus, there are numerous factors that impact user's evaluations of RSs and recommendation messages, and these factors are influenced by the RS message characteristics [37]. Indeed, the content and the format of recommendations have significant and varied impact on users' evaluations of recommender systems, thereby influencing the user's decision-making process [37, 44].

While text explanations were perceived as more persuasive than every visual format [45], the navigation and layout of recommendation presentation interfaces are also important, because they significantly influence users' satisfaction and their overall rating of the systems; also, interface design and display format influenced RS users' behaviors.

### **Explanations in recommendation messages**

Another important factor influencing the effectiveness of an RS message identified in the literature pertains to information, and more specifically explanations.

Explanation is a component of the explanation interface that consists of three elements: explanation, presentation and interaction, and is itself composed of three elements: (i) the content (ii) the provisioning mechanism and (iii) the presentation format [46].

There are two types of explanations, i.e. explaining the way the recommendation engine works and explaining why the user may or may not accept the recommendation [21]. Explanations are used to give more information to the users on the recommendation in order to help them to better understand the systems' outcomes and be sure they make the best choice, which leads to satisfaction, transparency, confidence, perceived ease of use and perceived usefulness [22].

Although they cannot compensate for poor recommendations, they can increase user acceptance of RSs, help users make decisions more quickly, convince them to accept the recommendation and develop users' trust in the system as a whole [47, 22]. So, a recommendation should use an explanation model that would help users understand the recommendation reasoning process [22] and positively influence transparency, scrutability, trust, effectiveness, efficiency, persuasiveness, and satisfaction [48].

However, users respond to explanations differently according to their context and intent, so there is a need to jointly optimize both recommendation (i.e., the solution) and explanation selections [49]. Different explanations have been tested over the last decade. In a taxonomy for generating explanations in RS, [48] argue that structural characteristics such as length, writing style or the confidence that is conveyed in explanations can be used as additional dimensions. Moreover, the authors encourage RS designers to exclude from an explanation all information and knowledge that are not relevant for answering a request. Also, users have a preference for knowledgeable explanations and the recommender may be formulated along the line of “You might (not) like Item A because...” to create an effective explanation [21]. Thereby, the richness of explanations plays a pivotal role in trust-building processes and recommendation should incorporate explanatory components that imitate more closely the way humans exchange information [50]. To enact it, [50] recommend combining different explanation styles in the recommendation, which lead to explanations with a higher perceived value and trust in the recommendation. Furthermore, arguments should contain only pertinent and cogent information, while titles are preferred to be presented in a natural and conversational language. For the recommendation of low-risk products, users were found to prefer short sentences. However, for high-risk products, users were found to prefer long and detailed sentences. Long and strongly confident explanations can be more effective in the acceptance of interval forecasts [46]. As context and intent are important in the decision-making process, personalized explanations are often linked to improved transparency, persuasiveness and satisfaction, when compared to non-personalized explanations [51]. In addition, generating familiar recommendations with detailed information and explanations regarding the underlying logic of how the recommendation was generated increases the users' perceived credibility of the system [37]. Successful recommendations also need to take into account user perceptions of recommendation properties such as diversity and serendipity, user short-term information needs, user context, and mood, i.e. what users are thinking [52].

Thus, in answering the above-stated RQ1 (“What comprises the current knowledge base of the antecedents to effective RS message design?”), a concept matrix of the current knowledge base of the antecedents to effective recommender system (RS) message design is presented in Table 3.

**Table 3.** Concept matrix: current knowledge base of the antecedents to effective recommender system (RS) message design.

| Article                      | Users perceptions and behaviors | Information message | Recommendation message content and format | Explanations in recommendation message |
|------------------------------|---------------------------------|---------------------|---|--|
| Coursaris et al. (2020)      | x                               |                     | x   |  |
| Kunkel et al. (2019)         |                                 |                     |   | x                                      |
| McIenerney et al. (2018)     |                                 |                     |   | x                                      |
| Nunes and Jannach (2017)     |                                 |                     |   | x                                      |
| Paniello et al. (2016)       |                                 |                     | x   |  |
| Guanawardana & Shani (2015)  |                                 |                     | x   |  |
| Jameson et al. (2015)        |                                 |                     | x   |  |
| Al-Taie and Kadry (2014)     |                                 |                     |   | x                                      |
| Pettersson (2014)            |                                 | x                   |   |  |
| Pettersson (2012)            |                                 | x                   |   |  |
| Tintarev and Masthoff (2012) |                                 |                     |   | x                                      |
| Yoo and Gretzel (2012)       |                                 |                     | x   | x                                      |
| Friedrich and Zanker (2011)  |                                 |                     |   | x                                      |
| Gedikli and Jannach (2011)   |                                 |                     |   | x                                      |

|                              |   |   |   |   |
|------------------------------|---|---|---|---|
| Mandl et al. (2011)          |   |   | x |   |
| Pu et al. (2011)             | x |   |   |   |
| Tintarev and Masthoff (2011) |   |   |   |   |
| Ozok et al. (2010)           |   |   | x |   |
| Pettersson (2010)            |   | x |   |   |
| Total                        | 2 | 3 | 7 | 8 |

Having presented the current knowledge base of the antecedents to effective RS message design, we now present statistically significant results from prior research that may inform scholars and practitioners' RS message design practices.

### **3.2 RQ2 What statistically significant results from past research can inform current scholars and practitioners of optimal RS message design practices?**

In what follows, we begin by focusing on relevant results from two studies. These two studies provide an ideal starting point as they offer an overarching classification of message design elements. Then, we turn to studies that extend the two previous studies by studying fewer factors in depth.

[17] proposed the *ResQue* model after conducting a user-centric study. This study has led to a better comprehension of the factors that impact the acceptance of recommendations and the use intentions of RSs. Indeed, all of the hypotheses presented in the *ResQue* model presented in the previous section have been statistically validated. Based on this work, [32] proposed 36 hypotheses to study the effects of message design on the user acceptance of Recommender Systems and the system-generated recommendations. Among the 36 hypotheses, 23 were statistically validated. The most interesting results for the RS message design practices found by [32] are that information specificity of the recommendation impacted information sufficiency and information transparency. In turn, information sufficiency (i.e., both problem and solution) influences perceived usefulness, and information transparency positively impacts confidence in recommendation and perceived

ease of use of the RS. This study also showed that a higher information specificity of both the problem and the solution increase the user's recommendation acceptance and reduce the decision-making time (when controlled for message length), while information sequence such that information is presented from problem to solution reduces the decision-making time.

[20] studied the influence of knowledgeable explanations on users' perception of a recommender system. The author conducted an online experiment on a real-world platform and found that knowledgeable explanations significantly increase the perceived usefulness of a recommender system. In another study on presenting explanations in RS [53], the authors developed an innovative study design for measuring the persuasion potential of different explanation styles (sentences, facts or argument styles) by comparing participants' robustness of preferences in face of additional explanations. Results indicate that fact-based explanations (i.e. only facts with keywords without sentences) have a stronger impact on participants' preference stability than sentence-based explanations. Further, argumentative facts and argumentative sentences impact stronger the users' preference than the solely facts. Thus, fact-based explanations and argumentative explanation style are preferred by the users than full sentences explanations.

[54] presents a system design featuring interactive explanations for mobile shopping recommender systems in the domain of fashion. Based on a framework for explanation generation [55] and a previously developed mobile recommender system [56] they developed a model of mobile recommender systems and generated explanations to increase transparency. Based on the fact that explanations must be concise and include variations in wording, they defined positive and negative argument aspects. They found that positive arguments convince the user of the relevance of the recommendation, whereas negative arguments increase the user's perceived honesty of the system regarding the recommendation.

In addition, [31] were interested in the transparency of a Recommender Assistant (RA). Their study reveals that transparent RA requiring low cognitive effort increases the user's perceived sense of control. Furthermore, results showed that participants' perceived RA credibility, decision quality, and satisfaction were positively affected by a transparent RA and were not impacted by the cognitive effort needed to access and understand the explanations of the RA.

Also, RS interface design and trust have previously been studied. [40] studied users' trust factors in music recommender systems by comparing different recommendation presentation factors (i.e. presentation, explanation, and priority). They found that the type of explanation to be used in an RS depends on the desired effect on the user. More precisely, persuasive explanation is suited to support the competence facet of the RS, while displaying a rating (there, IMDb score) will promote the honesty and objectivity of the RS. Then, [57] conducted a user study on the influence of interface design choices along two axes (i.e. information scent and information access cost) on feedback quality and quantity. The authors found that people have a preference for descriptions with a higher level of detail. Indeed, people preferred the interfaces that provided a strong information scent over the ones with weak information scent.

