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Développement et application d'un modèle de simulation à base d'agents

pour l'analyse de stratégies de logistique inverse :

une étude de cas sur les bouteilles de vin au Québec

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Thèse présentée en vue de l'obtention du diplôme de *Philosophiæ Doctor*

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POLYTECHNIQUE MONTRÉAL

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Cette thèse intitulée :

**Développement et application d'un modèle de simulation à base d'agents
pour l'analyse de stratégies de logistique inverse :
une étude de cas sur les bouteilles de vin au Québec**

présentée par **Alexandre LABELLE**

en vue de l'obtention du diplôme de *Philosophiæ Doctor*

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DÉDICACE

À

Perle,

Orcades,

Charles,

Victoria,

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&

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&

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RÉSUMÉ

Les réseaux de distribution visent à fournir les bons produits aux consommateurs au bon moment et au bon endroit. Lorsque les consommateurs retournent ces produits, un autre type de réseau logistique intervient. Cette fonction de retour des produits en fin de vie est appelée "logistique inverse". Une caractéristique essentielle de ces réseaux de logistique inverse est que leurs flux de matières dépendent souvent de l'action volontaire du consommateur. Par conséquent, le succès d'une stratégie de collecte des produits en fin de vie dépend de la capacité à comprendre les facteurs qui influencent le comportement des consommateurs afin d'anticiper le taux de collecte de ces produits en fin de vie dans des lieux spécifiques. Cependant, il n'existe pas d'outil ou de méthodologie établis pour évaluer l'impact des décisions des consommateurs sur les flux de matériaux de la logistique inverse. Par conséquent, cette thèse propose un outil de simulation à base d'agents pour analyser la performance d'un réseau de logistique inverse en tenant compte de d'une part de la localisation des points de collecte, mais aussi des caractéristiques sociodémographiques, des attitudes envers l'environnement ainsi que des profils de consommation de la population. Plus spécifiquement, cette thèse présente la configuration, la calibration et la validation du modèle développé à une étude de cas du programme de collecte volontaire de bouteilles de vin dans la région du Val-Saint-François au Québec. Comme ce programme de collecte a été officiellement lancé en 2019, deux échantillons empiriques ont été obtenus pour tester la validité du modèle et étudier comment les interactions sociales, telles que le bouche-à-oreille, contribuent au succès du programme de collecte. Le premier échantillon représente la quantité de verre collectée au cours des 26 dernières semaines de 2019, tandis que le second couvre les 13 premières semaines de 2020. Ayant observé une augmentation des taux de collecte entre 2019 et 2020, le bouche-à-oreille a été introduit dans le modèle pour expliquer ce phénomène. Les expériences démontrent que le modèle est effectivement valide avec l'inclusion de la diffusion de la sensibilisation au programme, car les résultats des simulations sont statistiquement cohérents avec les données empiriques. Les expériences mettent également en évidence la capacité de l'outil à fournir des informations utiles pour supporter la conception de stratégies de collecte qui maximisent les taux de retour et minimisent les coûts d'installation et d'exploitation en optimisant le nombre et l'emplacement de points de collecte dans le réseau de logistique inverse.

ABSTRACT

Distribution networks aim to get the right products to consumers at the right time and in the right place. When consumers return these products, another type of logistics network is involved. This function of returning end-of-life products is referred to as reverse logistics. A critical characteristic of these reverse logistics networks is that their material flows are often dependent on the voluntary action of the consumer. Therefore, the success of an end-of-life collection strategy depends on the ability to understand the factors that influence consumer behavior in order to anticipate the collection rate of end-of-life products at specific locations. However, there is no established tool or methodology for assessing the impact of consumer decisions on reverse logistics material flows. Consequently, this thesis proposes an agent-based simulation tool to analyze the performance of a reverse logistics network, taking into account not only the location of collection points, but also the socio-demographic characteristics, environmental attitudes and consumption profiles of the population. More specifically, this thesis presents the configuration, calibration and validation of the model developed to a case study of the voluntary wine bottle collection program in the Val-Saint-François region of Quebec. As this collection program was officially launched in 2019, two empirical samples were obtained to test the validity of the model and study how social interactions, such as word-of-mouth, contribute to the success of the collection program. The first sample represents the amount of glass collected during the last 26 weeks of 2019, while the second covers the first 13 weeks of 2020. Having observed an increase in collection rates between 2019 and 2020, word-of-mouth was introduced into the model to explain this phenomenon. The experiments demonstrate that the model is indeed valid with the inclusion of the program's awareness diffusion, as the simulation results are statistically consistent with the empirical data. The experiments also highlight the tool's ability to provide useful information to support the design of collection strategies that maximize return rates and minimize installation and operating costs by optimizing the number and location of collection points in the reverse logistics network.

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LISTE DES SIGLES ET ABRÉVIATIONS

ABMS	<i>Agent-Based Modeling and Simulation</i>
GMR	Gestion des matières résiduelles
MRC	Municipalité Régionale de Comté
MWMS	<i>Municipal Waste Management System</i>
RAM	<i>Relative Agreement Model</i>
SDDB	Saint-Denis-De-Brompton
SEM	Structural Equation Modeling
TBP	<i>Theory of Planned Behavior</i>
VSF	Val-Saint-François

CHAPITRE 1 INTRODUCTION

L'optimisation des ressources est un concept fondamental du génie industriel. Considérant que toutes les matières extraites par l'activité humaine ont un potentiel d'utilisation et de réutilisation optimal, enfouir ou détruire ces ressources prématurément constitue un gaspillage à tous les niveaux. Toutefois, force est de constater que globalement, l'utilisation des ressources naturelles est loin d'être optimale.

“Rising material extraction has shrunk global circularity: from 9.1% in 2018, to 8.6% 2020, and now 7.2% in 2023. This leaves a huge Circularity Gap: the globe almost exclusively relies on new (virgin) materials.”

-Circle Economy (2023). The Circularity Gap Report 2023

L'économie circulaire, tel que définie par la fondation Ellen MacArthur, vise à assurer le renouvellement de la *biosphère* et optimiser l'utilisation des ressources naturelles pour ralentir, voir freiner, leur dissipation dans la *technosphère*; de manière à assurer une durabilité des activités économiques actuelles et futures compte tenu des ressources limitées de la Terre (MacArthur, 2013).

Afin d'avoir des ressources qui circulent en boucle dans l'économie, ces dernières doivent d'abord et avant tout être collectées. Toutefois, dans les contextes où les flux de matières sont principalement dictés par les décisions des consommateurs, comme c'est le cas pour les bouteilles de vin et les matières résiduelles municipales en général, l'économie circulaire est complexe à mettre en œuvre. Effectivement, une étude publiée en 2016 a estimé que parmi les 1.47 milliards de tonnes de déchets solides générés au niveau municipal dans le monde, seulement 84% est collecté et de ce pourcentage, un faible 15% est recyclé (Zaman, 2016). Ce qui n'est pas recyclé se retrouve incinéré ou enfouis, soit deux fins de vies où la matière se retrouve dans un prématurément état non-valorisable d'un point de vue de circularité. Lorsqu'une matière n'est plus disponible pour être réutilisée dans la technosphère, c'est-à-dire disponible pour l'activité humaine, on dit que cette dernière est dissipée (Charpentier Poncelet et al., 2022).

Ainsi, pour éviter la dissipation des ressources, des stratégies de circularité doivent être mises en œuvre efficacement. Alors que la logistique en amont a pour but d'amener un produit d'un producteur à un consommateur; la logistique en aval (ou logistique inverse) a plutôt comme objectif

de faire revenir les produits post-consommation aux producteurs ou aux recycleurs qui pourront ensuite faire recirculer les matières en boucle dans l'économie.

Un exemple de stratégie de logistique inverse est l'implantation d'une consigne sur les bouteilles de vin au Québec prévue pour 2024. L'idée est de permettre et inciter les québécois à rapporter leurs bouteilles de vin vides à des endroits désignés, plutôt que de les mettre à la poubelle ou dans la collecte sélective; afin de faciliter le recyclage du verre et optimiser son utilisation dans l'économie québécoise. Toutefois, beaucoup de questions se posent dans la conception d'une telle stratégie :

- Quel devrait être le montant de la consigne?
- Combien de points de collecte devrait-on avoir?
- Où ces points de collecte devraient être positionnés?
- Quelle devrait être la capacité de ces points de collectes?
- Est-ce que nous avons besoin de plusieurs types de points de collectes?

Malheureusement, répondre à ces questions nécessite d'avoir une bonne compréhension du comportement des consommateurs à l'égard de leurs produits en fin de vie. Actuellement, aucune méthode ou outil ne permet d'anticiper précisément et de façon spécifique (ex., géolocalisée) ce genre de comportements. Par exemple, lorsque Opération Verre-Vert a lancé en 2019 le programme de dépôt volontaire pour les bouteilles de vin dans la MRC du Val-Saint-François, où on compte plus de 30 000 habitants, le taux de retour pour le programme avait été estimé à 40% en 2018 par Recyc-Québec (Deloitte, 2018), soit l'organisme gouvernemental responsable de la récupération et du recyclage au Québec. Toutefois, après 8 mois d'opérations, les taux de collecte des bouteilles de vin avaient atteint 60%. Ce qui correspond à une sous-estimation de 33% et ce, dans un contexte sans incitatif monétaire comme la consigne.

1.1 Objectifs de recherche

La modélisation et la simulation à base d'agent est une technologie très prometteuse qui commence à faire ces preuves dans le domaine de l'économie circulaire. En effet, sa capacité à modéliser et étudier les comportements individuels et les interactions d'entités diverses dans des univers virtuels en fait une technologie particulièrement bien adaptée à la problématique d'estimation des flux de logistique inverse induits par les comportements des consommateurs.

L'objectif général de cette thèse est donc de développer un modèle de simulation à base d'agents détaillé du comportement des consommateurs à l'égard de leurs produits en fin de vie afin de supporter la conception de stratégies de logistique inverse. Pour tester l'applicabilité du modèle à un cas réel, une étude de cas a été réalisée sur la fin de vie des bouteilles de vin au Québec et des échantillons de données empiriques du programme de dépôt volontaire de la MRC du Val-Saint-François ont été obtenus. Afin de parvenir à l'objectif de recherche, trois sous-objectifs ont été définis :

1. Développer un modèle général permettant de simuler le comportement des consommateurs concernant le choix de fin de vie de leurs produits (contribution #1);
2. Configurer le modèle général du comportement des consommateurs concernant la fin de vie de leurs bouteilles de vin pour la population québécoise moyenne (contribution #1);
3. Évaluer les besoins en données et les limites du modèle à travers une étude de cas et un échantillon de données empiriques (contribution #2);

Suite à l'analyse statistique d'un second échantillon empirique, les deux sous-objectifs suivants ont été ajoutés :

4. Implémentation d'interactions sociales (bouche-à-oreille) dans le modèle (contribution #3);
5. Évaluer la capacité du modèle à simuler l'évolution dynamique de la performance du système de collecte dans sa phase de lancement (contribution #3).

1.2 Structure de la thèse

Le chapitre 2, présente une revue de littérature pertinente au développement de modèles de simulation à base d'agent du comportement des consommateurs à l'égard de leurs produits en fin de vie. Le chapitre 3 présente l'organisation générale de la thèse et la cohérence des articles scientifiques qui la compose. Les chapitres 4 à 6 sont les articles scientifiques reliés à la présente thèse. Le 7^e chapitre contient une brève discussion générale qui porte sur l'ensemble des travaux réalisés dans le cadre de la thèse ainsi que sur les limites et futurs travaux liés au développement d'un tel outils d'aide à décision. Le chapitre 8 conclu.

CHAPITRE 2 REVUE DE LA LITTÉRATURE

La revue de littérature est composée des trois sections suivantes : la gestion des matières résiduelles, la modélisation du comportement humain dans un contexte de consommation et d'économie circulaire et la simulation.

2.1 Gestion des matières résiduelles

La gestion des matières résiduelles est un sujet particulièrement sensible parce qu'il concerne tout le monde. Dans les pays développés, tous les citoyens utilisent et financent la gestion des matières résiduelles (GMR). Au cours des dernières décennies, plusieurs politiques et stratégies ont été implantés dans plusieurs pays pour minimiser les coûts de la GMR. Des cibles pour les taux de recyclage et des coûts proportionnels aux volumes générés par les ménages sont des exemples de ces stratégies (Goddard, 1995). En 2010, des chercheurs ont décomposé et estimé les coûts de la GMR en fonction des types de services disponibles aux États-Unis (Bohm, Folz, Kinnaman, & Podolsky, 2010). D'autres chercheurs ont analysé les coûts du programme de recyclage ontarien en fonction des matières récupérés (Lakhan, 2015). Une des solutions proposées par les auteurs pour réduire les coûts sans avoir trop d'impact sur les taux de collecte est d'enlever les matières non-essentiels et moins rentables, tel que le verre, de la collecte sélective. Néanmoins, les enjeux de la GMR sont multicritères et la complexité qui en émerge réside dans la dichotomie entre les deux aspects complémentaires suivants : les coûts et les impacts environnementaux (Karmperis, Aravossis, Tatsiopoulos, & Sotirchos, 2013; Soltani, Hewage, Reza, & Sadiq, 2015).

Le lien entre les comportements des consommateurs et les flux de matières dans la GMR est bien reconnu dans la littérature scientifique. En 1995, la réduction à la source et le recyclage étaient des solutions qui étaient préconisées pour réduire les coûts et les impacts environnementaux de la GMR (Porter, Leeming, & Dwyer, 1995).

Des chercheurs ont réussi à développer des modèles mathématiques, basés sur des analyses de régressions, permettant de prévoir les flux macroscopiques de matières résiduelles au niveau d'une population (Ghinea et al., 2016; Spreutels, Héroux, & Legros, 2020). Bien que ce genre de modèles analytiques permette de faire des estimations de bonne qualité, toutes fin de vies confondues, ils ne permettent pas d'estimer la performance détaillée de stratégies spécifiques de logistique inverse (Kolekar, Hazra, & Chakrabarty, 2016).

2.2 Modélisation du comportement humain

Beaucoup de travaux ont été publiés décrivant et analysant les comportements humains pro-environnementaux tel que le recyclage. Ces travaux sont présentés dans le tableau 2.1 ci-dessous et classés en trois catégories : les modèles théoriques, les études empiriques et les combinaisons des deux.

Table 2.1 Articles portant sur la modélisation des comportements pro-environnementaux

Catégorie	Article	Sujet
Théorique	(Thøgersen, 1996)	- Revue de littérature et analyse des modèles de comportements suivants : <i>Subjective Expected Utility model & Theory of Reasoned Action</i>; - Proposition d'un autre modèle approprié au comportement du recyclage (<i>Schwartz's model of altruistic behavior</i>).
	(Stern, 2000)	Proposition d'un cadre conceptuel aux comportements qui ont un impact sur l'environnement (<i>value-belief-norm theory</i>).
	(Gifford & Nilsson, 2014)	- État de l'art des facteurs influençant les comportements pro-environnementaux; - Les 18 facteurs répertoriés sont classés en trois catégories : Personnels, sociaux et autres.
Études empiriques	(Sidique, Joshi, & Lupi, 2010)	- Revue des impacts qu'on eut diverses politiques visant à améliorer le recyclage et la gestion des matières résiduelles au Minnesota entre 1996-2004; - Cette étude lie des caractéristiques socio-démographiques aux changements dans les taux de recyclage et d'utilisation de centres de dépôt.
	(Sidique, Lupi, & Joshi, 2010)	Étude du profil des utilisateurs des 8 centres de dépôt au Michigan selon leurs attitudes et des facteurs socio-démographiques.
	(Best & Mayerl, 2013)	Étude empirique effectuée en Allemagne sur la participation des ménages au recyclage, selon le modèle « valeurs-croyances-attitudes ».