[58] developed a UTAUT2-based framework and tested it in a quantitative study with 266 participants on social recommender systems. The results of the survey showed that the integration of user's social information could improve the intention to use a recommender system. Thus, users prefer a system that provides recommendations based on a combination of user's social networking information, profile information and reading behavior, especially when the recommendations are from well-known and trustworthy people.

Thus, in answering the above-stated RQ2, a concept matrix of the statistically significant results from past research informing current scholars and practitioners of optimal RS message design practices is presented in Table 4.

**Table 4.** Concept matrix: statistically significant results from past research informing current scholars and Practitioners of optimal RS message design practices.

| Article                 | Study   | Results   |
|-------------------------|---|---|
| Pu et al. (2011)        | The <i>ResQue</i> model tested several factors for their impact on the acceptance of recommendations and the use intentions of the RS.                                    | All hypotheses have been statistically validated. |
| Coursaris et al. (2020) | A research model composed of 36 hypotheses to study the effects of message design on the user acceptance of Recommender Systems and the system-generated recommendations. | 23 hypotheses on 36 are validated.                |



|                                |   |  |
|--------------------------------|---|--|
| Zanker (2012)                  | An online experiment on a real-world platform on the impact of knowledgeable explanations on the RS users' perceptions.   | Knowledgeable explanations significantly increase the perceived usefulness of a recommender system.  |
| Zanker and Schoberegger (2014) | An innovative study design for measuring the persuasion potential of different explanation styles (sentences, facts or argument styles).  | Fact-based explanations and argumentative explanation style are preferred by the users than full sentences explanations.   |
| Lamche et al. (2014)           | A system design featuring interactive explanations for mobile shopping recommender systems in the domain of fashion to increase transparency and honesty in RS.   | Positive arguments convince the user of the relevance of the recommendation, whereas negative arguments increase the user's perceived honesty of the system regarding the recommendation.  |
| Bigras et al. (2019)           | A within-subject laboratory experiment conducted with twenty subjects investigating how assortment planners', perceptions, behavior, and decision quality are influenced by the way recommendations of an artificial intelligence (AI)-based recommendation agent (RA) are presented. | Transparent RA requiring low cognitive effort increases the user's perceived sense of control. RA credibility, decision quality, and satisfaction were positively affected by a transparent RA and were not impacted by the cognitive effort needed to access and understand the explanations of the RA. |
| Holliday et al. (2016)         | A study on users' trust factors in music recommender systems by comparing different recommendation presentation factors (i.e. presentation, explanation, and priority).   | The type of explanation to be used in an RS depends on the desired effect on the user.   |
| Schnabel et al. (2018)         | A user study on the influence of interface design choices along two axes (i.e. information scent and information access cost) on feedback quality and quantity.   | People have a preference for descriptions with a higher level of detail. They prefer the interfaces that provided a strong information scent over the ones with weak information scent.  |
| Oechslein et al. (2014)        | A UTAUT2-based framework and tested it in a quantitative study with 266 participants on social recommender systems.   | The integration of user's social information could improve the intention to use a recommender system.  |

### **3.3 RQ3 What are opportunities for future research subsequently potentially revealing guidelines on how to optimize RS message design in a managerial decision-making context?**

In order to unify the presentation of the above results from prior research, an iterative research process was applied. First, we describe in the following three identified domains of message design that provide insights and inspiration for the domain of recommendation message design, i.e., narrative messages, software update warning messages and information messages. Then, Table 5 presents relevant dimensions and characteristics for opportunities in RS message design.

### **Insights from narrative message design implications.**

[59] and [60] conducted studies on the influence of narrative messages on readers. They compared narrative messages vs. non-narrative message and found that narratives are more enjoyable, produce involvement, identification, and parasocial interaction with characters than non-narratives. [61] and [62] also studied the perceptions of narrative messages and observed that narrative messages reduce or circumvent negative reactions to persuasion and counterarguing and evoke emotional and cognitive responses. Also, when the legitimacy burden is greater, narratives are more persuasive because they mask the persuasive intent of the message [61, 63]. Furthermore, they encourage a greater belief in the realism of claims or the authenticity of the narrative world through a suspension of disbelief [64]. From a design perspective, narratives convey information in ways that may reduce feelings of being overloaded [65], have a more explicit story structure, are more understandable and involve less information overload [66]. Despite these benefits, the narrative message's style has never been used in recommendation messages. Thus, it would be interesting to conduct studies with narratives in recommender messages and observe their influence on the users' perceptions and behaviors.

### **Insights from the design of warning update software message.**

[67] studied warning message updates to identify design features that may significantly influence the level of confusion, annoyance, noticeability, and perceived importance experienced by users once a software update message is delivered. In their study, the authors showed 14 warning messages with different designs to the participants. The participants were asked to evaluate the warning message on various criteria and give feedback regarding their feelings. The study demonstrated that better designs could help alleviate annoyance and confusion while increasing importance and noticeability of updates. To this end, the update message must clearly mention what software is being updated, the risks, use simple language, explain the reason(s) behind the update, and explain the benefits clearly. Also, the placement and design of buttons underscore the importance of well-designed buttons on usability, which also help to reduce the level of confusion. Moreover, scare tactics, used to increase noticeability and importance in messages, correlates with higher annoyance, which may affect the message effectiveness in the long run.

### **Insights from the information message design.**

[68] studied message content and the format of recommendation messages and suggested that recommendation messages could elicit positive affective responses from users by utilizing affective language. Also, apologies, reward, or praise could be used to create positive affective responses [69]. Thus, affective language could increase (i.e. more positive) users' perceptions of the recommendation, recommendation acceptance, and use intentions.

[70] used typographical cues in a scientific Q&A forum context to observe users' perceptions. The results were not statistically significant, but the authors remain confident about the effect of typographical cues in messages on users and recommend testing them in a different context. [32] tested one typographical cue proposal (i.e. bold keyword vs. plain text) in a decision-making context but it did not impact the user's perceptions and behaviors. Other identified typographical cues that can be tested include italicizing, underlying, and using color among others.

Also, an extended study of [32] could be performed by focusing on the three factors (i.e., problem information specificity, solution information specificity and information sequence) that were found to be statistically significant in affecting recommendation and system-level outcomes, in order to find the best combination(s) of design choices regarding the presentation of the recommendation message.

In [71], the authors compared subjective versus objective language for the recommendation of a virtual agent and suggested testing the subjective language to measure the user's perception of the system and the recommendation, as well as their intent to accept the recommendation and use the system in the future.

Like [46], [51] suggest that long explanations in recommendation messages are more persuasive than short explanations. However, other studies recommend creating short and precise recommendations [72, 73, 74]. Thus, length and details or precision of the recommendation message should be tested in a managerial decision-making context in order to determine the effective length of a recommendation message, and how detailed the recommendation should be.

Thus, in answering the above-stated RQ3, a concept matrix of the opportunities for future research on how to optimize RS message design in a managerial decision-making context is presented in Table 5.

**Table 5.** Concept matrix: opportunities for future research on how to optimize RS message design in a managerial decision-making context.

| Concept              | Article                   | Opportunities for future research  |
|----------------------|---------------------------|--|
| Information messages | Coursaris et al. (2020)   | What is the effective combination of problem information specificity, solution information specificity and information sequence in a recommendation message? |
|                      | Makkan et al. (2020)      | What is the effect of affective language in recommendation messages on user behaviors and perceptions?   |
|                      | Matsui and Yamada (2019)  | How subjective and objective language influence the user's perception and intent for acceptance and future usage?  |
|                      | Schreiner et al. (2019)   | Are short and precise recommendations more efficient than long recommendations?  |
|                      | Zhang et al. (2019)       | What is the effect of typographical on user's perceptions and behaviors?   |
|                      | Li et al. (2017)          | Do apologies, reward and praise in recommendations create positive affective responses and influence users' decisions?                                       |
|                      | Nunes and Janach (2017)   | Are long explanations more persuasive than short explanations?   |
|                      | Al-Taie and Kadry (2014)  | Are long explanations more persuasive than short explanations?   |
|                      | Harbach et al. (2013)     | Are long explanations more persuasive than short explanations?   |
|                      | Bravo-Lillo et al. (2011) | Are long explanations more persuasive than short explanations?   |

|                                  |                           |   |
|----------------------------------|---------------------------|---|
| Software update warning messages | Fagan et al (2015)        | Which designs help alleviate annoyance and confusion while increasing importance and noticeability of the recommendation message?<br><br>Which place and design of buttons help to reduce the level of confusion in a recommendation message? |
| Narrative messages               | Barbour et al. (2015)     | Do recommendation messages using narrative's style are more explicit, more understandable and involve less information overload?  |
|                                  | Niederdeppe et al. (2014) | Does the narrative's style in recommendation messages increase the persuasion of the recommendation?  |
|                                  | Weber & Wirth (2014)      | Does the narrative's style in recommendation messages encourage a greater belief in the recommendation?   |
|                                  | Jensen et al. (2013)      | Does the narrative's style in recommendation messages reduce feelings of being overloaded?  |
|                                  | Moyé-Gusé et al. (2011)   | Do recommendation messages using narrative's style are more enjoyable, produce involvement, identification, and parasocial interaction than non-narrative?  |
|                                  | Moyé-Gusé and Nabi (2011) | Do recommendation messages using narrative's style are more enjoyable, produce involvement, identification, and parasocial interaction than non-narratives.   |
|                                  | Niederdeppe et al. (2011) | Do narratives mask the persuasive intent of the recommendation and increase its persuasion?   |
|                                  | Appel & Richter (2010)    | Do recommendation messages using narrative's style reduce or circumvent negative reactions to persuasion and counterarguing and evoke emotional and cognitive responses?  |

#### 4 Discussion and concluding comments

This paper provides a valuable contribution and step forward in our understanding of the antecedents to effective recommendation message design in a managerial decision-making

context. It does so by giving an overview of the current knowledge base, citing prior research, and summarizing opportunities for future research with a concept matrix.

The purpose of this literature review was to provide an overview of the current knowledge base of the antecedents to effective RS message design, identify statistically significant results from past research so as to inform current scholars and practitioners of optimal RS message design practices, and detect opportunities of future research subsequently potentially revealing guidelines on how to optimize RS message design in a managerial decision-making context. This work has been conducted on the basis of the systematic literature review protocol described in section 3. We retrieved 132 papers between 2010 and 2020, which were filtered for relevance and quality before being included for the final literature review analysis. After this filtering, 41 papers were preserved. Among this papers, nineteen (19) papers were used to inform the current knowledge of the antecedents to effective RS message design, eight (8) studies with statistically significant results were identified to inform current scholars and practitioners of optimal RS message design practices, and nineteen (19) papers were used to identify opportunities of future research subsequently potentially revealing guidelines on how to optimize RS message design in a managerial decision-making context and allocated in three (3) sections (i.e. narrative messages, warning software message updates and message information design). The opportunities are presented in Table 2.

Our literature review shows that relevant studies on this topic exist but are far from comprehensive and knowledge is fragmented between several studies that have never been unified. Indeed, most studies in this research space concern themselves with recommender systems and recommendations more broadly, but only a few have investigated the factors of relevance in optimizing the design of recommendation messages. Despite the limited prior research, these studies demonstrated the importance of recommendation message design and its impact on user experience.

Still, large research gaps in this domain persist. Two user-centric studies [17, 32] presented more holistically the qualities of effective and satisfactory recommendation messages, and in turn recommender systems. Those two studies have so far been extended only by a few studies that are primarily centered on explanations provided in recommendations; an even smaller number of

studies has focused on presentation details such as the recommendation's message length, information detail, information sequence, message format or typographical cues.

Future research is needed to enrich our understanding of the antecedents to effective recommendation messages, with three prime areas for opportunities for future research: narrative messages, software update warning messages, and information messages.

Narrative message inquiries could focus on the effect of narratives on the persuasion of the recommendation and information overload.

Studies related to software update warning messages could explore the effectiveness of a better design on the annoyance and confusion experienced by users, while increasing the importance and noticeability of the recommendation message and the placement and design of buttons on the level of confusion evoked by a recommendation message.

Our understanding of information messages could be extended by (i) exploring the effect of the explanation's length in recommendation messages on persuasion, (ii) the impact of affective, subjective and objective language on user behaviors and perceptions, and (iii) by defining the effective combination of problem information specificity, solution information specificity, and information sequence in a recommendation message.

While the contribution of this work is significant, limitations are also inherent. Due to the number of selected keywords used in the search, the volume and diversity of retrieved papers was limited.

Beside this limitation, we anticipate a significant impact on future research on the antecedents to effective RS message design in a managerial decision-making context. This paper provides the first systematic review, synthesis, and overview regarding knowledge, guidelines and future research opportunities for RS message design in a managerial decision-making context. Furthermore, we identified three research gaps that could be addressed by researchers through future research.

## Acknowledgement:

This study was financially supported by Blue Yonder, NSERC and Prompt (Grant number IRCPJ/514835-16).

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## **Chapitre 4**

### **Discussion et conclusions**

Le premier objectif de ce mémoire était d'identifier des composants de messages de recommandation générés par un système de recommandation dans un contexte de prise de décision managériale influençant positivement l'attitude et le comportement des utilisateurs pour les pousser à accepter la recommandation et utiliser à nouveau le système tout en réduisant leurs efforts cognitifs liés à cette prise de décision.

Pour se faire, une expérience intra-sujet a été menée en laboratoire à l'hiver 2020 pour tester les quatre (4) composants identifiés dans la littérature, à savoir i) la spécificité du problème, ii) la spécificité de la solution, iii) l'ordre de présentation de l'information et iv) la complexité de la situation, auprès de six (6) participants. Ces derniers devaient prendre une décision en acceptant la recommandation ou en demandant plus de détails s'ils n'avaient pas assez confiance en la recommandation face à une situation présentée composée d'un problème et d'une solution. Les participants ont fait face à 48 situations et avaient 10 secondes pour prendre leur décision. Passé ce délai, le stimulus disparaissait et le choix du participant était considéré comme nul. Les perceptions des participants face aux recommandations et au système étaient collectées après chaque décision par l'intermédiaire d'un questionnaire. Leurs données physiologiques ont également été collectées tout au long de leurs interactions avec les stimuli afin d'analyser leurs perceptions durant la phase de prise de décision. Les perceptions et le comportement des participants face aux recommandations et au système ont ensuite été comparées entre les situations afin d'évaluer l'impact des facteurs de conception des messages. Grâce à cette collecte de données, l'article présenté en chapitre 1 a pu être rédigé.

Le second objectif de ce mémoire était de fournir une vision générale des études menées jusqu'ici sur les antécédents des conceptions de message de système de recommandation efficaces, d'identifier les études présentant des résultats significatifs pouvant informer les praticiens des pratiques optimales de conception de message de recommandation et de proposer des opportunités de recherche futures pouvant informer la littérature et révéler des lignes directrices de conception de message de recommandation.



Pour répondre à cet objectif, une revue de littérature systématique a été menée durant l'été et l'automne 2020. Une méthodologie stricte et rigoureuse a été suivie, permettant de récolter 132 articles dans diverses bases de données scientifiques. Après analyse de ces articles, 41 ont été conservés grâce à leur pertinence et leur qualité, composant ainsi la revue de littérature présentée dans le chapitre 2 de ce mémoire.

Dans le chapitre qui suit, les questions de recherche de ce mémoire sont rappelées ainsi que les principaux résultats des deux articles. Les contributions pratiques et théoriques de ce mémoire sont également abordées, tout comme les limites de cette recherche et les futures recherches à mener pour poursuivre ce travail.