Table 2.2 (suite et fin)

	(Kormos & Gifford, 2014)	• Meta-analyse de la validité des mesures auto-rapportées lors de sondages sur les comportements pro-environnementaux.
	(Babaei et al., 2015)	• Analyse des réponses de 2400 questionnaires visant à évaluer des ménages par rapport à leurs comportements de recyclage. Le sondage a été réalisé dans la ville d'Abadan, en Iran.
	(Bissing-Olson, Fielding, & Iyer, 2016)	• Analyse d'un suivi qui a été fait avec 96 étudiants d'université (Australie) par rapport à la fierté et aux remords liés à des comportements pro-environnementaux.
Théorique / Études empiriques	(Tucker, 1999)	• À la suite d'observations faites sur un programme de collecte de papier journal en Angleterre, Tucker propose un modèle de l'influence sociale sur le comportement de recyclage.
	(Steg & Vlek, 2009)	• Revue critique de la littérature sur les comportements pro-environnementaux et l'efficacité des interventions répertoriées.
	(López-Mosquera, Lera-López, & Sánchez, 2015)	• À la suite d'un sondage effectué en Espagne, un modèle a été proposé pour expliquer trois comportements pro-environnementaux : les achats, le recyclage et l'utilisation de la voiture; • Le modèle est basé sur : l'attitude, la sensibilité environnementale, les caractéristiques socio-économiques et les caractéristiques socio-démographiques .
	(Morren & Grinstein, 2016)	• Meta-analyse d'études de comportements environnementaux qui ont utilisé le modèle de la théorie des comportement planifiés. • 67 études à travers 28 pays ont été répertoriées.

Bien que plusieurs modèles soient bien acceptés dans la littérature, la *Theory of planned behavior* (TPB) (Ajzen, 1991) est de loin la plus utilisée pour l'étude des comportements liés au recyclage.

La liste ci-dessous présente des modèles de comportements de recyclage tous basés sur le TPB. Une analyse de ces articles est présentée dans le chapitre 5.

- (Tonglet, Phillips, & Read, 2004) ont fait des observations ainsi que l'analyse de réponses de questionnaires (N=258) pour identifier les éléments du TPB qui ont le plus d'impact sur le comportement en plus d'y ajouter quelques facteurs tel que les normes morales et la préoccupation de l'environnement. L'étude a été faite en Angleterre.
- (White & Hyde, 2011) ont fait l'analyse de 148 sondages provenant du public général visant à cibler les facteurs du TPB qui expliquent les comportements de recyclage en plus d'y ajouter certain facteur tel qu'être consciencieux. L'étude a été faite en Australie.
- (Chan & Bishop, 2013) ont fait l'analyse de 271 sondages d'étudiants afin d'en faire ressortir les facteurs explicatifs du recyclage en proposant de remplacer le facteur *attitude* par les *normes morales*. L'étude a été faite par l'entremise d'un panel web.
- (Rhodes et al., 2014) ont suivi 176 ménages pendant une période d'un mois dans leur participation à un programme de récupération de matières recyclables via des centres de dépôts. En plus des facteurs traditionnels du TPB, il a été proposé d'ajouter les aspects de proximité et de planification des déplacements. L'étude a été faite au Canada.
- (Botetzagias, Dima, & Malesios, 2015) ont fait l'analyse de 293 sondages pour évaluer le potentiel d'ajouter les normes morales comme un facteur indépendant expliquant le comportement de recyclage. L'étude a été faite en Grèce.

Malheureusement, comme (Clayton et al., 2016) le soulignent, la discipline de l'étude des comportements à elle seule n'est pas suffisante pour se préparer aux défis environnementaux de demain. Les chercheurs de cette discipline doivent joindre leurs efforts à des experts dans d'autres domaines, tel que les mathématiciens et les informaticiens, pour former des équipes multidisciplinaires capable de travailler efficacement sur des problèmes environnementaux précis.

2.2.1 L'importance des réseaux sociaux

Dans la TPB, un individu peut être influencé au niveau de son intention à effectuer un comportement par l'opinion des membres de son réseau social. Cette forme d'influence, nommé la Norme Subjective par Ajzen, a été étudiée par des chercheurs en ce qui a trait au recyclage, mais les résultats ne sont pas unanimes. Par exemple, tandis que (Chan & Bishop, 2013; White & Hyde, 2011) ont identifiés que la norme subjective pouvait être un précurseur de l'intention à recycler,

(Botetzagias et al., 2015; Rhodes et al., 2014; Tonglet et al., 2004) n'ont trouvé aucune importance significative de l'aspect de cette norme subjective.

Toutefois, comme l'a fait ressortir (Wood, 2000), il est possible d'influencer et même de modifier l'attitude d'individus face à un comportement à travers des interactions sociales, contrairement à influencer l'intention d'effectuer un comportement. Deux modèles de simulations à base d'agents ont utilisé ce concept pour inclure l'impact de ces formes d'influence sociale (Kaufmann, Stagl, & Franks, 2009; Rai & Robinson, 2015). Pour cela, ces auteurs ont utilisé le *Relative Agreement Model* de (Deffuant, Amblard, Weisbuch, & Faure, 2002) qui propose un modèle permettant de reproduire l'impact d'interactions sociales sur l'opinions d'individus.

Une autre façon de modéliser l'impact des réseaux sociaux sur le comportement des individus, voire des organisations, concerne la diffusion des connaissances au sein de réseaux sociaux qui ultimement mène à l'adoption de nouveaux comportements. Par exemple, Ghali et al. (2017) utilisent les concepts de confiance et de partage des connaissances dans un contexte de création de synergies industrielles entre organisations. Cette étude démontre notamment que la dynamique et la topologie des réseaux sociaux entre organisation a un impact potentiel important sur la formation et l'évolution de symbioses industrielles. Pour réaliser cette étude, les auteurs utilisent la simulation à base d'agents pour évaluer et étudier l'impact de la diffusion des connaissances sur l'émergence de comportements collectifs. La sous-section suivante présente plus en détails ce type d'approche méthodologique.

2.3 La simulation pour étudier les comportements humains

La modélisation et la simulation ont une multitude d'applications. Que ce soit pour mieux comprendre, découvrir ou analyser des systèmes, il n'y a que très peu de limites conceptuelles à ce qui peut être modéliser et simulé (Borshchev, 2013). En général, les limites se situent généralement au niveau des capacités des machines de simulation (i.e. ordinateurs). Dans cette sous-section, d'abord sera présenté l'aspect de la modélisation et ensuite celui de la simulation.

2.3.1.1 Modélisation du comportement humain pour la simulation

Outil fondamental du génie industriel, la simulation est devenue un outil privilégié par les chercheurs et les industries de tous les domaines (Borshchev, 2013), mais aussi dans les sciences

sociales (Axelrod, 1997). Grâce à cet outil, il est possible d'étudier des modèles de systèmes dans des univers virtuels sans risque d'impacts négatifs dans le monde réel.

L'objectif de modéliser un comportement est de le simplifier afin d'être en mesure de l'analyser en l'intégrant dans des outils de simulation. Cependant, puisqu'une simulation est sensiblement toujours basée sur un modèle mathématique implicite ou explicite, celui-ci doit être représentatif de la réalité, sinon il ne sera pas utile comme le dit George Box « *All models are wrong, but some models are useful* » (Law, 2008). Dans le livre « Handbook of real-world applications in modeling and simulation », (Sokolowski & Banks, 2012) fait une revue des méthodes de modélisation de la prise de décision humaine.

2.3.1.2 La simulation avec AnyLogic

La simulation est un outil plus accessible que jamais; c'est-à-dire que n'importe quel ordinateur de bureau ayant accès à Excel est capable de faire de la simulation (i.e. Monte Carlo). Cependant, pour faire des simulations avec des modèles complexes, il est préférable d'utiliser des outils avancés tel que des logiciels de simulation. Pour la réalisation de cette thèse, le logiciel AnyLogic a été utilisé. Ce logiciel permet de faire trois types de simulation, sans compter les modèles hybrides :

- **Discrete event simulation:** Utilisé principalement pour des systèmes linéaires tel que des lignes de production, des réseaux de transport simples et des situations avec des files d'attentes; cette méthode est généralement composée de postes de travaux, d'entités ou de ressources qui sont connectés entre elles par des d'organigrammes. Dans ces simulations, le temps est divisé en unités temporelles discrètes. (Wang, Brême, & Moon, 2014; Zeigler, Praehofer, & Kim, 2000).
- **System dynamics:** Contrairement à la simulation à événement discret, l'intérêt n'est pas sur les comportements ou actions effectués par des entités et/ou ressources, mais bien sur les interactions et les liens entre celles-ci. Pour analyser le système à l'étude, celui-ci doit être décomposé en variables et en flux. Ces variables et ces flux sont incrustés dans un diagramme de causalité qui représente les interdépendances et les relations entre les variables (Sokolowski & Banks, 2012).
- **Agent-based:** Le concept fondamental dans la simulation à base d'agents est qu'elle est composée d'agents, soit des entités logicielles. Celles-ci sont autonomes et ont leurs propres comportements afin d'atteindre leurs objectifs. Ces agents peuvent être intelligents,

modifier leur environnement, entrer en contact avec d'autres agents, évoluer, voire de naître ou mourir. Contrairement aux deux paradigmes de simulation précédents, celui-ci est caractérisé par le fait qu'il est utilisé avec des modèles qui sont développés avec une approche hiérarchique ascendante (du bas vers le haut), c'est-à-dire que ce sont les composantes d'un système qui définissent le système et non l'inverse. Puisque ces agents sont programmés de manière individuelle, les comportements globaux des systèmes ne sont pas nécessairement connus à priori, ce qui peut mener à des découvertes intéressantes. Considérant que les humains partagent beaucoup de similitudes avec les agents, notamment l'autonomie, l'intelligence, la poursuite d'objectifs et les interactions diverses, il ne fait aucun doute que la simulation à base d'agents est un paradigme très intuitif et naturel, voire anthropomorphique, pour la simulation de système humains. (Macal, 2016).

2.3.2 Exemples d'applications de simulation du comportement humain

La simulation appliquée aux sciences sociales, comme les comportements pro-environnementaux, est un domaine de recherche qui donne du pouvoir aux données empiriques et aux modèles théoriques en les combinant pour leur donner vie (Axelrod, 1997; Conte, Edmonds, Moss, & Sawyer, 2001; Küppers & Lenhard, 2005). Bien que ce domaine ait émergé dans les années 90, ce champ de recherche est maintenant bien défini (Conte et al., 2001).

Un des premiers modèles de simulation développés pour la GMR était un modèle mathématique stochastique des flux de matières du processus de recyclage de papier journaux par les ménages. Ce modèle avait pour but de prédire la performance d'une stratégie de recyclage de papier journal en mettant l'accent sur la modélisation du comportement des consommateurs. Il est à noter que pour modéliser le comportement, (Tucker, Murney, & Lamont, 1998) ont utilisé la TPB. (Tucker & Smith, 1999) a aussi démontré la faisabilité de modéliser et simuler des sociétés artificielles complexes composées de ménages individuels qui sont capables de prendre des décisions quant à la gestion de l'ensemble de leurs matières résiduelles en plus d'interagir entre eux. Ce deuxième modèle est sensiblement une extension du premier étant donné qu'il n'a qu'été calibré et validé pour une stratégie touchant le papier journal.

Grâce à son approche du bas vers le haut (« bottom-up »), la modélisation et simulation à base d'agents est utilisée dans une grande variété de domaines (Macal, 2016) et particulièrement pour l'étude des systèmes humains, comme la diffusion de l'innovation (Bonabeau, 2002); un domaine

qui partage beaucoup de similitudes avec l'adoption de comportements de recyclage. Étant donné que la diffusion d'innovation est un domaine où les phénomènes sont difficilement reproductible dans la réalité, c'est pour cette raison que beaucoup de chercheurs ont adoptés la simulation à base d'agents (Kiesling, Günther, Stummer, & Wakolbinger, 2012).

Le concept fondamental de la modélisation à base d'agents est que les entités modélisées sont autonomes et ont des comportements distincts. Grâce à sa simplicité à modéliser des comportements, la TPB n'a pas tardé à faire son entrée dans les modèles à base d'agents. Par exemple, (Schwarz & Ernst, 2009) ont développé un modèle de diffusion d'innovations environnementales alors que (Kaufmann et al., 2009) ont simulé la diffusion de pratiques d'agriculture pro-environnementales. Plus récemment, (Ceschi, Dorofeeva, Sartori, Dickert, & Scalco, 2015) ont utilisé la modélisation par équations structurelles et la TPB pour estimer des taux de recyclages au niveau des ménages tandis que (Ghali, Frayret, & Ahabchane, 2017) ont simulé l'émergence de relations industrielles symbiotiques. D'autres comportements complexes ont aussi été reproduits artificiellement en utilisant la modélisation et simulation à base d'agents tel que l'approvisionnement de papier post-consommation pour une usine de fabrication de pulpe de papier (Sauvageau & Frayret, 2015) ainsi que l'adoption de la technologie photovoltaïque par les consommateurs (Rai & Robinson, 2015).

Un modèle de simulation à grande échelle a été développé pour comparer des stratégies de GMR pour l'état de la Floride aux États-Unis (Shi, Thanos, & Celik, 2014). Un autre exemple est celui de (Wang et al., 2014), où ils ont démontré la faisabilité de combiner la modélisation à base d'agents et d'autres techniques de simulation pour compléter une ACV sur les choix des consommateurs quant aux types de breuvages qu'ils choisissent pour se désaltérer.

Le lecteur intéressé par une revue des applications de la modélisation et de la simulation dans le contexte de l'économie circulaire est référé à (Walzberg, Burton, et al., 2022; Walzberg, Carpenter, & Heath, 2021; Walzberg, Cooperman, et al., 2022; Walzberg, Frayret, Eberle, Carpenter, & Heath, 2023; Walzberg et al., 2020).

2.4 Analyse critique de la littérature

Trois constats principaux émergent de la revue de littérature. Premièrement, par sa grande popularité, sa simplicité et sa capacité à s'adapter une grande variété de contextes, le TPB semble bien adéquat pour modéliser les choix que font les consommateurs à l'égard de leurs bouteilles de vin en fin de vie. En revanche, il n'y a pas de convergence évidente quant aux facteurs du TPB qui sont significatifs dans ce contexte spécifique, ni à l'intensité d'influence de ces derniers. L'attitude étant sensiblement le seul facteur qui est systématiquement significatif pour expliquer les comportements de recyclage ou de gestion des matières résiduelles.

Deuxièmement, la plupart des études qui utilisent la TPB, utilisent également la « *structural equation modeling* » (SEM), où des coefficients qui mesurent l'influence des facteurs explicatifs sont inférés à partir de questionnaires. Cependant, le manque d'uniformité dans les questionnaires utilisés et les contextes étudiés étant différents; les modèles basés sur les SEM sont difficilement généralisables ou applicables à d'autres contextes que ceux où ils ont été développés. D'ailleurs, il n'y a aucun modèle basé sur le TPB spécifiquement adapté à la problématique des bouteilles de vin et de leur fin de vies. Ce manque dans la littérature rend donc complexe et difficile la prévision de la performance d'une nouvelle stratégie de logistique inverse des bouteilles de vin au Québec.