### **Rappel des questions de recherche et des principaux résultats**

Ce mémoire cherchait à répondre aux questions de recherches suivantes :

*Dans quelle mesure les choix de présentation de message de recommandation influencent-ils les perceptions et le comportement des utilisateurs de systèmes de recommandation dans un contexte organisationnel managérial?*

*De quoi se compose la littérature des messages de recommandation et quel est le format de présentation des messages de recommandations d'un système de recommandation le plus efficace concernant les perceptions et le comportement des utilisateurs de tels systèmes?*

Pour répondre à ces deux questions de recherches, deux études distinctes, mais complémentaires, ont été menées. La première, une expérience intra-sujet en laboratoire menée à l'hiver 2020 a permis de répondre à la première question de recherche. Lors de cette expérience, quatre (4) composants de conception de message ont été testés, à savoir la complexité de la situation (simple vs. complexe), la spécificité du problème (spécifique vs. vague), la spécificité de la solution (spécifique vs. vague) et l'ordre de présentation de l'information (problème puis solution vs. solution puis problème) afin d'étudier leur impact sur le comportement, l'attitude et les réponses cognitives des utilisateurs de système de recommandation. Les principaux résultats neuropsychologique de cette étude ont montré que la valence était positivement lié à la présence d'information de la solution, que la visualisation du suivi du regard des participants a montré que la solution était lue une deuxième fois lorsque celle-ci est présentée au début de la

recommandation, contrairement à une seule fois lorsqu'elle est à la fin du message et que la pente d'excitation associée à la prise de décision était plus élevée lorsque les décisions à prendre étaient complexes. Concernant le comportement des participants, les résultats ont montré que les recommandations contenant des informations spécifiques au problème et à la solution étaient plus souvent acceptées que celles qui contenaient des informations vagues. Ainsi, pour influencer positivement le comportement et les perceptions des utilisateurs de système de recommandation, les concepteurs de message de recommandation peuvent modifier l'ordre de présentation du message, la quantité d'information présentée et la complexité de la recommandation.

La seconde étude menée est une revue de la littérature systématique qui permet de répondre à la deuxième question de recherche. Grâce à la collecte et l'analyse de nombreux articles sur les domaines de la conception de message et des systèmes de recommandation, les lacunes identifiées dans la littérature ont pu être comblées. Les connaissances sur la conception de messages de système de recommandation efficaces ont été mises en lumière par l'identification de 19 articles dans la littérature. Les résultats ont été regroupés en quatre groupes, à savoir les perceptions et le comportement des utilisateurs, la conception de l'information, le format et le contenu du message de recommandation et les explications de messages de recommandation. De plus, 9 articles possédant des résultats statistiques significatifs pouvant informer les praticiens de pratiques optimales pour la conception de message de système de recommandation ont été présentés dans cette revue de littérature.

De nouvelles opportunités de recherche ont également été identifiées suite à cette revue de littérature. En effet, les messages narratifs et les messages d'alerte de mise à jour de logiciel possèdent une conception de message efficace qui n'a pas encore été appliquée au domaine des systèmes de recommandation. Le premier permet au lecteur de mieux se projeter dans la situation qui lui est présentée, et ainsi être plus concerné par celle-ci. Le deuxième permet de montrer l'importance et l'urgence d'agir, ce qui pousse le lecteur à prendre une décision plus fréquemment et rapidement. D'autres opportunités de recherche ont été identifiées dans le domaine des messages d'information comme les indices typographiques, la longueur du message et le langage utilisé (affectif, subjectif ou objectif) qui permettent d'influencer les perceptions des lecteurs et de mieux organiser l'information pour réduire leurs efforts cognitifs et influencer leur décision.

## **Contributions**

D'un point de vue théorique, par les résultats qu'il présente, ce mémoire contribue à combler le manque dans la littérature sur la conception des messages de recommandation des systèmes de recommandation. Tout d'abord, une première étude menée sur des composants de conception de message de recommandation permet d'ajouter de nouvelles connaissances sur l'interaction humain-système par la démonstration de l'influence de plusieurs composants sur l'expérience utilisateur. Ces résultats viennent donc compléter les études antérieures en validant leurs conclusions sur l'effet des choix de conception de message de recommandation sur le comportement et les perceptions des utilisateurs [2, 5]. Par la suite, ce mémoire permet de regrouper les études pertinentes sur la conception des messages de recommandation et ainsi avoir une vision d'ensemble des connaissances sur le sujet, chose qui n'avait jusque-là jamais été faite. Enfin, grâce à l'identification d'opportunités de recherche à mener sur des composants de conception de message de recommandation, ce mémoire propose des recherches futures à mener pour poursuivre le travail accompli et ainsi poursuivre l'expansion de la littérature sur la conception de message de recommandation.

D'un point de vue pratique, ce mémoire permet aux concepteurs de système de recommandation d'obtenir une meilleure compréhension de l'impact de leurs choix de conception de message de recommandation sur l'expérience des utilisateurs. En utilisant les résultats présentés dans ce mémoire, les développeurs de système de recommandation pourront ainsi créer des messages de recommandation plus efficaces, demandant moins d'efforts cognitifs aux utilisateurs pour lire la recommandation et prendre une décision, ce qui augmentera les chances qu'ils acceptent la recommandation et utilisent à nouveau le système. De plus, les résultats proposent des lignes directrices aux concepteurs de message de recommandation. En effet, il leur est recommandé de présenter le problème avant la solution dans le message afin de réduire les efforts cognitifs du lecteur. Il est également préférable de donner des spécificités sur le problème et la solution afin d'augmenter les chances que la recommandation soit acceptée, d'autant plus que les détails d'informations [15] et les explications [12] sont appréciés par les utilisateurs de systèmes de recommandation, notamment lorsque ces dernières sont bien informées [13].

## **Limites et recherches futures**

Malgré sa contribution significative pour l'avancée de la littérature sur les systèmes de recommandation et la conception de message, certaines limites de ce mémoire peuvent être mises en lumière. En effet, l'étude présentée dans le chapitre 1 s'est concentrée sur des situations de problèmes logistiques où les participants devaient agir en tant que manager de restaurant. Bien que différents scénarios aient été présentés, le contexte était toujours le même. Ainsi, les recherches futures peuvent se concentrer sur divers contextes organisationnels afin de corroborer avec les résultats que nous avons présentés. De plus, l'échantillon de participants était plutôt faible, bien que cela n'impacte pas la validité des résultats de l'étude. Cependant, cette étude a été étendue par [16] via une étude en ligne menée à l'été 2020 auprès d'un plus grand échantillon (c.-à.-d. 843 participants, dont 614 de réponses valides) et de nouveaux facteurs étudiés (c.-à.-d. le surlignage en gras de mots-clés), permettant de passer outre cette limite et de valider les résultats présentés dans l'étude précédente.

Concernant la revue de littérature présentée dans le chapitre 2, celle-ci se concentrait sur la conception de message de recommandation dans un contexte organisationnel managérial, limitant ainsi la recherche d'articles sur ce domaine. Ainsi, de nouvelles recherches peuvent être menées pour étendre les résultats de cette étude à d'autres domaines. De plus, les résultats devront être testés dans différents contextes afin de les généraliser.

Pour conclure, la recherche sur la conception de message de recommandation doit être poursuivie. Ce mémoire a identifié trois domaines de la conception de message qui peuvent donner des idées de recherches à appliquer au domaine des messages de recommandation. Ces domaines concernent les messages narratifs, les messages d'alerte de mise à jour de logiciel et les messages d'information. Les travaux présentés dans l'article 1 et dans l'article en annexe 1 peuvent également être poursuivis, notamment

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## Annexes

Annexe 1 - Article publié à la conférence *SIGHCI 2020* en tant que co-auteur et poursuivant les recherches présentées dans le chapitre 1.

# Improving user acceptance of Recommender Systems and their recommendations: Effects of message design

## Completed Research

**Abstract.** Recommender Systems (RS) are used to improve users' decision quality and reduce decision-related effort. Prior research has focused on the impact of the system in its entirety on user's perceptions and behaviors, whereas limited attention has been given to the impact of message design on recommendation acceptance and system use intentions. A comprehensive model was developed and tested to explore the presentation choices (i.e., recommendation message characteristics) that influence users' confidence in and likelihood to accept recommendations generated by the RS. Findings indicate that problem and solution specificity of the recommendation increase both user intention and actual acceptance of recommendations while decreasing decision-making time; shorter decision-making time was also observed when structuring the recommendation in the problem-to-solution sequence. Finally, information specificity correlates with information sufficiency and transparency, confirming prior research support for links between user beliefs, user attitudes, and behavioral intentions. Implications for theory and practice are discussed.

**Keywords:** Decision Making, Recommender Systems, Use Intention, Recommendation Acceptance, Message Design, Information.

### 1. Introduction

With the massive increase of available data in recent years, many techniques and technologies have emerged to help businesses, workers, and customers process such data more efficiently.

Various Recommender Systems (RS) have been developed since the mid-1990s, and many sorts have been applied on a variety of tasks [1, 2, 3].

Due to the great opportunities and challenges for many domains (e.g., business, government, education and healthcare) numerous studies have been conducted on RSs [1, 2, 3], especially on the comprehension of their performance [4] their design implications [5, 6, 7] and the recommendation's techniques [3, 8]. Thus, significant research has addressed design implications at the system level [6, 7], but researchers and scientists have mostly disregarded the design of the interface [9]. In the rare instances where extant literature has focused on RS interface design, recommendations are produced and put forth following the collection of a user's interaction data and subsequently juxtaposed against attributes of artifacts stored in large repositories. Yet, to date, the impact of the recommendation message's presentation on the user's perception, attitude toward and behavior with the recommendation has been significantly understudied.

However, the system's design alone will not shape the user's perceptions of trust and likelihood to accept a recommendation. The nature of message content is also likely to play a significant role in affecting user's beliefs, attitudes and behaviors, particularly in the context of managerial decision-making [7]. So, as content elements and interaction elements (e.g., buttons) would jointly comprise the user's information processing of recommendations, a simultaneous and granular analysis of both design elements' effects is required. Hence, this study will explore which presentation approach of recommendation messages will increase the likelihood that users' RS trust and accept system-generated recommendations with minimal effort required. Specifically, our research aims to answer the following research questions:

1. What is the effect of message design (characteristics) on a user's beliefs about system-generated recommendations?
2. What is the effect of message design (characteristics) on a user's beliefs regarding the ease of use and usefulness of the RS?
3. What is the effect of message design (characteristics) on a user's attitudes and behavioral intentions toward the recommendations and the RS?
4. What is the effect of message design (characteristics) on a user's behaviors vis-à-vis decision-making time and the likelihood to accept system-generated recommendations?



## 2. Theoretical background

### 2.1 Recommendation systems

Extensive research has been performed on evaluating RSs in their entirety [6, 7, 10, 11]. RSs have progressed technologically to include machine learning and multi-modal interaction elements (e.g., Apple's Siri, Amazon's Alexa). Despite the technological progress and extensive research on the user experience of RSs as a whole, fundamental investigation into the optimal construction of a recommendation messages has not yet been comprehensively explored, as summarized in a conceptual piece on the state of RS literature:

“Explanations can vary, for example, with respect to (i) their length; (ii) the adopted vocabulary if natural language is used; (iii) the presentation format, and so on. When explanation forms are compared in user studies that are entirely different in these respects, it is impossible to understand how these details impact the results. Therefore, more studies are required to investigate the impact of these variables” [12, p. 425]. Hence, to create a more stable foundation for RS researchers and designers, studies are needed on the fine-grained presentation details of recommendation messages [12].

### 2.2 Message design in recommendation systems

A typical recommendation message contains two core components, i.e. a described problem and a suggested solution, which is a frequent rhetorical pattern used in technical academic writing [13]. For example, in the message “I noticed that you are running out of soft drinks. Shall I order more?”, the first sentence is the problem while the second is the solution. Within the problem and solution construct of recommendation messages, several elements can vary in their form, including Information Specificity - which can relate to either the problem and/or the solution - Information Sequence, Message Styling, and Situational Complexity; these are defined below.

**Problem specificity and solution specificity** is motivated by the functional principle of conveying information in a clear manner [14], and that people have a preference for descriptions with a higher level of detail [15]. **Information sequence**, presenting the problem, then the solution or the solution, then the problem is motivated by extant healthcare literature that indicates merit for both threat (problem)-then-solution and solution-then-problem in health communication messages [16]. **Situational complexity** consists of “simple, technically complicated, socially complicated, and complex situations” [17] and is inversely related to the amount of information

available [18], i.e. situational complexity arises when there is uncertainty about the available options in the specified context and how the available options intermingle with cognitive demand due to tensions between contradictory elements in the situation [19]. Lastly, recommendation **messages' (text) styling** (e.g., font-weight properties such as bold) may also affect user's perceptions, based on an empirical study on perceived professionalism in scientific question-and-answer forums [20]. Although text styling was not observed in [20] to have an impact, researchers urged for continued examination of typographical cues (i.e., bold, italics and underline) in other applications; in RS, where decision-making time is critical, styling cues such as bolding text could help the users focus on the most pertinent information at hand. This study extends prior literature [7] by taking a mixed-methods approach to explore the effects of message design (characteristics) on a user's experience with both the presented information and the RS.

### 3. Hypotheses development

Our hypotheses build on the *ResQue (Recommender systems' Quality of user experience)* model [7] and are partitioned into the following sets of endogenous variables: user beliefs regarding the recommendation message - **information sufficiency and transparency** - and the system - **perceived usefulness and perceived ease of use** - as well as user attitudes toward both the recommendation message and system (see Figure 1), and **behavioural outcomes** (see Figure 2). In what follows, we will present our hypotheses for each of these sets of dependent variables.

#### 3.1 Information sufficiency and information transparency

Information transparency is an aggregate user assessment of three dimensions: clarity, disclosure, and accuracy [21]. Changes in problem and solution specificity are likely to yield changes in user perceptions of the clarity, disclosure, and accuracy of the information in the recommendation message, and by extension perceived information transparency as a whole. Linking the latter to message characteristics, it is plausible that user perceptions of information transparency will be positively affected by (i) changing the message (text) **styling** by bolding key parts of the message (i.e. bolding the object being discussed), (ii) **sequencing** the information presentation as problem-then-solution (rather than the reverse), and (iii) communicating simple rather than **complex(ity) situations**.

Information sufficiency refers to whether the amount of content presented to the user is enough for the user to understand the information, and in some cases to act on it [22]. By varying the degree of **specificity** of the information (i.e., problem and/or solution) and the **situational complexity**, the amount of information available and the way the information is conveyed to the user, user perceptions of information are likely to be augmented. Similarly, choices regarding message (text) **styling** and information **sequence** may make it easier for the user to understand the presented information, hence a change in information sufficiency may also be observed.

Thus, the following effects of a message's characteristics are hypothesized:

H1: Problem specificity positively impacts information sufficiency

H2: Problem specificity positively impacts information transparency

H3: Solution specificity positively impacts information sufficiency

H4: Solution specificity positively impacts information transparency

H5: Text styling positively impacts information sufficiency, such that styled (bold) text is associated with greater perceived information sufficiency than plain text.

H6: Text styling positively impacts information transparency, such that styled (bold) text is associated with greater perceived information transparency than plain text.

H7: Information sequence affects information sufficiency, such that a problem-to-solution sequence positively impacts information sufficiency

H8: Information sequence affects information sufficiency, such that a problem-to-solution sequence positively impacts information transparency

H9: Situational complexity negatively impacts information sufficiency

H10: Situational complexity negatively impacts information transparency

### **3.2 Perceived usefulness and perceived ease of use**

User attitudes are affected by their beliefs regarding a message's information properties [7]. For example, information sufficiency has been shown to impact the perceived usefulness of RS [7, 23]. Also, the sufficiency of the information may depend on its quality [24, 25, 26, 27] and the greater the quality of the information presented, the more useful it was found to be [28]. Thus, the following effects of a recommendation message's characteristics are hypothesized:

H11: Text styling positively affects perceived usefulness, such that recommendation messages with styled (bold) text are associated with greater perceived usefulness of the RS than plain text.

H12: Information sequence affects perceived ease of use, such that a problem-to-solution sequence positively impacts perceived ease of use of the RS

H13: Information sufficiency positively impacts perceived usefulness of the RS

H14: Information transparency positively impacts perceived ease of use of the RS

### **3.3 System and recommendation outcomes**

For an RS to be successful vis-a-vis its adoption, users should have confidence in the system-generated recommendations and trust the system [12]. Transparency has an important role in users' confidence in recommendations as it may encourage or deter users' trust in a system [29, 30] and recommendations perceived as transparent by the users increase their confidence [31]. User perceptions such as ease of use and usefulness are both positively related to each other [10, 32, 33, 34] and to system attitudes such as those toward the system's use and system satisfaction [10, 28, 33, 34, 35]. Moreover, confidence in the system positively influences trust in the system [36] and the user's behavioral intentions with the system, including the intention to accept a system-generated recommendation [28]. In the context of I.S. use, trust has been shown to positively affect satisfaction [37], which in turn has been shown to encourage users to use the system [38, 39].