Troisièmement, malgré que les modèles mathématiques de régression puissent permettre des estimations de bonne qualité à grande échelle pour différents flux de matières, ces derniers n'ont pas comme objectifs de faire des estimations précises, avec systèmes d'informations géographiques par exemple, de stratégies de logistique inverses.

La présente thèse propose donc de combler ces lacunes dans la littérature en proposant un modèle de simulation du comportement des consommateurs à l'égard de leurs produits en fin de vie qui est basé sur le TPB et adaptable à différents produits, contextes géographiques, populations, et ce, sans utilisation de SEM.

CHAPITRE 3 ORGANISATION GÉNÉRALE DE LA THÈSE

La présente thèse est composée des trois articles scientifiques suivants :

1. Agent-based model for end-of-life product flow analysis;

Publié dans *Resources*, 7(3), 42;

2. First-mile reverse logistics: an agent-based modeling and simulation application for glass bottle recovery;

Publié dans *Journal of Cleaner Production*, 422 (2023): 138574;

3. Word-of-mouth in agent-based simulation model of reverse logistics;

Soumis le 20 juillet 2023 à *Frontiers in Sustainability*.

Cette section présente une vue unifiée et cohérente des trois articles ainsi que leurs contributions respectives dans l'atteinte des objectifs de recherche. Le tableau 3.1 illustre la chronologie de la thèse et l'évolution du modèle de simulation à travers le temps.

Dans l'ensemble, les trois articles forment une évolution graduelle de la complexité et de la précision du modèle de simulation. Le premier article présente les fondements mathématiques du modèle ainsi une calibration de celui-ci à la population moyenne québécoise. Le deuxième article fait l'introduction d'un système d'information géographique dans le modèle, ce qui permis de configurer le modèle à une population et un contexte spécifique, soit la MRC du Val-Saint-François et son programme de dépôt volontaire des bouteilles de vin. Les résultats de simulation ont été comparés aux données empiriques pour évaluer la capacité du modèle à reproduire un cas d'étude. Dans le troisième article, un deuxième échantillon de données empiriques a été ajouté. Une analyse statistique des échantillons a identifié une croissance dans les taux de collectes entre 2019 et 2020. Alors que le programme a été officiellement lancé en 2019, un mécanisme de diffusion de l'information a été introduit à travers des interactions entre les agents consommateurs pour reproduire la croissance observée dans les données empiriques.

Les figures suivantes (3.1, 3.2 et 3.3) présentent l'état général du modèle de simulation à chaque publication. Les éléments en rouge dans les figures 3.2 et 3.3 sont ceux qui ont été ajoutés par rapport à la publication qui lui précède.

Table 3.1 Évolution du modèle de simulation à travers les trois publications

	(Labelle & Frayret, 2018)	(Labelle & Frayret, 2023)	Publication #3
Environnement de simulation	Espace continu générique	Système d'information géographique (Open Street map)	Système d'information géographique (Open Street map)
Population simulée	Population moyenne québécoise (urbaine, banlieu, rurale)	Population de la MRC du Val-Saint-François (30686 habitants)	Population de la MRC du Val-Saint-François (30686 habitants)
Stratégie de collecte	1 à 3 points de dépôts placés aléatoirement dans l'espace continu	6 points de dépôt géolocalisé selon leurs emplacements réels dans le système d'information géographique	6 points de dépôt géolocalisé selon leurs emplacements réels dans le système d'information géographique
	Consigne de 0.15\$ et 0.35\$	Aucune consigne (dépôt volontaire)	Aucune consigne (dépôt volontaire)
Validation du modèle de simulation	Validation qualitative	Validation quantitative simple avec un échantillon de données empiriques	Validation quantitative par analyse statistique avec deux échantillons de données empiriques
Contribution aux objectifs de recherche	1.Développer un modèle de simulation à base d'agents du comportement des consommateurs à l'égard de leurs produits en fin de vie. 2.Configurer le modèle pour des bouteilles de vin avec la population québécoise moyenne.	3.Évaluer les besoins en données et les limites du modèle à travers une étude de cas et un échantillon de données empiriques.	4.Ajout d'interactions sociales dans le modèle de simulation. 5.Évaluer la capacité du modèle à simulé l'évolution dynamique de la performance du système de collecte dans sa phase de lancement.

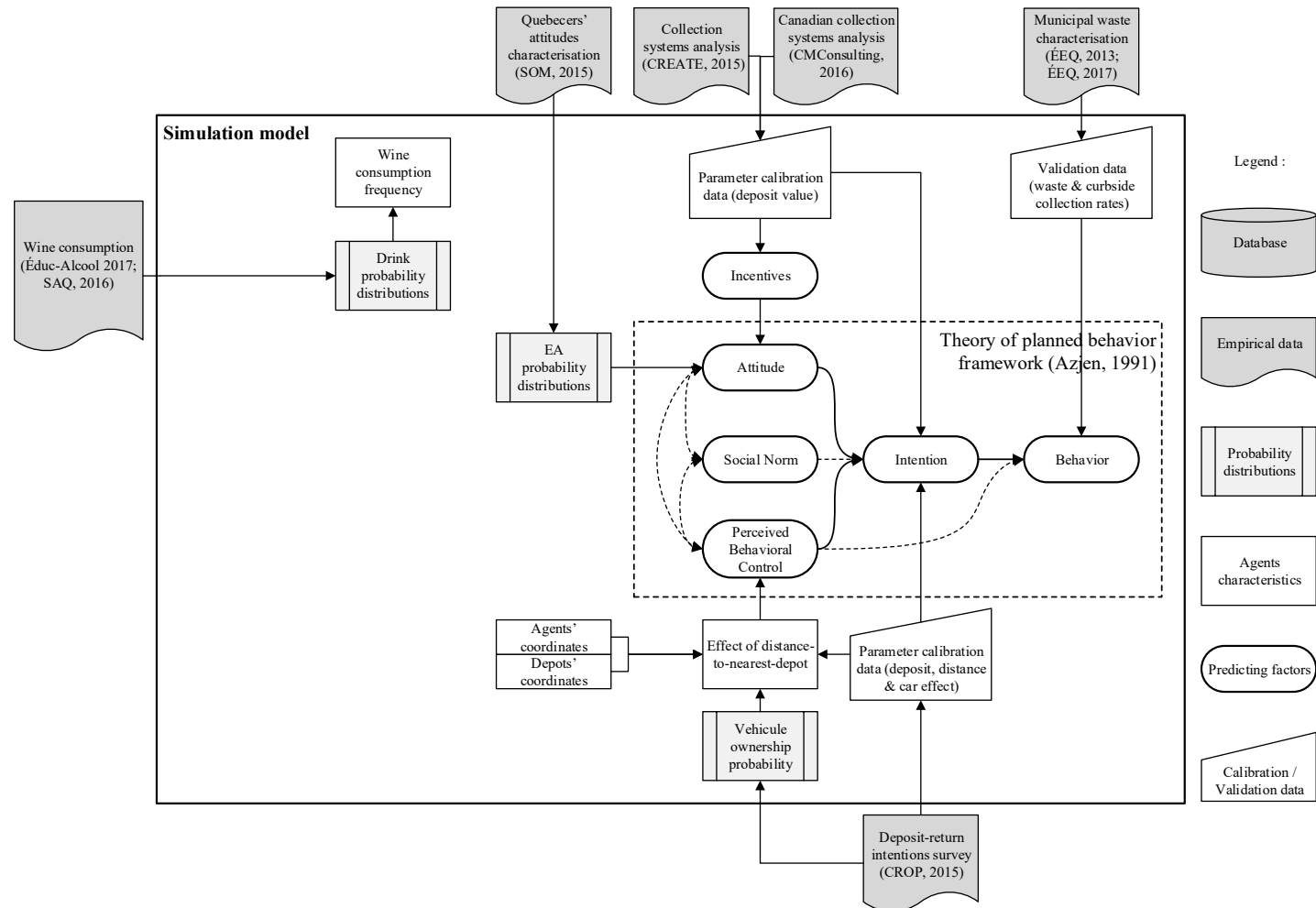


Figure 3.1 Modèle de simulation à la publication 1 (voir chapitre 4 pour plus de détails)

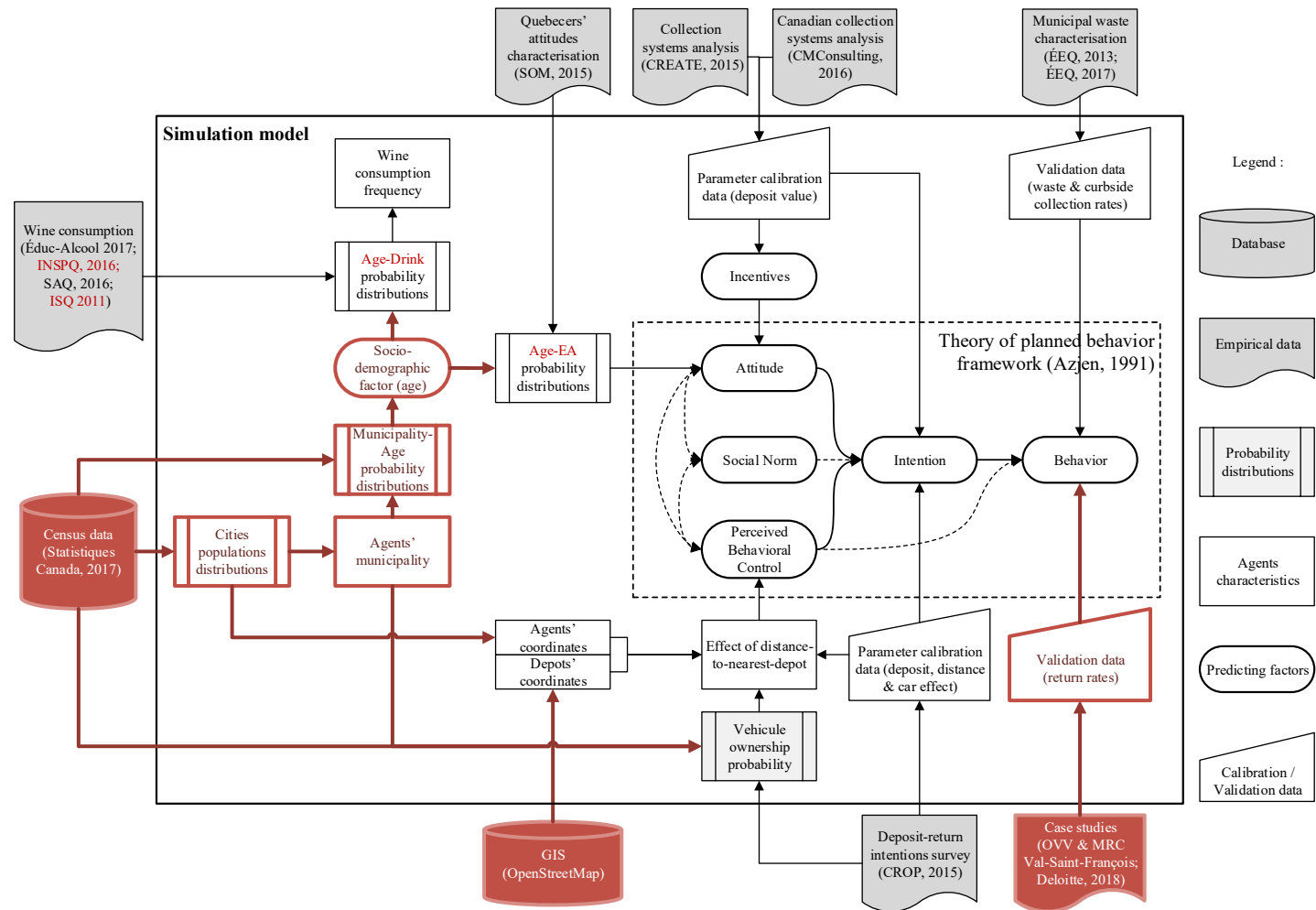


Figure 3.2 Modèle de simulation à la publication 2 (voir chapitre 5 pour plus de détails)

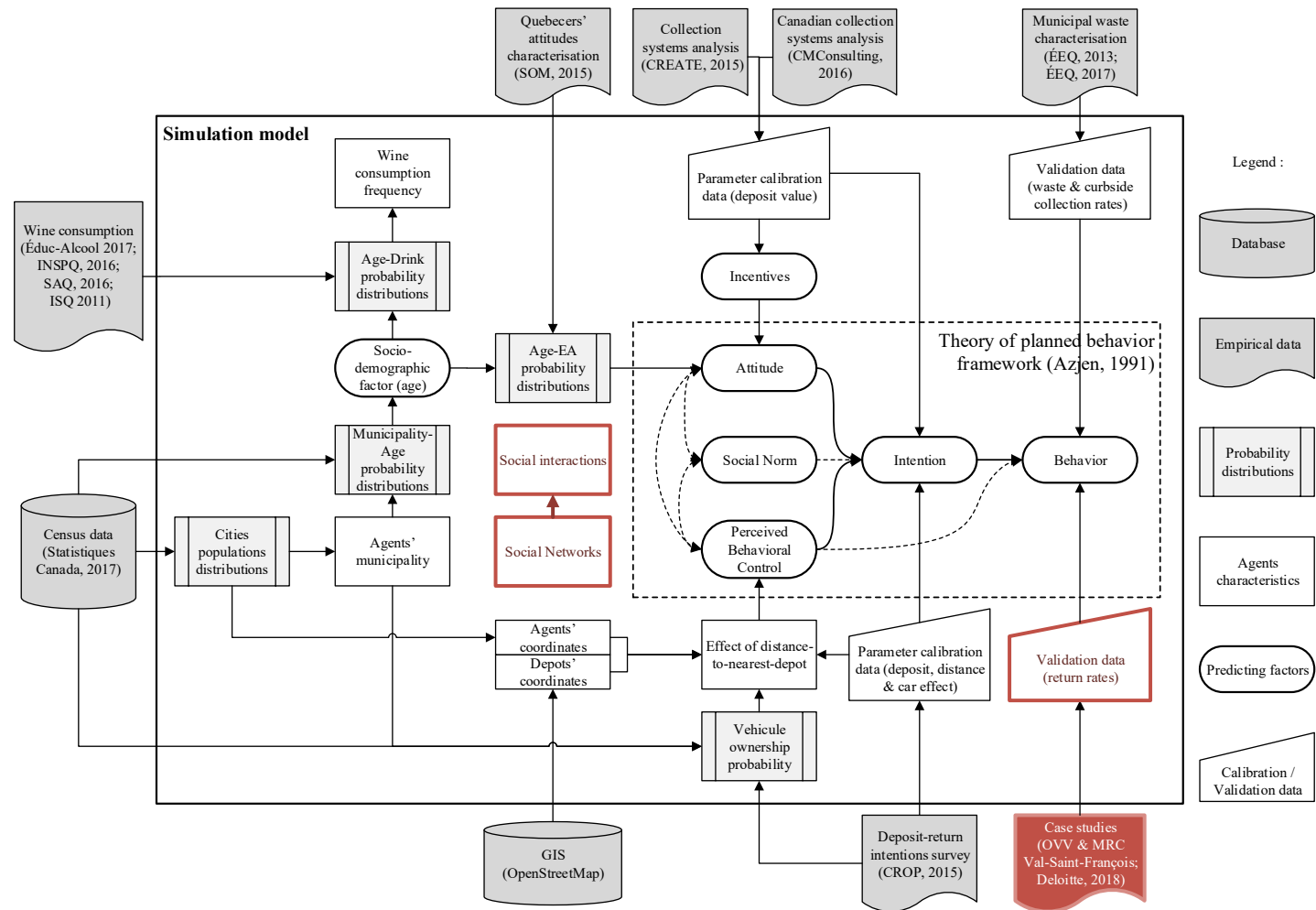


Figure 3.3 Modèle de simulation à la publication 3 (voir chapitre 6 pour plus de détails)

CHAPITRE 4 ARTICLE 1: AGENT-BASED MODEL FOR END-OF-LIFE PRODUCT FLOW ANALYSIS

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Resources

Published on July 12, 2018

This paper presents an agent-based simulation model for end-of-life product flow analysis in recuperation and recycling supply networks that focuses on individual consumer behaviors. The simulation model is applied to a deposit-return program on wine bottles that could be developed in the province of Quebec. Canadian data was used to calibrate and validate the model. A series of experiments were then conducted with three artificial populations to analyse how they would react to several implementation scenarios of this end-of-life product flow strategy. The results suggest that the distance to the nearest depot is an impactful decision factor, but less predominant than the ownership of a private vehicle and the deposit value. The results also indicate that the use of agent-based modeling combined with the Theory of Planned Behavior can produce modular behavior models, that are intuitive and simple, to better understand consumer-behavior-driven supply chains. Such models can be used to give insights to decision-makers and policy makers about the potential performance of end-of-life product flows strategies and further facilitate efficient resource management.