Hence, the following hypotheses are proposed:

H15: Information transparency positively impacts recommendation confidence

H16: RS ease of use positively impacts its usefulness

H17: RS ease of use positively impacts user satisfaction

H18: RS usefulness positively impacts user satisfaction

H19: RS usefulness positively impacts RS trust

H20: RS usefulness positively impacts RS confidence

H21: Recommendation confidence positively impacts recommendation acceptance intentions

H22: Recommendation confidence positively impacts RS confidence

H23: RS confidence positively impacts RS trust

H24: RS confidence positively impacts recommendation acceptance intentions

H25: RS trust positively impacts RS satisfaction

H26: RS satisfaction positively impacts RS use intentions

### 3.4 Behavioral outcomes

Both the content and format of a recommendation may influence a user's beliefs and attitudes [6, 7], and in turn affect behavioral intentions [6, 7, 10, 12] and actual behaviors. Providing explanations regarding recommendations may make the decision faster for users and drive them to better choices [40, 41]. Also, the way messages convey problems faced and related information may impact user's perceptions and decisions [42, 43, 44]. Thus, the following hypotheses are proposed:

HB1: Problem specificity will negatively impact user's decision-making time (i.e. less time)

HB2: Solution specificity will negatively impact user's decision-making time

HB3: Text styling will affect user's decision-making time, such that styled (bold) text will be associated with shorter decision-making time than plain text

HB4: Information sequence will affect user's decision-making time, such that problem-to-solution sequencing will be associated with less time than solution-to-problem

HB5: Situational complexity will positively impact user's decision-making time (i.e., more time)

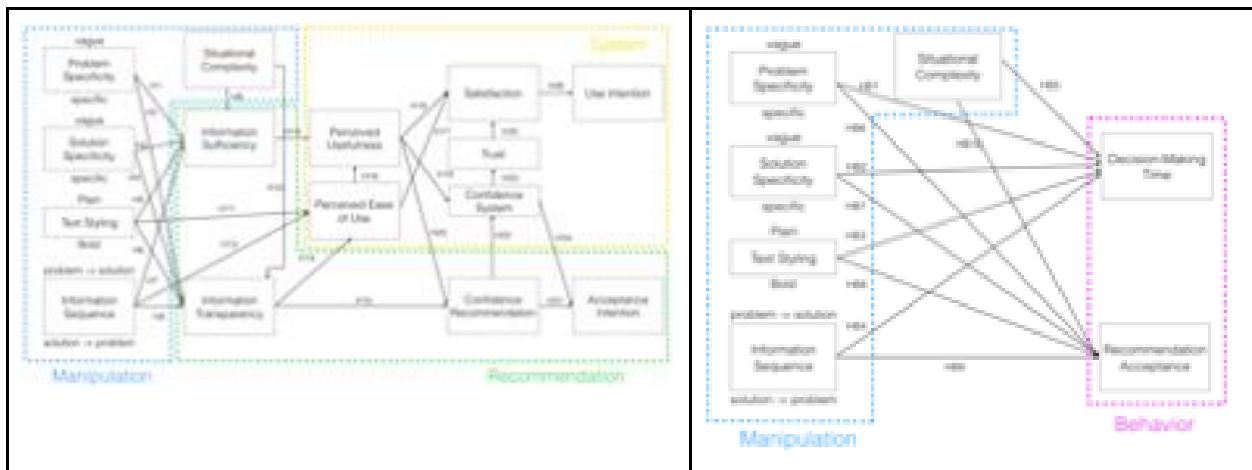
HB6: Problem specificity will positively impact user's recommendation acceptance rate

HB7: Solution specificity will positively impact user's recommendation acceptance rate

HB8: Text styling will affect user's recommendation acceptance, such that styled (bold) text will be associated with greater recommendation acceptance rate than plain text

HB9: Information sequence will affect user's recommendation acceptance rate, such that problem-to-solution recommendations will be associated with a greater acceptance rate

HB10: Situational complexity will negatively impact user's recommendation acceptance rate



**Figure 1. Proposed research model, self-reported**

**Figure 2. Proposed research model, behavioral**

### **3. Methodology**

#### **3.1 Pilot study**

A pilot study was conducted with three aims: (i) to gauge the appropriateness of the stimuli, (ii) collect attentional and psychophysiological data to inform the main experiment, and (iii) offer preliminary support for the hypothesized relationships. An experiment with a within-subjects research design involving four factors, each with two levels (i.e., 2x2x2x2) was conducted [45]. The pilot study involved fewer factors (i.e., 4 instead of 5) and by extension fewer conditions (i.e., 16 vs. 32) and stimuli (i.e., 48 vs. 96), as well as fewer participants (n=6 vs. n=614) than the study presented below, which also used a different data collection approach (i.e., lab-based pilot vs. Amazon MTurk).

#### **3.3 Experimental Design**

An experiment was conducted entailing a counterbalanced mixed (between-within) subjects design involving five (5) factors (i.e., counterbalanced 2x2x2x2x2 for a total of 32 conditions), tested via three (3) stimuli per condition (i.e., 96 stimuli). Factors involved (i) Information Sequence (Problem-to-Solution vs. Solution-to-Problem); Information Specificity comprises (ii) Problem Specificity (Vague vs. Specific) and (iii) Solution Specificity (Vague vs. Specific); (iv) Decision Complexity (Simple Decision vs. Complex Decision) and (v) Text Styling (Plain vs. Bold). In order to reduce the time needed to complete a session, the study was divided into eight groups, each comprising 4 of the 32 conditions (corresponding to 12 stimuli per participant), and required approximately 15 minutes to complete.

#### **3.4 Participants**

Participants were recruited on the online platform Amazon Mechanical Turk (MTurk). To participate in the study, these "Turkers" were screened for a minimum HIT approval rate of 90% and being located in the U.S. Participants were only allowed to complete a single session. Recruiting a minimum of 100 participants for each of the eight groups (i.e., per 4 conditions) resulted in a total of 843 people being recruited in our study, of which 614 yielded valid responses

used for subsequent analysis (with minimum of 70 responses per group). 229 responses were not used, as participants either failed the attention check (n=207) or were unable to confirm their participation (n=22). Participants were compensated US\$1.40 for their time.

### **3.5 Experiment procedure, stimuli and measurement**

The experiment involved a scenario, where participants assumed the role of a restaurant manager in charge of inventory and were required to make logistics decisions regarding *inventory replenishment* and/or order *delivery rerouting* based on the recommendations proposed by the RS. RS messages themselves varied in their presentation according to the abovementioned five factors that were being manipulated. Successive text-only messages showing situations (i.e., a problem and an RS-recommended solution) were used as stimuli. Two buttons («ACCEPT» and «DETAILS ») corresponding to the two decision options available to users were shown below each message (see Figure 3). Participants had to either *confirm* the recommendation as-is if they felt that the recommendation was appropriate for the shown situation, or request additional *details* if they felt otherwise. The details themselves would not be shown to the participant (which was indicated to them in the instructions), as doing so would introduce additional factors in the study that are beyond the scope of the research questions. Participants entered their choice by using a keyboard and were not able to navigate backwards.

Two behavioral measures were collected automatically by the experiment platform used (described further below) at this point: (i) the time taken to decide (i.e., from stimulus exposure to choice entry), and (ii) the choice entered. After each choice, three (3) questions regarding the recommendation message were asked of the participants to measure the perceived sufficiency and transparency of the information and the user's confidence in the recommendation. After evaluating three (3) consecutive recommendation messages, seven (7) questions were asked regarding RS-related perceptions including ease of use, usefulness, confidence, and trust, as well as participants' satisfaction with the RS, and their intentions to use the RS and/or accept RS-generated recommendations (see Figure 4 for an example). The questionnaire consisted of single-item scales adapted from previously validated scales [7, 10] measuring constructs reflected in the proposed research model. Answers were provided along a 7-point Likert scale from extremely disagree (1) to extremely agree (7). To respond, participants could either click on the scale or enter the corresponding number on the keyboard. Constructs were measured through the use of adapted

(reduced) single-item constructs [7], a choice that was made given the significant duration and thus cognitive burden of the experiment, as shown in Table 1.