4.1 Introduction

With Earth Overshoot Day getting sooner and sooner every year, it is more important than ever before to manage earth's resources in effective ways. Considering that over 1.47 billion tons of municipal solid waste is generated each year (Zaman, 2016), and only 15% out of the 84% collected waste is recycled, it comes with no surprises that municipal waste management actual practices are not sustainable. With resources scarcity lurking, the application of Circular Economy (CE) models to end-of-life (EOL) product flow networks can offer great opportunities to strive towards a more sustainable future.

In this context of new business and product flow models, the ability to compare both economically and environmentally multiple product flow strategies is undoubtedly relevant to decision-makers willing to progress towards CE's goals (Karmperis et al., 2013; Soltani et al., 2015). A difficult aspect of the analysis of new strategy introduction is human factor. It is indeed difficult to predict how people may react when faced with various options, which, in turn, makes it difficult to assess technical feasibility and profitability. In order to address this issue, computer simulation offers a compelling analytical approach since it enables both macro and micro modeling capabilities in a risk-free environment (Borshchev, 2013). This paper proposes a simulation model of consumer behavior for end-of-life product flow to work towards finding more sustainable end-of-life product flow strategies. It is applied to a case study of Quebec's wine bottle potential deposit-return scheme that is currently being looked at by policy makers. The simulation model can be used to estimate the percentages of products that are sent in each end-of-life option according to various parameters such as the deposit value, the consumer-to-depot maximum distance and proportion of the population owning a vehicle. The model is calibrated and validated with various independent data sources. Merging these data sources in one single model enables the emergence of behavior tendencies that would not be observable without the consumer behavior simulation model.

4.1.1 Solid Waste Management

Waste management is a sensitive field of research as it concerns everybody; each citizen living in the developed world uses & pays for Municipal Waste Management Systems (MWMS). Over the past decades, many strategies and policies have been implemented all over the world, such as high recycling targets or household level user fees, to maximise the benefits and minimise the costs of municipal solid waste management (Goddard, 1995). To facilitate the analysis and development of

these programs and policies, researchers have decomposed and estimated the costs of MWMS (Bohm et al., 2010; Lakhan, 2015). However, the complexity of the MWMS comes from the dichotomy between its two complementary aspects : the economic costs and the environmental impacts of the strategies (Karmperis et al., 2013; Soltani et al., 2015). Many researchers completed multiple assessments of MWMS environmental impacts (Cleary, 2009; De Feo & Malvano, 2009), from single stream collection versus the separation of recyclables (Fitzgerald, Krones, & Themelis, 2012), to specific products (Simon, Amor, & Földényi, 2016), such as PET and glass bottles (Komly, Azzaro-Pantel, Hubert, Pibouleau, & Archambault, 2012; Vellini & Savioli, 2009). However, the complex link between consumers behaviors and MWMS mass flows remains a significant and sensitive element of these assessment studies. In order to address this issues, (Ghinea et al., 2016) have successfully developed a mathematical model to forecast municipal solid waste generation based on prognostic tools and regression analysis. Although such models are well suited to assess MWMS in stable conditions, they can hardly capture social impacts such as incentives, media campaigns or social interactions between households.

4.1.2 Behavioral Theories

There is a growing literature studying pro-environmental behaviors, such as recycling, using theoretical models (Stern, 2000; Thøgersen, 1996), empirical data (Babaei et al., 2015; Bissing-Olson et al., 2016; López-Mosquera et al., 2015; Sidique, Joshi, et al., 2010; Sidique, Lupi, et al., 2010) or a combination of both (Best & Mayerl, 2013; Gifford & Nilsson, 2014; Kormos & Gifford, 2014; Morren & Grinstein, 2016; Steg & Vlek, 2009; Tucker, 1999). Although there are several types of models, the Theory of Planned Behavior (TPB) (Ajzen, 1991) seems to be the most frequently used here (Botetzagias et al., 2015; Chan & Bishop, 2013; Rhodes et al., 2014; Tonglet et al., 2004; White & Hyde, 2011). The model presented in this paper exploits this theoretical model, which is discussed hereafter.

4.1.3 Simulation of waste management operations

The first models developed for household waste management were stochastic mathematical models created to predict the performance of a newspaper recycling strategy (Tucker et al., 1998) and to provide a proof-of-concept for the simulation of a complex artificial society composed of individual households with waste management behaviors (Tucker & Smith, 1999).

After the popularization of agent-based modeling and simulation (ABMS) (Bonabeau, 2002), a new generation of model began to appear. Particularly used to study the diffusion of innovations, which share some similarities with recycling behavior adoption, these agent-based models were now able to capture the sophisticated effects of human interactions and their emergent phenomenon's (Kiesling et al., 2012). Largely used among behaviorists, the TPB also made its way into ABMS (Scalco et al., 2017). (Schwarz & Ernst, 2009) developed an environmental innovation diffusion model, while (Kaufmann et al., 2009) simulated pro-environmental farming practices diffusion. More recently, (Ceschi et al., 2015) used structural equation modeling within the TPB framework to predict household recycling outcomes and (Ghali et al., 2017) simulated the emergence of self-organized industrial symbiosis relations .

ABMS is also used for multi-objective analyses. For example, a large-scale simulation model was developed to compare single-stream and dual-stream solid waste management alternatives in the state of Florida, US (Shi et al., 2014). Another example is the model of (Wang et al., 2014), in which they show how to couple ABMS with other modeling methods in the context of life-cycle assessments.

4.2 Objective and methodology

This paper proposes a simulation model for EOL product flow analysis in municipal waste management systems (MWMS) that focuses on individual consumer behaviors. In the model, autonomous entities known as *agents* purchase, consume, and eventually discard products in a way that is similar to how real consumers, from specific populations, would behave. With an artificial population, it becomes possible to estimate each proportion of materials diverted to every end-of-life option. Having the ability to simulate a whole population of diverse consumers enables the study and analysis of new waste management strategies and policies without having to implement them in the real world, thus minimizing the risks of failure and unexpected drawbacks. ABMS was chosen for this paper's model because it facilitates the implementation of key concepts, such as autonomous and individual decision making across a population of various types of consumers as well as complex social interactions that will soon be implemented into the model (Bonabeau, 2002). This consumer behavior model is applied to the study case of Quebec's wine bottles whereas a deposit scheme would be implemented as a new municipal waste management policy.

4.3 The Model

First and foremost, since the point of interest in the system is where the wine bottles are diverted to one of each EOL options, this model is limited to the consumers and their decisions. A mathematical model of the consumer behavior decision process was developed to estimate the proportions of bottles sent towards the landfills and recycling facilities through the choices that consumers make; whether it is to put the bottles in the waste containers, the curbside container (also called blue bin) for collection or brought back to return centers. As shown in Figure 1, bottles are purchased at a liquor store, then stored until they are emptied and eventually discarded. Depending on the consumers' decisions, the bottles could end up either in landfills or recycling centers. It is assumed that the decisions are made for each individual bottle and that the process through the studied system is cyclic.

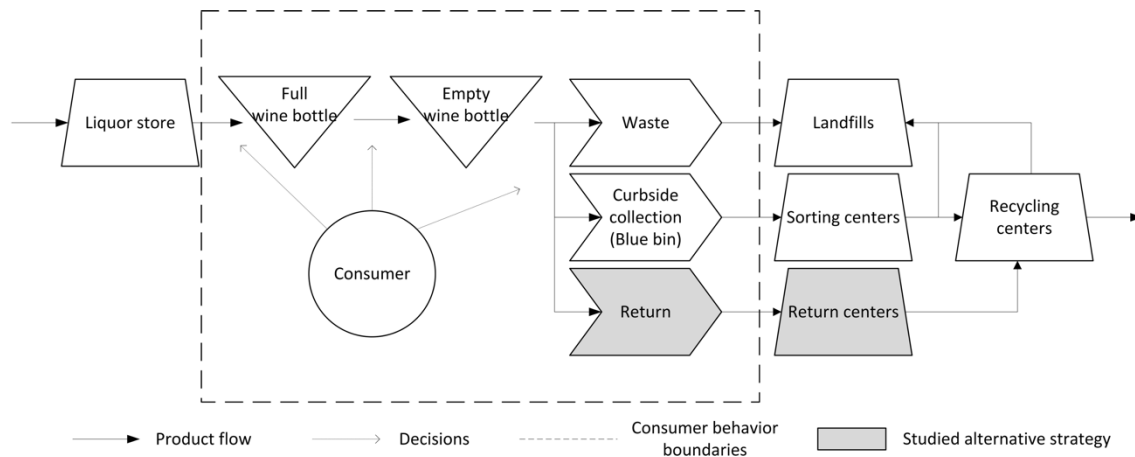


Figure 4.1 How wine bottles go from the store to the landfills or recycling centers

4.3.1 Behavior and Decision Making

In the theory of planned behaviour, inputs are generally categorized and gathered into constructs. These theoretical artifacts are usually a combination of factors affecting the output of the model that have been – or could – be empirically validated (Armitage & Conner, 2001). In his original TPB framework, (Ajzen, 1991) suggested that behavior is influenced by intentions and perceived behavioral control (PBC), while Intention would be defined by the constructs of attitude, subjective norm and PBC. The proposed model uses the same key concepts, plus an Incentive construct, as shown in Figure 2.

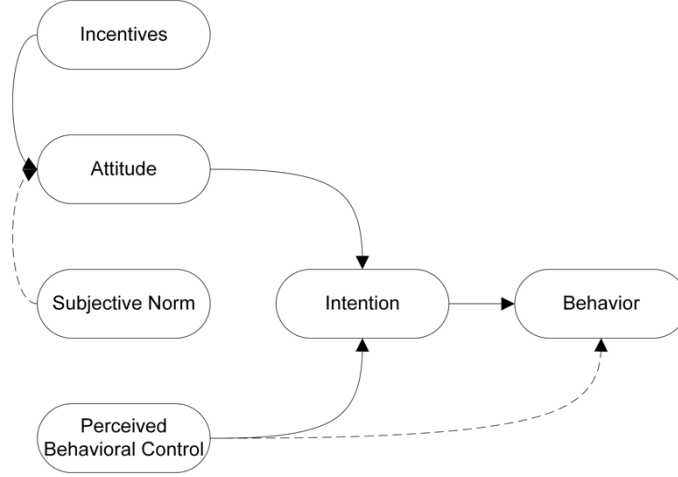


Figure 4.2 Modified TPB

In the proposed model, Equations (1) and (2) show how behavior is calculated based on the TPB decision model. Here, i stands for the unique identification of each agent, b stands for the different behaviors, and t stands for the simulation time steps, which in this case are weeks. If an agent has an empty wine bottle, the calculation is done for each individual behavior, and the one with the highest $Behavior_{i,t,b}$ value is performed by the agent. If there are equal maximum behavior values, the performed behavior is randomly selected.

In the existing literature, whether it is in technology diffusion (Kaufmann et al., 2009; Rai & Robinson, 2015; Schwarz & Ernst, 2009) or recycling (Scalco et al., 2017; Tucker et al., 1998; Tucker & Smith, 1999), the simulated behavior always depicts binary decisions. In the first case, it is “adopt or don’t adopt”, where in the second case it is “recycle or don’t recycle”. Thus, developing specific equations for each behavior in the model enables the analysis of complex situations that have more than two possible behaviors without using thresholds.

$$Behavior_{i,t,b} = Intention_{i,t,b} \quad (4.1)$$

$$Intention_{i,t,b} = Attitude_{i,t,b} + PBC_{i,t,b}(intention) \quad (4.2)$$

4.3.2 Attitude: Opinions and Incentives

Besides being influenced by subjective norms, which will be developed in the next iteration of this paper’s model, $Attitude_{i,t,b}$ is primarily defined by opinions ($OV_{i,t,b}$) and incentives (IV_b). The core aspect of the model, Opinions, represents how agents perceive each behavior on an environmental standpoint. As for Incentives, (Maki, Burns, Ha, & Rothman, 2016; Thøgersen, 1996) supports the

hypothesis that measures, such as deposits, can alter the perception of consumers toward environmental friendly behaviors. Therefore, it was implemented alongside Opinions, rather than as a distinct construct.

Attitude, used in Equation (2), is calculated using Equation (3). $OV_{i,t,b}$ and IV_b are the two variables respectively corresponding to the agents' opinions and the incentives. Ranging from 0 to 1, γ is the relative importance of $OV_{i,t,b}$ over IV_b . This parameter is there to reflect the differences in consumers appreciation towards incentives. For example, a consumer who is not pro-environmental may be tempted to return their bottles solely for the deposit, while a pro-environmental consumer could be indifferent to the incentives. Specific to the population studied, γ follows a normal distribution that must be calibrated to fit a specific population or could be used to discover emergent population characteristics.

$$Attitude_{i,t,b} = \gamma \times OV_{i,t,b} + (1 - \gamma) \times IV_b \quad (4.3)$$

An interesting feature of the proposed model is that it offers the possibility to have a continuous spectrum for environmental concerns (EC) – instead of a discrete categorisation of agents – while also keeping the notion of population segmentation that is often used in surveys. To do so, the model uses Fuzzy Logic to model a continuous form of membership of agents to segments. In other words, this framework enables the population to be segmented into 3 EC categories in a fuzzy manner: negative, neutral, and positive, as shown in Figure 3.

The segments S do not directly depict the environmental concerns of agents towards a specific behavior. Instead, it is rather an artifact created to categorise and group together agents with homogenous interests, just as opinions are shared in political parties for example. Politicians can have slightly varying point of views yet share the same core values. Therefore, this division lets each segment have a relative attitude towards each behavior without encasing them into discrete opinion values.

As illustrated in Figure 3, every segment has a membership function μ_s that delineates the shape of the segment. The Universe of Discourse (UOD) X , referring to environmental concerns, has values of $x_{i,t}$ ranging continuously from 0 to 100. The shapes seamlessly blend into one another, creating smooth transitions between the segments.

Agents can be members of a single segments, or partially part of two segments. Within the UOD, each value of X has three corresponding membership values, ranging from 0 to 1. In the Fuzzy Logic approach, the sum of all the membership values $\mu V_{i,s,t}$ must always be equal to 1 for all the possible values of X in the UOD. For example, agent q in Figure 3 is a member of both segments 1 and 2 with his membership values being respectively 0.4 and 0.6. On the other hand, agent r is only part of segment 3, with his membership values being equal to 1 while $\mu V_{r,1,t}$ and $\mu V_{r,2,t}$ are both equal to 0.

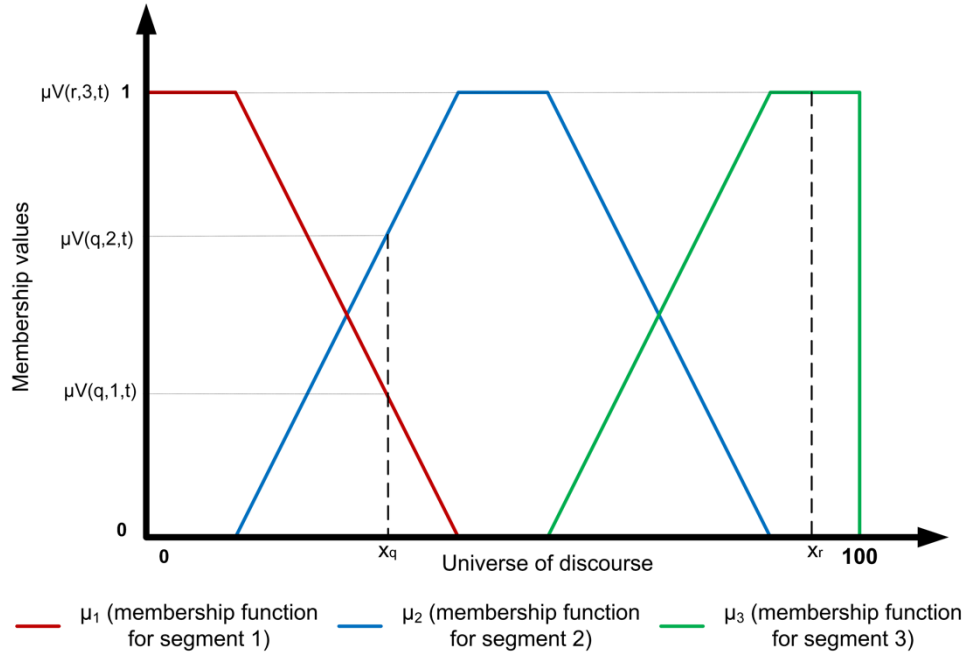


Figure 4.3 Fuzzy Logic membership functions with 3 segments

Below is the equation (4) that defines an agents' $OV_{i,t,b}$ according to their membership values and the Segment's Opinion Values Matrix (SOVM). Calculated for all the behaviors, it is the summation of the agents' membership values $\mu V_{i,s,t}$ multiplied by the corresponding values in the SOVM.

$$OV_{i,t,b} = \sum_{s \in S} [\mu V_{i,s,t} \times SOV_{b,s}] \quad (4.4)$$

The SOVM, shown below, represents the distinct opinion values of the segments for all three behaviors. This matrix will be used with the membership values $\mu V_{i,s,t}$ of each segment to calculate agents.

$$\begin{bmatrix} SOV_{11} & SOV_{12} & SOV_{13} \\ SOV_{21} & SOV_{22} & SOV_{23} \\ SOV_{31} & SOV_{32} & SOV_{33} \end{bmatrix} \forall SOV_{b,s} \in [0,100] \quad (4.5)$$

Finally, for the IV_b values, the only incentive in this paper's case study is the deposit on the bottles. IV_b is implemented in the model as a discrete value where one unit equal one cent.

4.3.3 The Perceived Behavioral Control

The PBC can be described as how consumers perceive themselves capable of accomplishing a specific behavior with their current capabilities and factors such as available resources or any socio-demographic characteristic. In the current model, only vehicle ownership and the distance to the nearest depot were taken into consideration.

The results of a provincial survey (CROP, 2015) suggest that the intention to bring back the bottles generally decreases as the distance to the nearest depot increases. As it can be seen in Figure 4, there are two piecewise linear functions, one for each type of transport, where the different sections represent the three distance brackets. In equation (7), a and b are parameters calibrated with the survey data while d is the distance to the nearest depot, a characteristic randomised for each agent based on the scenario simulated. db stands for the distance brackets. Therefore, the PBC is equal to the opposite of the perceived cost of the behavior (PCB). Similar findings are presented in (Sidique, Lupi, & Joshi, 2013), where increasing travel costs can reduce the intention to visit drop-off centers.

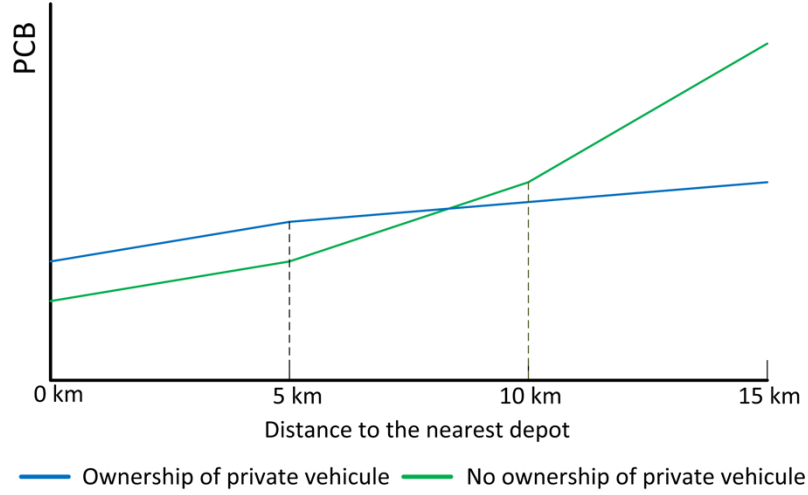


Figure 4.4 The cost of the return behaviour according to the distance of the nearest depot

$$PBC_{i,t,b}(intention) = -(PCB) \quad (4.6)$$

$$PCB = a_{i,db,c} \times d_i + b_{i,db,c} \quad (4.7)$$

Since the population density distribution in the areas where people have been surveyed in is unknown, a uniform distribution was assumed for the development of this part of the model. This means that the simulated population's density is the same throughout a circle with a 15km radius.

4.4 Results

This section presents the calibration and validation of the simulation model with data from various Canadian and Quebec sources. A series of experiments was also conducted to observe how the model reacts under different combinations of parameters that are not the base calibration parameters and potentially give insights on the effectiveness of the studied strategy. *AnyLogic 7 university edition* was used to develop the simulation model and execute the simulation experiments.

4.4.1 Model calibration

In the first of two calibration phases, the membership function shapes of the environmental concern segments were adjusted to fit the segmentations in the survey about Quebecers behaviors and attitudes towards the 3R hierarchy (N=2068) (SOM, 2015). To validate this aspect, the first values of the matrix were defined: SOV_{11} , SOV_{22} and SOV_{33} were set to 100 while the other values were set to 0. The simulation results with this simple diagonal matrix provided a good enough qualitative

fit with the estimated percentages of wine bottles found in the province's curbside collection (blue bin) program (ÉEQ, 2013). The rest of the matrix was then calibrated using AnyLogic calibration experiment functions.

The original scenario, without the deposit-return scheme, was first quantitatively validated and provided a tight fit within 0.5% of the 85.1% target for the curbside collection value (ÉEQ, 2013). The values used for γ (μ , σ) in this phase were respectively 1 and 0.

Next, the number of agents needed to be optimized. Figure 5 shows the model stability and validity as a function of the number of replications. Shortly after 10 repetitions, the simulations with 10 000 agents begin to show stable results. However, the simulations with only 2 000 agents seems to be the closest to the target value but is less stable.

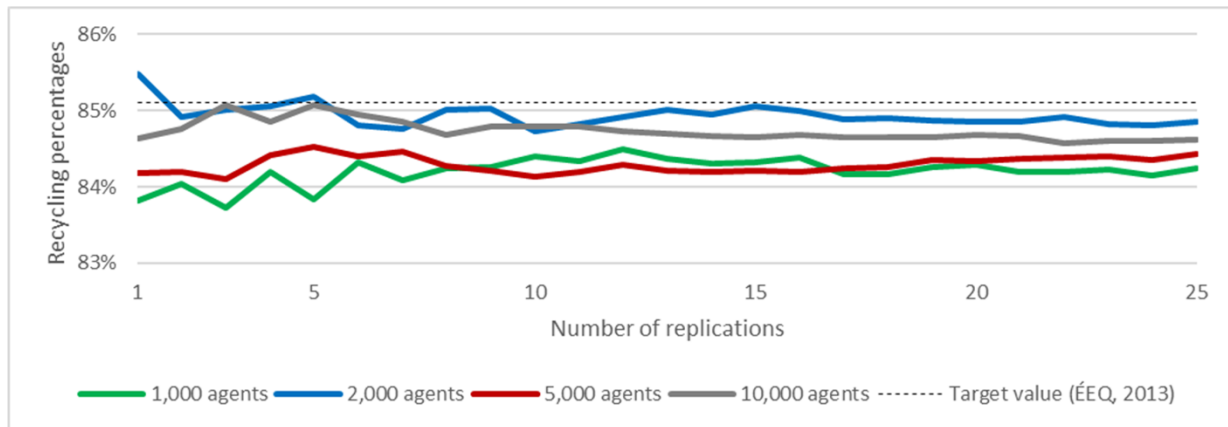


Figure 4.5 Curbside collection (blue bin) percentages cumulative averages per number of simulation replications (52 weeks/simulation)

The second phase consisted of the calibration and qualitative validation of the effects of incentives and PBC on the return behavior, as well as the recalibration of the matrix values. Since all these aspects can affect the decision process quite substantially on their own, the calibration had to be done with all of phase 2 parameters at the same time. Thus, to validate the fit of the model, a custom theoretical dataset was calculated to reflect the combination of effects from all the aspects and their respective empirical data. In other words, for every distance bracket, there were two target values, one for agents with cars, and another for agents without. These target values represented the theoretical number of agents that should bring back their bottles according to the incentive value and the effect of the distance to the nearest depot over agents' return intentions (CROP, 2015). To reflect the statistical data from Alberta (CMConsulting, 2014, 2016) and the survey from

(CREATE, 2015), the incentives values were increased twice over a 8 year period during the simulations in the calibration process to capture the impact of deposit-value increase, in order to be coherent with the empirical data found in the literature. The values used for incentives were adjusted to fit Quebec's proposed deposit values (CROP, 2015). Following the 0.05\$ increase of the deposit value of wine bottles in Alberta, return rates increased by 4% after 4 years and 6% after 8 years. Data from Alberta was used because it is the only Canadian province to have increased the deposit-values over the past years, thus limiting the model's validity. As for the CREATE survey (CREATE, 2015), it was found that by having a 0.35\$ deposit fee on wine bottles, 90% of Quebecers would bring their bottles back to depot centers. In the CROP survey (CROP, 2015), 88.1% of respondents owned a vehicle, which is the percentage used throughout all the simulations performed for the calibration process.

The model was also calibrated to reflect the wine drinking habits of Quebecers with data from the Société des Alcools du Québec and Éduc-Alcool. According to 2016's report of the Société des Alcools du Québec, each Quebecers drank approximately 30.3 bottles of wine in 2016 (SAQ, 2016). However, it would be unreasonable to assume that everyone drinks the same amount of wine through a year. Therefore, data from the 2017 Éduc-Alcool survey on alcohol consumption was used to calibrate a weekly wine consumption distribution (Éduc-Alcool, 2017). At the end of 25 simulations with 10 000 agents, the average total number of bottles consumed over a year differed from the target value by only +7%.

4.4.2 Model validation

Simulations were performed to estimate the product flows resulting from 6 different scenarios. The Figures below display the average percentages of bottles flowing into each EOL options for 10 simulations of each scenario with 52 weeks simulated per simulations. Two groups of scenarios were executed to compare the results with empirical data; the first with a deposit value of 0.15\$ and the second with 0.35\$. Each scenario groups were divided into 3 unique scenarios, which tested three cases of maximum distances between agent to the nearest depot: 5 km, 10 km, or 15 km.

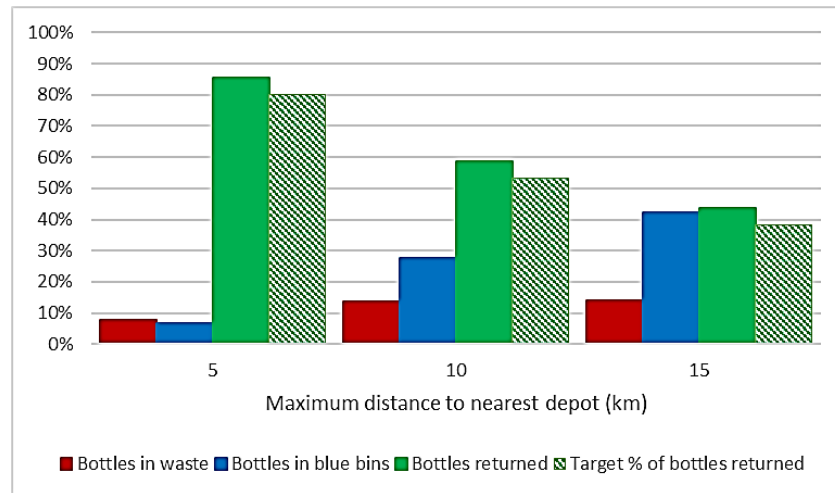


Figure 4.6 Averages of 10 simulations for each scenario with a deposit value of 0.15\$

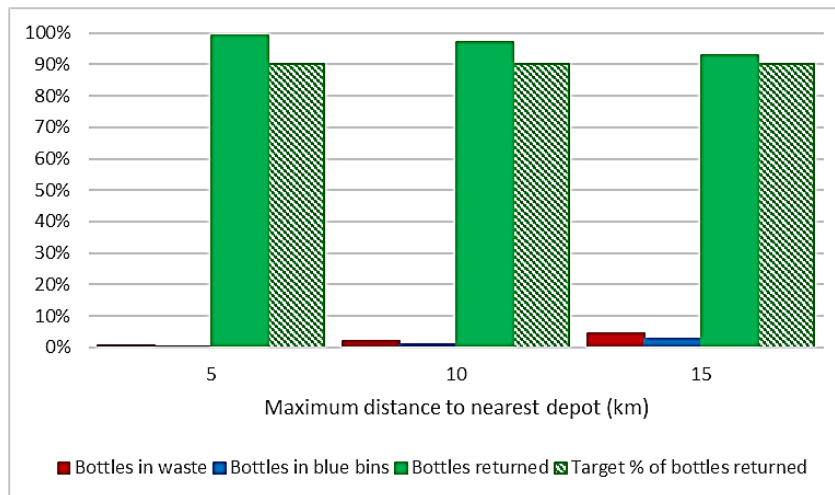


Figure 4.7 Averages of 10 simulations for each scenario with a deposit value of 0.35\$

Compared to the empirical data there is an average difference of +5% and +9%, respectively for the 0.15\$ (CROP, 2015) and 0.35\$ (CREATE, 2015) deposit fee scenarios, with the percentages of consumers bringing back their bottles to depot centers in the simulations and in the surveys. However, it must be noted that the empirical data for the 0.35\$ deposit value was from a survey that did not specify any distance that would need to be traveled to reach the depot center. Therefore, the target value was the same for each scenario. Nevertheless, the logic that the distance affects the intention to bring back can be seen in both experiences, which greatly contributes to the difference between the simulations results of the 0.35\$ deposit value and the empirical data.