| <i>Recommendation Message</i>      |  | <i>Recommendation System</i> |   |
|------------------------------------|--|------------------------------|---|
| Sufficiency                        | The information provided was sufficient for me to make a decision to accept the recommendation | Ease of Use                  | The recommender system was easy to use                            |
|                                    |  | Usefulness                   | The system gave me good recommendations                           |
| Transparency                       | I understood why this recommendation was made to me  | Confidence                   | I am convinced of the suggestions recommended to me by the system |
| Confidence                         | I am convinced of the recommendation made to me  | Trust                        | The recommender system can be trusted                             |
| Intention to Accept Recommendation | I would accept the next recommendation   | Satisfaction                 | I am satisfied with the recommender system                        |
|                                    |  | Use Intention                | I would use this recommender system again                         |

**Table 1. Measurement items (self-reported)**

|   |  |
|---|--|
| <p>I noticed that you only have 10 bottles of Coca-Cola left in stock. I recommend ordering additional soft drinks. Shall I proceed with the order?</p> <p style="text-align: center;"> <input type="button" value="ACCEPT"/> <input type="button" value="DETAILS"/> </p> | <p>The information provided was sufficient for me to make a decision to accept the recommendation.</p> <p style="text-align: center;"> <small>Extremely Disagree</small>   <small>Disagree</small>   <small>Neutral</small>   <small>Agree</small>   <small>Extremely Agree</small> </p> |
| <p><b>Figure 3. Example of study stimulus</b></p>   | <p><b>Figure 4. Example of Likert-scale question</b></p>   |



### 3.6 Apparatus

Three web-based systems were used to conduct this study. First, CognitionLib (BeriSoft, Inc, Redwood City, Ca) is a free open source community for ERTS Scripts, providing an online editor, and is being used by hundreds of academic institutions to create cognitive task paradigms and to set up cognitive experiments. Using the ERTS language, we were able to code all of the requisite elements for the experiment (all as black-and-white to control for the effect of color), including the stimuli as text messages, the survey questions, and the response scales. When the scripts were coded, they were imported into Cognition Lab (BeriSoft, Inc, Redwood City, Ca), a web-based runtime environment that hosts experiments. The third platform used was Amazon's MTurk (Amazon Inc, Bellevue, WA), a crowdsourcing marketplace that connects business to individuals who can perform their tasks virtually, and where participants were recruited from.

## 4. Analysis and Results

Data were analyzed by means of a cumulative logistic regression with random intercept modeling the probability of having lower values. To analyze the effect on decision-making time, the method employed was linear regression with random intercept for participants. To analyse for the effects on the decisions made by the participants, a logistic regression with random intercept was used, modeling the probability that response type is "ACCEPT" (i.e., accept the recommendation). In what follows, results from the analyses corresponding to each of the study's three research questions are presented below.

*RQ1. What is the effect of message design (characteristics) on a user's beliefs about system-generated recommendations?*

**Information specificity** impacted information *sufficiency* (problem-specificity effect H1:  $b=.3039, p<.0001$ ; solution-specificity effect H3:  $b=.3714, p<.0001$ ) and information *transparency* (problem-specificity effect H2:  $b=.1814, p<.0001$ ; solution-specificity effect H4:  $b=.1499, p<.0011$ ). On the other hand, the remaining hypotheses corresponding RQ1 were not supported, i.e. regarding the effect of text **styling** on information *sufficiency* (H5:  $b=.0254, p=.8754$ ), information *transparency* (H6:  $b=.1729, p=.2697$ ), and the effect of **information sequence** on information *sufficiency* (H7:  $b=-.0357, p=.6756$ ), information *transparency* (H8:  $b=.0608, p=.4865$ ), as well as **situational complexity** was not observed to have a significant effect on

information *sufficiency* (H9:  $b=.0672$ ,  $p=.6804$ ) and information *transparency* (H10:  $b=.191$ ,  $p=.2258$ ).

*RQ2. What is the effect of message design (characteristics) on a user's beliefs regarding the ease of use and usefulness of the RS?*

The relationship between text **styling** (bolding) and perceived *ease of use* was not supported (H11:  $b=0.1327$ ,  $p=.5836$ ), and **information sequence** was not found to significantly impact perceived *ease of use* (H12:  $b=.0486$ ,  $p=.7519$ ). On the other hand, significant effects of *information sufficiency* on *usefulness* (H13:  $b=1.6193$ ,  $p<.0001$ ) and *information transparency* on *ease of use* (H14:  $b=1.3461$ ,  $p<.0001$ ) were shown.

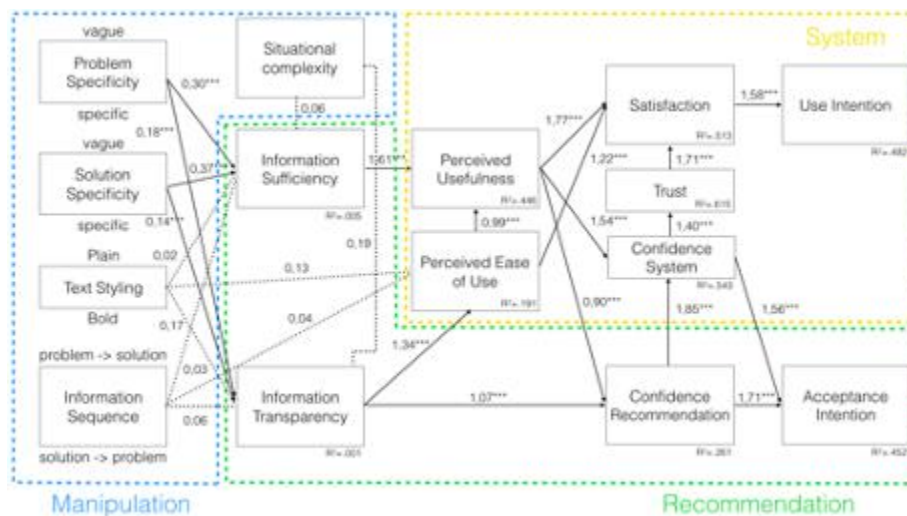
*RQ3. What is the effect of message design (characteristics) on a user's attitudes and behavioral intentions toward the recommendations and the RS?*

**Information transparency** positively impacted *recommendation confidence* (H15:  $b=1.0743$ ,  $p<.0001$ ), the latter also being affected by *RS usefulness* (H20:  $b=.9111$ ,  $p<.0001$ ) and in turn positively affecting the *intention to accept the recommendation* (H21:  $b=1.715$ ,  $p<.0001$ ), which was also affected by *RS confidence* (H24:  $b=1.5625$ ,  $p<.0001$ ). System *ease of use* positively impacted both system *usefulness* (H16:  $b=.993$ ,  $p<.0001$ ) and system *satisfaction* (H17:  $b=1.2254$ ,  $p<.0001$ ). *Usefulness* positively impacted system *satisfaction* (H18:  $b=1.7252$ ,  $p<.0001$ ) and system *confidence* (H19:  $b=1.5487$ ,  $p<.0001$ ). *Recommendation confidence* positively affected system *confidence* (H22:  $b=1.8567$ ,  $p<.0001$ ), which positively impacted system *trust* (H23:  $b=1.402$ ,  $p<.0001$ ) and finally system *satisfaction* (H25:  $b=1.7122$ ,  $p<.0001$ ). Lastly, system *satisfaction* positively impacted the *intention to use the recommender system* (H26:  $b=1.5809$ ,  $p<.0001$ ). Lastly, all system-level mediating constructs demonstrated great explanation of the variance in their respective DVs, including 45.2% in *recommendation acceptance intention* at 45.2% and 49.2% in *system use intention*, as shown in the model (see Figure 5a).