To be able to validate this calibrated simulation model quantitatively, it would require independent survey or study of an actual deposit-return program in Quebec. Nonetheless, the current model can easily be adapted and calibrated to scenarios and even other products to give some interesting insights to decision-makers and policy makers.

4.4.3 Experiments

A series of experiences were conducted with the validated model to get insights on how several of the parameters can have an impact on the results. Overall, 18 different scenarios were selected to be analysed with 10 simulation runs of each scenario for a total of 180 simulation runs. As can be seen in table 1, the scenarios are divided into two group that are each divided again into subgroups. There is no difference between the two main groups beside the deposit value, which is respectively 0.15\$ for the first and 0.35\$ for the second. The subgroups represent three different population types characterised by population density and private car ownership. Three different alternatives were tested for each subgroup: 1 depot center, 2 depot centers and 3 depot centers. Populations sizes and densities were inspired from real Quebec cities (Québec, 2011), while the car ownership percentages were estimated with data from Canada, Sweden, United Kingdom and Ireland (Pyddoke & Creutzer, 2014; Roque & Masoumi, 2016; Turcotte, 2008).

Table 4.1 Parameters of the scenarios simulated

Groups	Populations	Population density (hab./km ²)	Private car ownership (%)	Deposit value (\$)	Number of depot centers
1	(A) Urban	3500	45	0.15	1, 2 and 3
	(B) Suburban	1000	70		
	(C) Rural	200	80		
2	(A) Urban	3500	45	0.35	1, 2 and 3
	(B) Suburban	1000	70		
	(C) Rural	200	80		

To reflect the regions that these scenarios are based upon, the simulated population size was increased from 10 000 to 50 000. This number of agents was used for all scenarios. In each

simulation runs, agents and depot centers were randomly placed in a square territory. The sizes of these areas are respectively 14.29 km² for population (A), 50 km² for (B) and 250 km² for (C). At the beginning of the simulations, agents select their preferred depot center by calculating the distance between their position and all the depot centers' positions. They choose the closest one and then always return their bottles to it. Even if an agent never returns a bottle, it will still have a preferred depot center. Also, if two depot centers are equally distanced from a consumer agent's position, the agent will randomly choose one or the other when the simulation begins.

In the following sections, only the results of the first group will be presented because there is no significant difference between all the results of the second group. Each of the nine scenarios produced average return percentages above 95% with very low standard deviations.

Graphical representations of the scenarios can be seen in Appendix A, where the agents are presented with colored humanoid shapes (black for non-drinkers, red for those who put their bottles to waste, yellow for those who put their bottles in curbside collection program and green for those who return their bottles to depot centers). The color of these agents is defined by their last behavior. Depot centers are presented as blue buildings.

4.4.3.1 Model Stability

In a similar way to how the model was calibrated, model stability had to be verified since the scenarios are different than the base scenario used for calibration. Figure 8 illustrates the results of the model stability under new scenarios. It appears that the cumulative averages for each scenario, both for the percentage of returned bottles and the number of bottles returned per depot center, tend to stabilize after 4 simulations. These results indicate that, even by adding multiple depot centers, increasing the population size and varying the percentages of private car ownership outside the base calibration scenario values, the model remains stable.

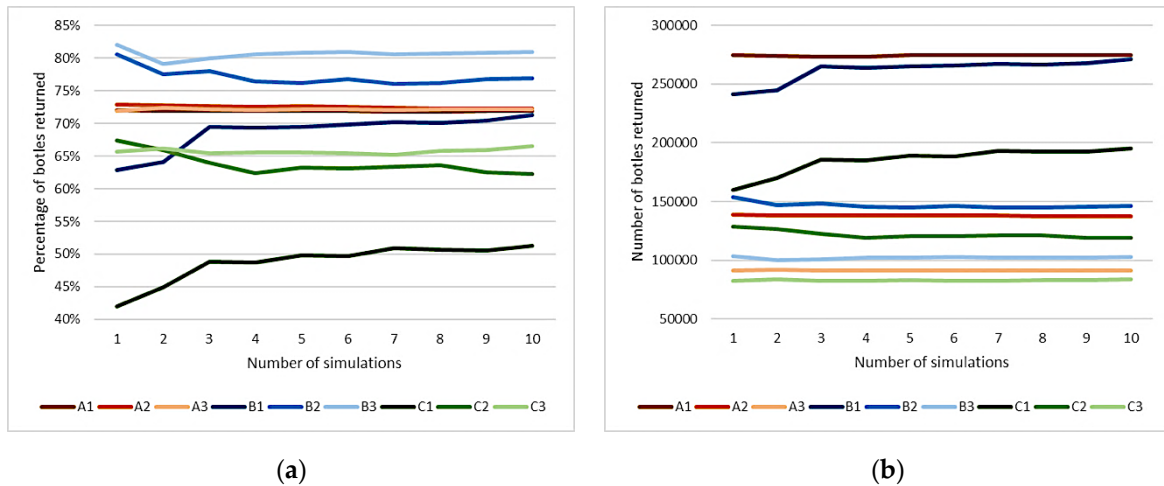


Figure 4.8 (a) Shows the cumulative average percentage of bottles returned for 10 successive simulation runs. (b) Shows the cumulative average of the number of bottles returned, with all depot centers combined, for 10 successive simulation runs.

4.4.3.2 Bottle returns percentages

The table 2 below shows the percentages of bottles returned by the populations. The results indicate that the number of bottles returned is proportional to the number of depot center. The only exception is scenario A2 (population A with 2 depot centers), where the average and maximum return percentages are slightly higher than scenario A3. Given that these results are extremely close, a higher number of repetitions could most certainly bring the return percentages of scenario A3 above those of scenario A2.

Another observation is that, the suburban population type seems to be the most efficient at returning bottles. Considering that suburban population territory is nearly 3 times the size of the urban population territory, the percentage of car ownership appears to have a greater positive effect on the return percentages than the negative effect of the distance between the nearest depot center. However, the lower return percentages of the rural population also indicate that there is a threshold where the dissuading effect of the distance becomes greater than advantages of easily accessible transportation, even if the number of consumers owning a private vehicle increases.

For the urban population, there is no clear indication on which scenario would be better on a logistic standpoint alone. For such cases, economic considerations on the costs of depot centers operations would be mandatory to identify the optimal scenario. For the suburban population, the maximum of the scenario B1 is respectively only around 1% and 2.5% below the average and maximum of

scenario B3. These findings show that even if the suburban population return their bottles the most, positioning of the depot centers can considerably alter the efficiency of the strategy. For the rural population, the results support the findings of the (B) population.

Table 4.2 The percentages of bottles returned for 10 simulations of each scenario

Population	Number of depot centers	Average (%)	Standard deviation	Min (%)	Max (%)
Urban (A)	1	71.92	0.31	71.28	72.34
	2	72.23	0.49	71.35	72.84
	3	72.22	0.47	71.56	72.80
Suburban (B)	1	71.77	5.38	62.85	80.04
	2	76.89	3.55	71.52	81.29
	3	81.01	2.01	76.20	82.46
Rural (C)	1	51.33	5.23	42.02	58.09
	2	62.31	4.24	53.99	67.35
	3	66.59	2.77	63.79	72.59

4.4.3.3 Number of bottles returned in depot center

The table 3 and 4 shows the averages and the number of bottles returned per depot centers. Illustrations of the results can be found in Appendix B and C.

Consistent with the previous results, all the maximum average values from the urban populations are lower than the maximum averages of the suburban population. Interestingly, the maximum average of the scenario C3 is only 695 bottles behind the maximum average of the A3 population. Therefore, even across 250 km², if the depots are optimally positioned, the bottle return potential is similar to the urban population, which fits in less than 15 km². However, the higher standard deviation and the lower average values for the rural scenarios indicates that the effectiveness of the strategy is crucially dependent of the depot centers placements. The similar standard deviations values of scenarios B1 and C1 also suggests that even if the distance increases considerably, a slight increase in the percentage of private vehicle ownership is enough to stabilize the results around the mean.

Table 4.3 Average number of bottles returned at depot centers for 10 simulations of each scenario

Population	Number of depot centers	Average	Standard deviation	Min	Max
Urban (A)	1	274 587	1 568	272 275	278 084
	2	137 704	917	136 262	139 091
	3	91 512	656	90 003	92 232
Suburban (B)	1	271 327	20 729	241 391	304 499
	2	146 143	6 902	136 311	154 599
	3	102 685	2 739	96 336	104 880
Rural (C)	1	195 079	20 607	159 608	221 672
	2	118 841	8 463	102 805	128 791
	3	84 070	3 294	80 925	91 537

As for the number of bottles per depot centers, the averages for the urban and suburban scenarios are considerably similar. On the other hand, the standard deviations of the (A) population are all much lower than the (B), which indicates that the first population is less sensible to the depot center locations than its counterparts. Nevertheless, with only one depot center strategically placed, it is possible in the suburban population to surpass the maximum number of bottles returned for population (A), even if its average is lower.

It must be noted that increasing the number of depot centers can have some unexpected effects. For the populations (A) and (B), there is a steep augmentation in the standard deviations between 1 and 2 depot centers. It then seems lowers as the number of depot center keeps increasing. The model can cause this phenomenon itself, since agents have a preferred depot center. In reality, the split between the amount of bottle returned would probably be less intense since agents could potentially go to both depot centers depending on their travel habits. It is still reasonable to assume that beyond two depot centers the standard deviation decreases continually, after having a peak between one and two depot centers.

Table 4.4 Number of bottles returned per depot centers for 10 simulations of each scenario

Population	Number of depot centers	Average	Standard deviation	Min	Max
Urban (A)	1	274 587	1 568	272 275	278 084
	2	137 704	43 795	62 468	206 999
	3	91 512	35 804	14 971	172 254
Suburban (B)	1	271 327	20 729	241 391	304 499
	2	146 143	50 375	43 246	197 962
	3	102 685	37 975	18 752	161 188
Rural (C)	1	195 079	20 607	159 608	221 672
	2	118 841	31 816	65 393	170 538
	3	84 070	41 121	18 854	180 556

4.5 Discussion

The proposed simulation model, along with his calibration process and series of experiences, enables the analysis a potential EOF product flow strategy that is, at the time of the study, still at a proposition phase. Waste management and EOL product flow strategies usually have large scale implications and impacts. If these strategies are not thoroughly analysed before they are developed, they can have unexpected negative impacts or simply be ineffective and become a waste of time and resources (Goddard, 1995). The two following section presents the general insights provided by the model as well as its limitations.

4.5.1 General insights

The results shown in table 2, 3 and 4 give insights over the relative importance of several parameters of the model over the return percentage behavior. While the results are not to be taken as quantitatively accurate evidences, they most certainly provide some qualitative evidences. First, there is no doubt that the value of the deposit has a significant impact on the decision of the consumers. Coherent with the empirical data (CREATE, 2015), a deposit value of 0.35\$ provide some striking results with a 95% minimum return rate, regardless of the population. These results are in line with Canadian data, where the deposit fee in Ontario for wine and spirits bottles is

respectively 0.10\$ and 0.20\$ for bottles below and above 630 ml. The Ontario recycling rate is 87%, which is not the percentage of bottles returned, but rather the percentage of bottles that were returned *and* recycled (CMConsulting, 2016). Results also suggests that the distance to the nearest depot and the ownership of private vehicle can have a substantial impact on return percentages. Between the two, the second seems to have a greater impact than the distance, up to a certain point. It is, however, difficult to identify where this threshold stands with this papers experiments. Another finding is that the positioning of the depot centers would be crucial to the success of the strategy. For example, when there is only one depot center, the urban population returns more bottles on average, but a well positioned depot center in the suburban population can result in a higher return percentage. For this specific case, the maximum return percentage of the suburban population for one depot center is 9.5% above the maximum of the urban population for its equivalent scenario.

The simulation model can also be used to give insights on the capacity needed for the depot centers. Since the model was calibrated with Quebecers wine consumption, it is possible to even estimate the costs of specific scenarios with their respective depot centers capacity needs. Data on the estimation of depot centers operations costs can be found in a report produced for the Société des Alcools du Québec (LIDD, 2015).

4.5.2 Model limitations and future works

The simulation model proposed in this paper is not to be taken without its limitations. Future works will focus using heterogeneous populations. At the moment, results are altered by the fact that the populations (A), (B) and (C) used in the experiments are homogeneous. Real life city and districts are not homogeneous. Therefore, replication of this papers experiments with heterogeneous populations may produce substantially different results.

Another limitation of the model is that it was calibrated with a 0 to 15 km territory. Thus, the calculation of the PBC beyond 15 km, especially for the rural scenarios, may not be accurate. Nevertheless, having simulated territories defined as closed squares also add some level of inconstancies. For example, in scenario C1, agents that are located near the borders of the territory and far from the depot centers could actually be near another depot center from an adjacent territory. Hence, the 15 km calibration limit may not be as much of an impacting factor as the simulated territories size limitations.

Considering that the survey used for the calibration of the PBC had 88.1% of the participants owning a vehicle at the time of the study (CROP, 2015), compared to the empirical data used to define the experiences (Pyddoke & Creutzer, 2014; Roque & Masoumi, 2016; Turcotte, 2008), the percentage of private vehicle ownership may have been overestimated in the calibration process. While the main reason to own a vehicle is to facilitate the travel over longer distances, participants from the survey could be more sensible to travel distances. Consequently, the impact of the distance to the nearest depot on the populations analyzed in the experiments may not be accurately representative of how comparable real populations would behave over this aspect.

One last notable limitation of the model is how agents have preferred depot centers. Future works will enable agents to have multiple favorites depot centers. For instance, within a 10% distance range, agents could alternate between multiple accessible depot centers.

4.6 Conclusions

Even with its limitations, this model could be used by policymakers to get insights on various aspects of the studied strategy, such as the deposit value as well as the size and placement of depot centers. However, the simulation model must not be taken as an optimisation tool. The model could compare specific scenarios of depot center sizes and placements for example, but they must be defined beforehand. The accuracy of the model must also be taken in to account, as, for the time being, it can only represent homogeneous populations. Thus, it is more suitable for small to medium scale cities. Indeed, extensive work needs to be done before the model can simulate large scale cities that have significant variations in their population density.

The proposed model builds upon the existing literature by taking an approach that enables the simulation of multiple and complex behaviors. The model also integrates parts of the logistics aspect that recycling behavior simulations do not usually consider.

The implementation of agent-based modeling and simulation into municipal waste management systems strategies analyses enables the reproduction of complex behaviors that are crucial when studying systems that are human-driven. Using artificial societies to empower the circular economy ideology seems more than appropriate when considering that this framework addresses large-scale networks that are composed of many entities with their own behaviors and characteristics that can be represented by autonomous agents. This paper proposes a methodology to apply behavior models with the help of appropriate empirical data to analyse mass flow driven by human decision

and complex social interactions. Future research will focus on adding socio-demographics characteristics to the populations, in order to take into account their heterogeneity, as well as the impact of social networks and medias on the consumer behavior. The model will then be used to simulate scenarios with populations that are based on actual cities and evaluate their respective performances. Eventually, the model could also be adapted to new products and analyse other waste diversion strategies such as centralized depot centers that accept multiple EOL products. Even if some aspect of the model were less successfully captured, the first attempt at calibrating and validating the model has proven to be substantially successful and opens the doors to multi-disciplinary models where psychology, computer simulation and engineering experts can thrive on common objectives.

Future research will also use the developed methodology and model to estimate the environmental impacts and costs of alternative municipal waste management strategies within a CE framework. Joint with the construction costs and operating costs of depot centers according to their sizes and capacities (LIDD, 2015), multiple logistic strategies can be analysed and compared. By enabling decision-makers and policy makers to have insights on the efficiencies of potential end-of-life product flow strategies, the risk associated with implementing large-scale strategies can be greatly diminished. To further increase the success potential of these strategies, pilot projects can be used to re-calibrate and re-validate existing consumer behavior models with new data to find the optimal solutions for specific populations and regions.

4.7 Appendix A: Graphical representations of the scenarios (AnyLogic)

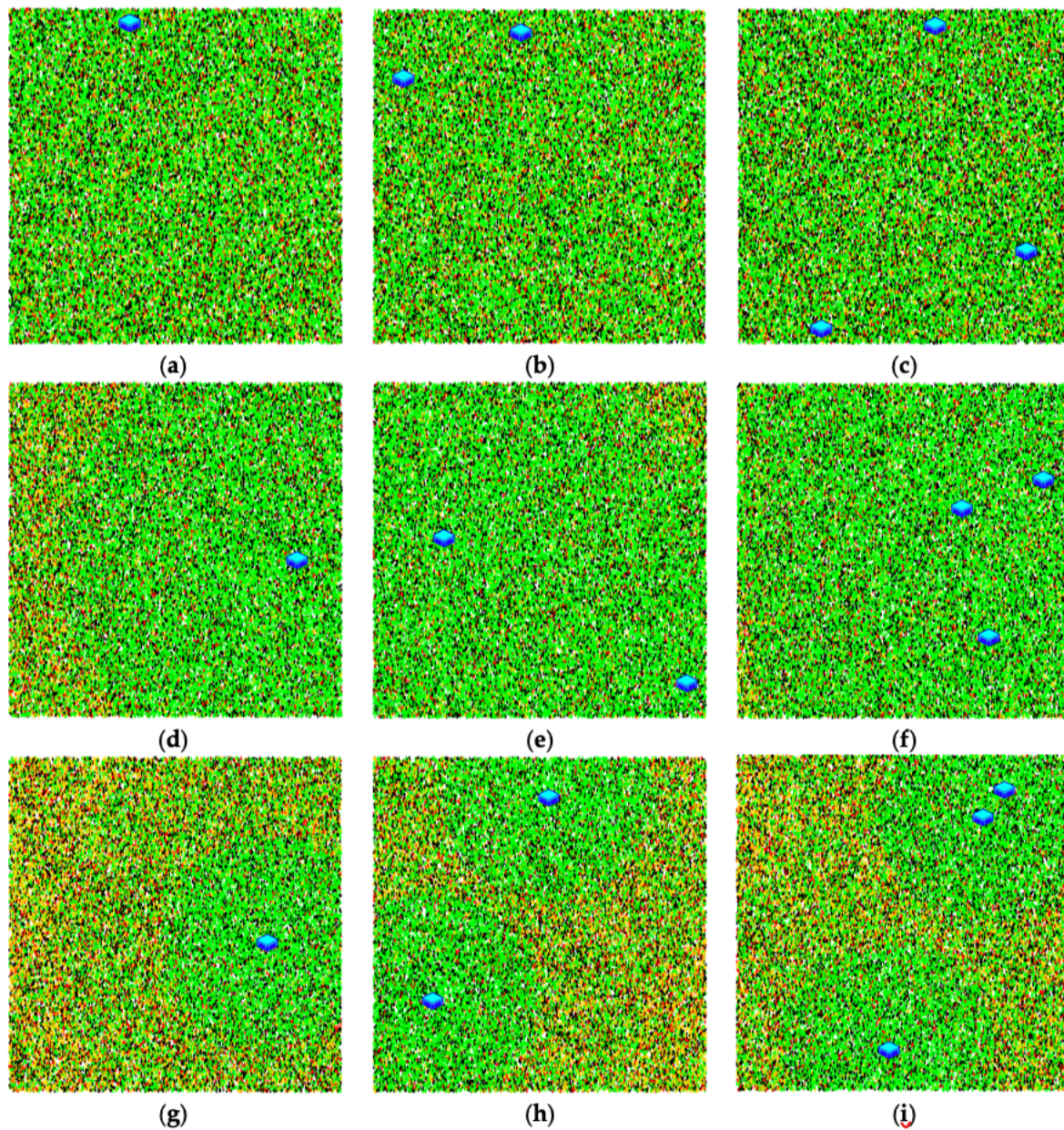


Figure 4.9 One of the 10 simulations executed for each scenario with a 0.15\$ deposit value. (a) Scenario A1. (b) Scenario A2. (c) Scenario A3. (d) Scenario B1. (e) Scenario B2. (f) Scenario B3. (g) Scenario C1. (h) Scenario C2. (i) Scenario C3

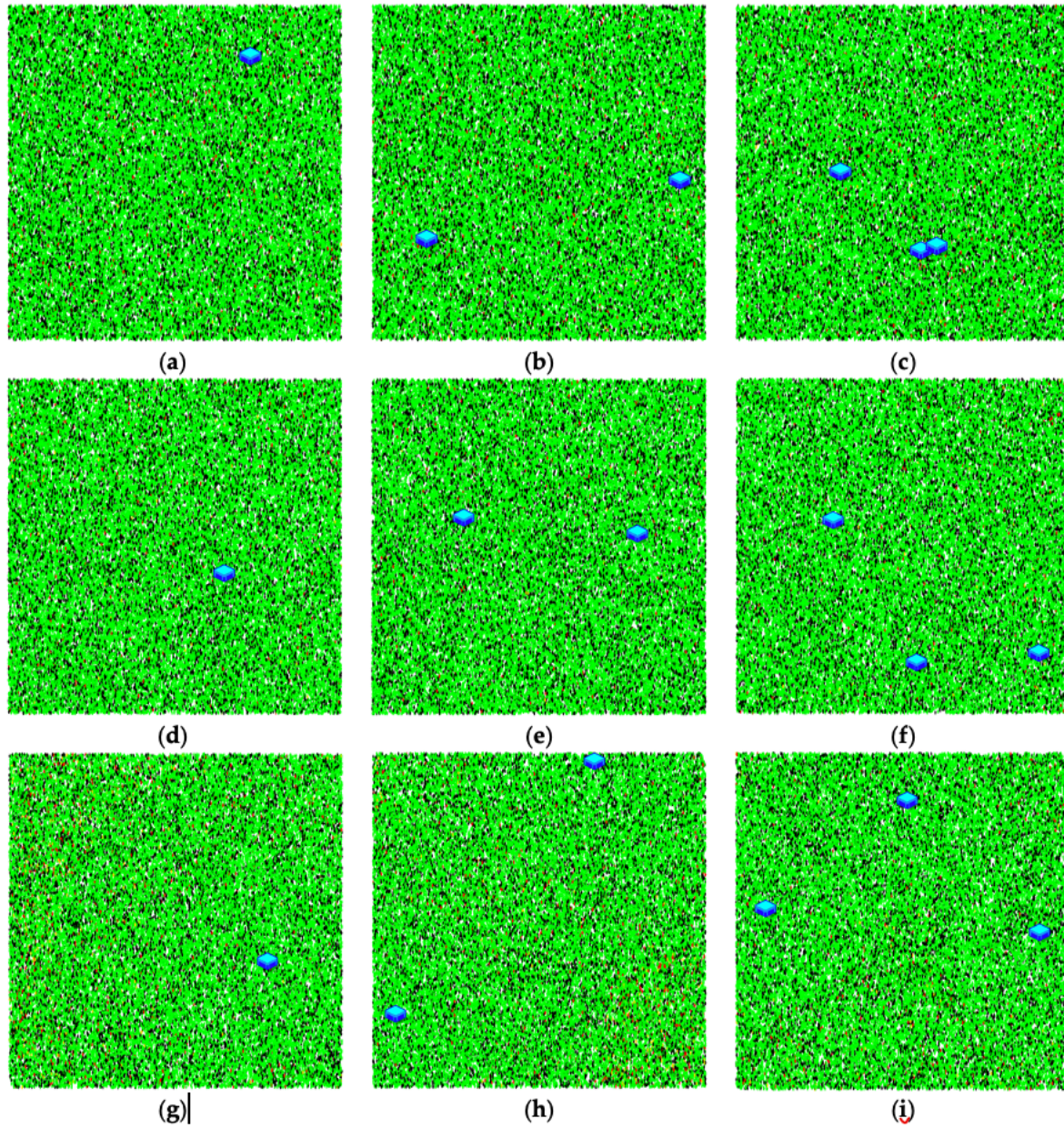


Figure 4.10 One of the 10 simulations executed for each scenario with a 0.35\$ deposit value. (a) Scenario A1. (b) Scenario A2. (c) Scenario A3. (d) Scenario B1. (e) Scenario B2. (f) Scenario B3. (g) Scenario C1. (h) Scenario C2. (i) Scenario C3

4.8 Appendix B: Average number of bottles returned per depot centers for each simulation runs

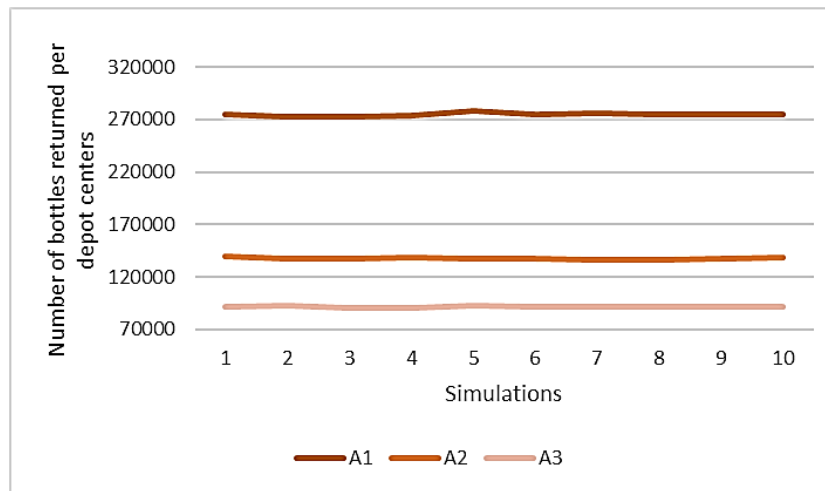


Figure 4.11 Average number of bottles returned per depot centers for the simulations of the three scenarios A with a 0.15\$ deposit value

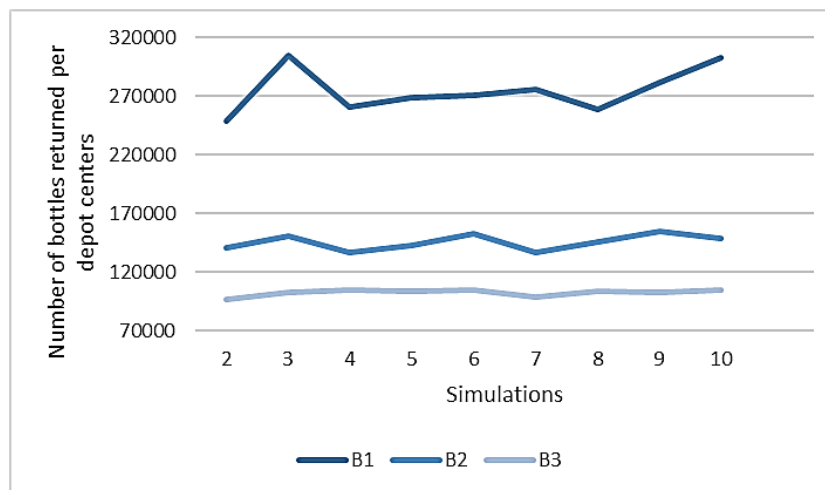


Figure 4.12 Average number of bottles returned per depot centers for the simulations of the three scenarios B with a 0.15\$ deposit value

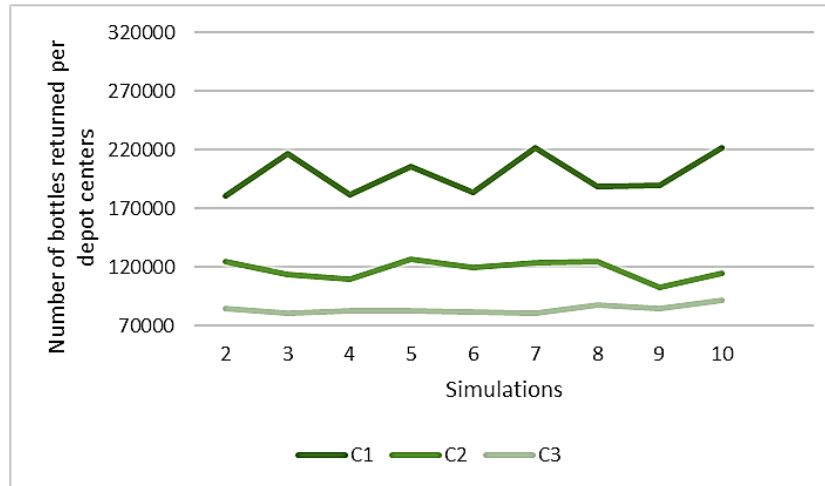


Figure 4.13 Average number of bottles returned per depot centers for the simulations of the three scenarios C with a 0.15\$ deposit value

4.9 Appendix C: Number of bottles returned per depot centers for each simulation runs

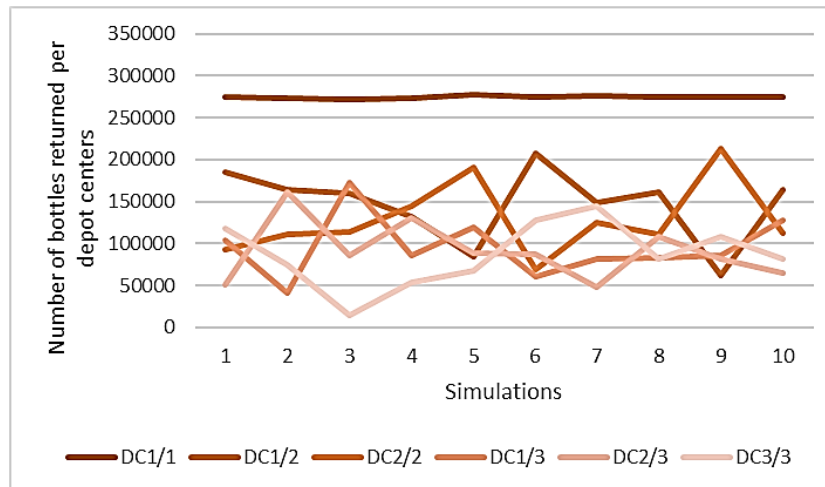


Figure 4.14 Number of bottles returned per depot centers for the simulations of the three scenarios A with a 0.15\$ deposit value