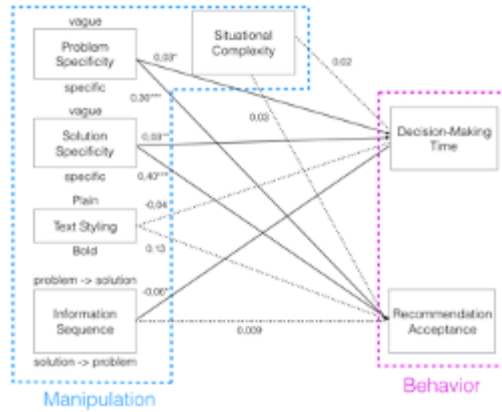
*RQ4. What is the effect of message design (characteristics) on a user's behaviors vis-à-vis decision-making time and the likelihood to accept system-generated recommendations?*

**Problem specificity** had a significant positive effect on decision-making time (HB1:  $b=.0337$ ,  $p<.05$ ), as did **solution specificity** (HB2:  $b=.03746$ ,  $p<.01$ ). In contrast, **information sequence**

from *problem-to-solution* reduces *decision-making time* (HB4:  $b=.06418$ ,  $p<.05$ ). On the other hand, text **styling** and **situational complexity** do not impact *decision-making time* (HB3:  $b=.04046$ ,  $p=.4545$  and HB5:  $b=.02226$ ,  $p=.6831$ ). Moreover, both **problem specificity** (HB6:  $b=.3006$ ,  $p<.0001$ ) and **solution specificity** (HB7:  $b=.4073$ ,  $p<.0001$ ) will increase *recommendation acceptance*, whereas text *styling*, *information sequence* and *situational complexity* have no influence on the latter (HB8:  $b=.1392$ ,  $p=.2674$  ;HB9:  $b=.009365$ ,  $p=.9183$  and HB10:  $b=.03508$ ,  $p=.7815$ ). In addition to the observed effect of information specificity on increasing decision-making time, it was also observed that users were significantly more likely to *accept the recommendation* if the messages stated *specific* (rather than vague) *problems* (HB6:  $b=.3006$ ,  $p<.0001$ ) and *specific* (rather than vague) *solutions* (HB7:  $b=.4073$ ,  $p<.0001$ ). *Information sequence*, *text styling* and *situational complexity* had no significant effects on user's behaviors vis-a-vis recommendation acceptance (HB8:  $b=.009365$ ,  $p=.9183$ ; HB9:  $b=.1392$ ,  $p=.2674$  and HB10:  $b=.03508$ ,  $p=.7815$ ). All behavioral results are shown in Figure 5b. Lastly, a post-hoc analysis further reinforced the favorable effect of information specificity: specific recommendation messages were significantly longer ( $p<.05$  all cases) in character count, for both problem- and solution-specificity, whether counting with spaces or without spaces; yet, the decision-making time on a per character basis was significantly lower ( $p<.001$  all cases).



**Figure 5a. Validated research model (self-reported data)**



**Figure 5b. Validated research model (behavioral data)**

*Note: Solid lines represent statistically supported relationships; dashed lines were not supported*

## 5. Discussion and Conclusion

This empirical study investigated the effects of message design on user behaviors vis-à-vis the likelihood to accept system-generated recommendations and the time taken to decide, as well as user attitudes toward the recommendation and the RS. The study's findings provide clear, evidence-based answers to the four research questions that initially motivated the paper. The answers should be of interest to academic researchers, designers of RS, and current or potential providers as well as users of RS, but also generalize to other use contexts and domains.

### 5.1 Contributions to Research

Prior research on RS interface design has focused mostly at the system level. Thus, the impact of the recommendations message's design on the user's interaction with and behavior toward the recommendation and the RS more broadly have not been studied. This paper has attempted to extend RS literature by identifying new factors of message design that may impact the likelihood that users accept system-generated recommendations as well as their intention to use the recommender system. Five (5) factors were manipulated (i) Information Sequence (Problem-to-Solution vs. Solution-to-Problem); Information Specificity comprising (ii) Problem Specificity (Vague vs. Specific) and (iii) Solution Specificity (Vague vs. Specific); (iv) Decision Complexity (Simple vs. Complex) and (v) Text Styling (Plain vs. Bold). Findings reveal that the specificity of the information embedded in the recommendation message has a positive influence on the user's

perceptions of information sufficiency and information transparency (i.e., information sufficiency and information transparency were considered to be higher when the information regarding either problem and/or the solution information were specific rather than vague). Information specificity also impacted users' behaviors. Higher information specificity increases the likelihood that the user will accept the recommendation (vis-a-vis the measured acceptance intention), and it offers the additional benefit for the user needing less time to make the decision. Findings also reveal that information sequence does not have an impact either on user perceptions of information transparency or information sufficiency rather was found to reduce decision-making time when the information was presented in the problem-to-solution sequence. Neither text styling nor decision complexity were found to affect information transparency or information sufficiency. Focusing on the impact of users' beliefs (i.e., perceived usefulness and perceived ease of use) and users' attitudes (i.e., confidence in the recommendation and the RS, as well as trust and satisfaction with the RS), the study confirms that user's beliefs influence users' attitudes, which motivate the intentions to accept the recommendation and use the RS.

## **5.2 Contributions to Practice**

This study has improved the understanding of the impact of message design on the users' intention to accept a recommendation proposed to them and the intention to use the RS that provided the recommendation. Study findings inform RS designers in how to construct (design) system-generated recommendation messages in order to either minimize the time needed by the user to make a decision and/or to accept the recommendation or the system at large, for example, if the RS is used during a demo or trial period. Results showed that information sequence helps reduce decision-making time. Indeed, when the problem was presented before the solution, users experienced less cognitive load and spent less time before making a decision than when they were shown recommendations consisting of the solution first and followed by the problem. Hence, an emergent best practice emerges for RS designers to structure the content of recommendation messages in a manner progressing from the description of the problem, presentation of supporting information, and concluding with the recommended solution. However, and extending from the scenario and focus of this study on new RS users, it is plausible that as user trust in the system-generated recommendations increases over time (i.e., during the continued use of the RS), users may eventually prefer to quickly review the recommendation and approve it without processing

the underlying problem and supporting information. In this special use case, the reverse sequence (i.e., solution-to-problem) may be preferred by the user; if so, a second recommendation might be to allow for the user to specify the recommendation message's construction. This would be feasible if at the system level such recommendations are generated not as Event-to-Outcome rules, where recommendations are designed in full a priori for each exception event alert specifically, but are instead generated by combining message elements that are marked-up or tagged according to a library identifying each content element by its property (e.g., product name; product quantity; exception event; delivery mode; etc.) and synthesized according to the exception event. However, before formally putting forth such a recommendation, additional research would be needed so as to obtain support for this anticipated utility.

Another recommendation emerging from this study's findings is for RS designers to embed sufficient detail regarding both the problem and the solution, so as to boost perceptions of information transparency and information sufficiency. Doing so would result in a significantly more frequent acceptance of system-generated recommendations, thereby saving users time as they would not need to delve deeper (e.g., by clicking on 'details') before making a decision.

### **5.3 Limitations and Opportunities for Future Research**

Despite the scenario used in this study and the validation of the two levels of situational complexity through a manipulation check prior to their use, Situational Complexity was not found to have any effects on either user beliefs or behaviors. This was an unexpected finding as the factor and its two levels were tested through two rounds of manipulation checks involving (i) nine (9) participants prior to the start of this study, who reported unanimously that the high complexity situation was indeed more complex than the low complexity situation, based on the information presented in the recommendation messages, and (ii) 30 participants responding to the question "How challenging was the situation you were faced with? (Simple = 1... 5=Complex). It is plausible that while the High Complexity stimuli were indeed significantly higher than the Low Complexity stimuli, given the brevity of the messages, they were not sufficiently high so as to induce significantly higher levels of cognitive load (and by extension, time needed), more negative emotions (either valence or arousal), and/or worse beliefs and attitudes. Future research that aims to inform RS design according to situational complexity should first explore for situational complexity 'thresholds'

above which effects are observed in regard to users' cognition, emotion, or behavior, and design stimuli accordingly.

While this study undertook an investigation of an extended research model, observing the variance extracted in the mediating and dependent variables, exploring the effects of additional factors on message- and system-level outcomes is needed. Other factors that can be identified in the literature and could be tested in future studies include message detail, message length, the use of subjective versus objective language, personification, affective language use, personality and complicated language [46, 47, 48, 49, 50, 51, 52, 53].

Building upon results from this experiment, future works should also involve triangulated attentional and physiological measurements to gain a richer understanding of the phenomena. Using eye-fixation related potential [54], future research could explore the cognitive mechanism involved in user decision making at the moment of the recommendation's consideration. Lastly, future research should explore potential interactions between message characteristics, e.g. revisiting situational complexity, such user perceptions may in fact be outcomes of interactions with specificity and information sequence as they are inherently all dimensions that add to or reduce message complexity, thus revealing that situational complexity is a second-order construct comprised of various message characteristics that add to complexity. Finally, an extended study can also be performed with the three (3) significant factors (i.e., problem information specificity, solution information specificity and information sequence) to find the best combination for an optimal presentation of recommendation messages.

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