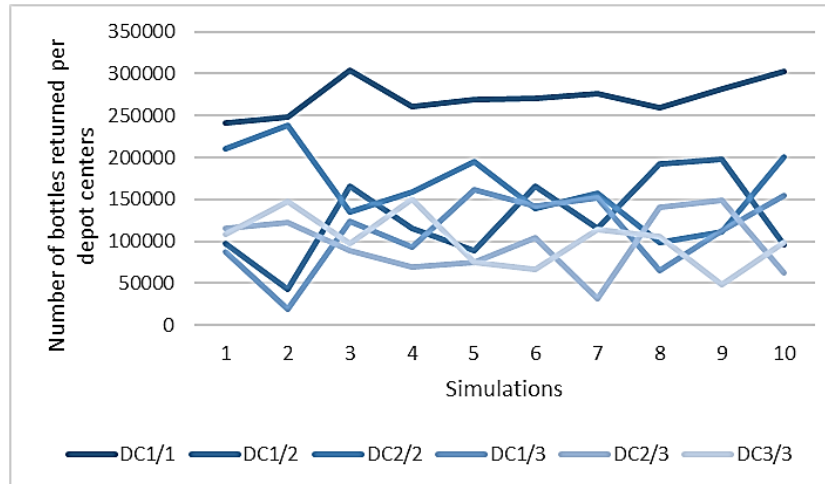


Figure 4.15 Number of bottles returned per depot centers for the simulations of the three scenarios A with a 0.15\$ deposit value

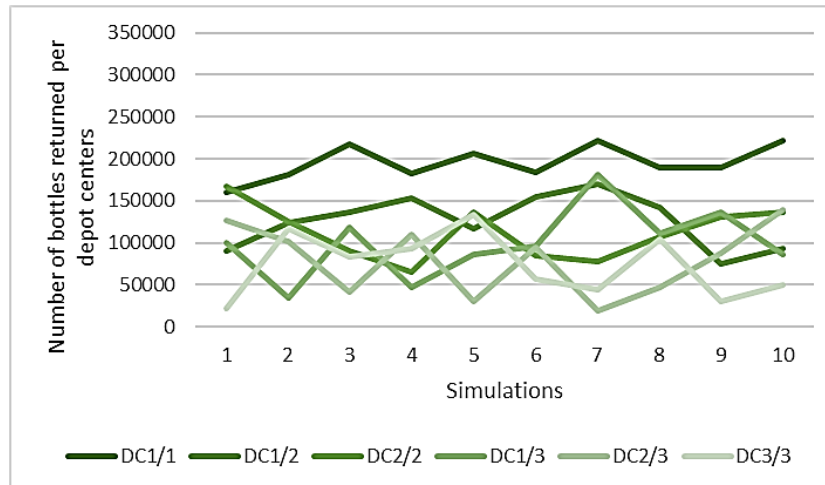


Figure 4.16 Number of bottles returned per depot centers for the simulations of the three scenarios A with a 0.15\$ deposit value

CHAPITRE 5 ARTICLE 2: FIRST-MILE REVERSE LOGISTICS: AN AGENT-BASED MODELING AND SIMULATION APPLICATION FOR GLASS BOTTLE RECOVERY

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Distribution networks aim to get the right products to consumers at the right time and in the right place. When consumers return these products, another type of logistics network is involved. This function of returning end-of-life products is referred to as reverse logistics. A critical characteristic of these reverse logistics networks is that their material flows are often dependent on the voluntary action of the consumer. Therefore, the success of an end-of-life collection strategy depends on the ability to understand the factors that influence consumer behavior in order to anticipate the collection rate of end-of-life products at specific locations. However, there is no established tool or methodology for assessing the impact of consumer decisions on reverse logistics material flows. Therefore, this paper proposes an agent-based simulation tool to predict the performance of a reverse logistics network, taking into account the location of collection points, socio-demographic information, attitudes towards sustainable development, as well as the consumption profile. More specifically, this paper presents the configuration, calibration and validation of a simulation model of the return of empty glass bottles in a small group of municipalities in Québec, Canada. Experiments also demonstrate the tool's ability to provide useful information to support the design of collection strategies that maximize return rates and minimize installation and operating costs by optimizing the number of drop-off depots visited in the reverse logistics network

5.1 Introduction

Distribution networks aim to get the right products to consumers at the right time and in the right place. When consumers return these products (e.g., deposits, e-waste, used batteries), a different type of logistics network is involved. This function of returning end-of-life (EoL) products - as well as other types of goods such as pallets, containers, defective products - is referred to as reverse logistics. A critical feature of these reverse logistics networks is that their material flows are often dependent on the voluntary action of consumers. Therefore, the success of an EoL collection strategy depends on the ability to understand the factors that influence consumer behavior in order to anticipate the EoL collection rate at specific locations.

When EoL products are collected, municipal waste management systems (MWMS) or voluntary collection networks are set up. In both systems, consumer behavior regarding product consumption and return or disposal is central, as the return rate of EoL products is influenced by the convenience or ease of return, incentives, as well as consumer attitudes towards sustainable development and other socio-demographic factors. However, due to the complexity and intricacy of these factors, few tools exist to analyze the impact of waste and EoL product collection systems on consumer decisions, and in particular on their decision to return their EoL products.

Based on the premise that the consumer is the point in a value chain where material flows are diverted towards their respective EoL or, in some cases, their new life, actors in the reverse value chain, such as collectors, conditioners and recyclers, are affected by the decisions made by waste generators. From a resource conservation perspective, the worst decision a consumer can make with their EoL products is often to dispose of them (i.e., landfill). Alternatively, if conditions allow (e.g., technology, infrastructure, standards), these EoL products can also be properly collected to enter a reverse value chain and ultimately be recycled. In 2016, 32 million tons were processed through Canada's municipal waste management systems. Unfortunately, only 27% was diverted from landfills through recycling or composting (E. a. C. C. Canada, 2018).

In Québec, part of this responsibility is being transferred to the industrial sector through municipal waste management policies. In fact, since 2013, Quebec's selective collection program has been 100% financed by producers and first importers of paper, cardboard and packaging. Between 2005 and 2017, more than \$1 billion in compensation was paid to municipalities to cover the costs of this program (CMConsulting, 2018). However, there are limits to this strategy. While it

incentivizes companies to improve their products and packaging designs to reduce their contribution to this funding program, if consumers do not participate in collection programs, materials may still end up in landfills. In addition, this program does not encourage sorting at source, which makes recycling more difficult. In addition, a recent review by Boz et al. highlights the importance of considering consumers in the development and implementation of sustainable packaging designs (Boz, Korhonen, & Koelsch Sand, 2020).

To study the impact of collection system design on consumer behavior and collection rates, a simulation model was proposed in Labelle & Frayret (2018). This tool was specifically calibrated to reproduce consumer behavior related to EoL wine bottles using general demographics, wine consumption, and recycling behavior data from Quebec.

To validate the ability of this model to be configured and calibrated for a region using specific demographic data (S. Canada, 2017) and its ability to provide useful information to support the strategic design of a collection system for this region, this paper presents a comprehensive case study analysis dedicated to the voluntary glass depot program of the Regional County Municipality (RCM) of Val-Saint-François. The authors worked with the Opération Verre-Vert (OVV) committee to obtain data on the quantities of glass collected through this incentive-free voluntary return program.

This paper is organized as follows. Section 2 presents a review of the relevant literature. Section 3 presents the theoretical model, its general assumptions in the context of the Quebec population, and an overview of the empirical data used to calibrate the initial configuration of the model. Next, Section 4 presents the various extensions made to this model, their calibrations, and a comparative analysis of the impact of these extensions on the ability of the model to be calibrated to fit the empirical data of the case study. Then, Section 5 presents a study of the usefulness of this model in the context of designing a reverse logistic network. Section 8 concludes.

5.2 Literature review

The field of consumer behavior psychology alone is not sufficient to prepare for tomorrow's behavioral environmental challenges (Clayton et al., 2016). Researchers in the field need to collaborate with experts from other disciplines, such as mathematicians, engineers, and computer scientists, to form multidisciplinary teams capable of effectively addressing these multifaceted challenges. Specifically, papers dealing with recycling behavior (see Table 1) either propose,

describe, or classify factors such as sociodemographic characteristics or cognitive constructs (e.g., attitudes, social norms, perceived behavioral control) that may be significant determinants of behavior (Babaei et al., 2015; Best & Mayerl, 2013; Bissing-Olson et al., 2016; Botetzagias et al., 2015; Chan & Bishop, 2013; Gifford & Nilsson, 2014; Kormos & Gifford, 2014; López-Mosquera et al., 2015; Morren & Grinstein, 2016; Rhodes et al., 2014; Sidique, Joshi, et al., 2010; Sidique, Lupi, et al., 2010; Steg & Vlek, 2009; Stern, 2000; Thøgersen, 1996; Tonglet et al., 2004; Tucker, 1999; White & Hyde, 2011). However, very little research has been done to develop tools to model the complex relationship between these behavioral determinants (i.e., independent variables) and actual behavior (i.e., dependent variables) to predict or estimate recycling behavior for reverse logistics strategy design and analysis.

Table 5.1 Identified potential predictors of recycling behaviour

	TPB	Attitude	Social norm	PBC	Socio-demographic
(Tonglet et al., 2004)	X	X			
(Sidique, Joshi, et al., 2010)					X
(Sidique, Lupi, et al., 2010)		X			X
(White & Hyde, 2011)	X	X	X		
(Chan & Bishop, 2013)*	X	X	X	X	
(Rhodes et al., 2014)	X	X		X	
(López-Mosquera et al., 2015)		X			X
(Morren & Grinstein, 2016)	X	X			

*In this case, attitude was replaced with moral norms.

In the literature related to this issue (Labelle & Frayret, 2018; Mashhadi, Behdad, & Zhuang, 2016; Meng, Wen, & Qian, 2018; Scalco et al., 2017; Tong et al., 2018), simulation is undoubtedly a tool that stands out by showing great effectiveness and flexibility in addressing problems that are difficult to solve in reverse logistics (Abid, Radji, & Mhada, 2019).

Simulation, in particular agent-based modelling and simulation (ABMS), can be used in a variety of contexts to emulate human behavior in order to better understand, analyze, or design the systems in which they operate (Bonabeau, 2002). Agent-based modelling and simulation is a powerful and well-suited tool for working with systems that are complex and distributed by nature, such as

municipal waste management (Axtell, Andrews, & Small, 2001). As early as 1998, Tucker, Murney & Lamont presented a clear picture of how ABMS could alleviate the challenge of understanding the municipal waste management system's reliance on voluntary consumer action (Tucker et al., 1998). Tucker then developed a proof-of-concept for a complex residential waste simulation model composed of autonomous entities representing individual households, each with its own sociodemographic characteristics, attitudes, and social interactions (Tucker & Smith, 1999). However, due to the complexity of their models, a significant amount of data was required to configure and calibrate them. In fact, this is a recurring problem in behavioral simulation because the available data are often either too aggregated or of insufficient quality. As a result, researchers often resort to the common practice of estimating certain aspects of their models using stochastic distributions based on common sense and intuition rather than empirical data.

Another challenge in developing such tools is that the variety of data required for configuration and calibration often requires data information from a variety of different sources. It is therefore critical to merge multiple data sets in a coherent and consistent manner. In some cases, when data come from similar but different contexts (e.g., another region), assumptions must be explicitly made to justify their integration into the model. Ideally, these assumptions should be supported by the literature, as not all behavioral findings can be generalized from one context to another. The meta-analyses by Armitage & Conner (2001) and Morren & Grinstein (2016) are good examples of studies that support such assumptions (Armitage & Conner, 2001; Morren & Grinstein, 2016). The former is concerned with analyzing the validity of the most widely used model in sustainable behavior research (i.e., the Theory of Planned Behavior, TPB) (Boz et al., 2020), while the latter discusses the variation in behavioral determinants across countries and cultures. It should be noted that Tucker and Smith's models were also inspired by Ajzen's TPB model (Ajzen, 1991). The interested reader is referred to Scalco et al. (2017) for a comprehensive review of the use of Ajzen's framework to develop simulation experiments for recycling behavior (Scalco et al., 2017).

Finally, in their recent review of simulation models applied to reverse logistics, Abid et al. (2019) conclude that there is a need for additional research on the simulation of EoL product flows, as well as more transparency in the publication of tools dedicated to these issues. In this sense, Janssen & Ostrom (2006) provide an overview of how agent-based modelling can benefit from its combination with empirical methods for practical applications. One of the main challenges

highlighted in this review is the difficulty of developing consistent models that are both generalizable and applicable to specific cases (Janssen & Ostrom, 2006).

The main contribution of this paper is to address these limitations and challenges by proposing an agent-based simulation model that is almost entirely calibrated and configured with empirical data from various sources. In other words, almost every aspect of the model - from attitude distributions to the effects of incentives or travel distances - is calibrated using empirical data and available information. This results in a model that is representative of reality and can be used to evaluate specific reverse logistics scenarios, such as the choice of types, sizes, and locations of return depots. The ability to provide reliable estimates of return rates facilitates the design of consumer-centric collection strategies. While the approach proposed in this paper is applied to wine bottles, it has the potential to be extended to a variety of other products, such as e-waste, used batteries, or other deposit returnable containers.

5.3 Simulation model

In this section, we describe the initial configuration of the agent-based simulation model presented in Labelle & Frayret (2018). The simulation model has been implemented using AnyLogic. The purpose of this model is to simulate, in a Geographic Information System (GIS) environment, a population composed of consumer agents that can autonomously decide to dispose or return their EoL products, in order to evaluate the impact of different independent variables (e.g., reverse logistics strategies, socio-demographic factors) on a set of dependent variables (e.g., return rates of collection points). Agents are virtual consumers populating a digital environment in which they act autonomously and, in this specific application, without mutual influence or social norms. These consumer agents have the following characteristics: GIS address, age, mode of transportation, wine-drinking habits, as well as other attributes that characterize their individual behavior (e.g., perceived behavioral control, attitudes toward sustainable development).

5.3.1 Model initial assumptions

Although this initial configuration of the model is based almost entirely on empirical data, which was used either to specify the statistical distribution of some parameters or to calibrate others, two assumptions were made to configure the model. According to a report by the Société des Alcools du Québec (SAQ), the average Quebecer consumed 30.3 bottles of wine in 2016, or approximately

0.58 bottles per person per week (SAQ, 2016). Since the amount of wine consumed per person per occasion is not reported in the available surveys (Éduc-Alcool, 2017; INSPQ, 2016; ISQ, 2011; SAQ, 2016), this value was assumed to be an average of 0.5 bottles of wine per person per occasion. Similarly, although wine bottles vary in shape and weight, the second assumption is the weight of empty wine bottles, which is assumed to be 0.5 kg for all bottles.

5.3.2 Model overview

This model is based on the Theory of Planned Behavior (TPB) (Ajzen, 1991). In short, the TPB proposes that behavior can be predicted with relative accuracy by factors such as attitudes, social norms, and perceived behavioral control (PBC). Often, sociodemographic factors such as age, income, education, or household size are also identified as potential predictors of behavior, although they may help to specify attitudes, social norms, and PBC. While the first version of the model included both attitudes and PBC, a single sociodemographic factor (i.e., age) was used as a proxy to define a consumer agent's attitudes as well as his or her wine consumption habits. More specifically, age was used in conjunction with specific empirical probability distributions from various data sources to specify the individual attitudinal and wine consumption profiles of the agents. For example, two consumer agents in different age groups would not have the same probability of being pro-environmental.

The general conceptual framework of the simulation model is shown in Figure 1 (solid rectangle). Its core (dashed rectangle) is the TPB, to which we have added an incentive factor to account for a deposit-return program. Since the collect program in the Le-Val-Saint-François case study presented below is voluntary, the incentive value was not used in the experiments presented in Sections 4 and 5. Next, empirical probability distributions (double-line rectangles) based on publicly available empirical data were used to represent the actual variability of the population of consumer agents. All sources of empirical data needed to configure and calibrate the model are presented outside the black line rectangle. The following subsections present the mathematical framework of the model and the data used in the configuration and calibration process.

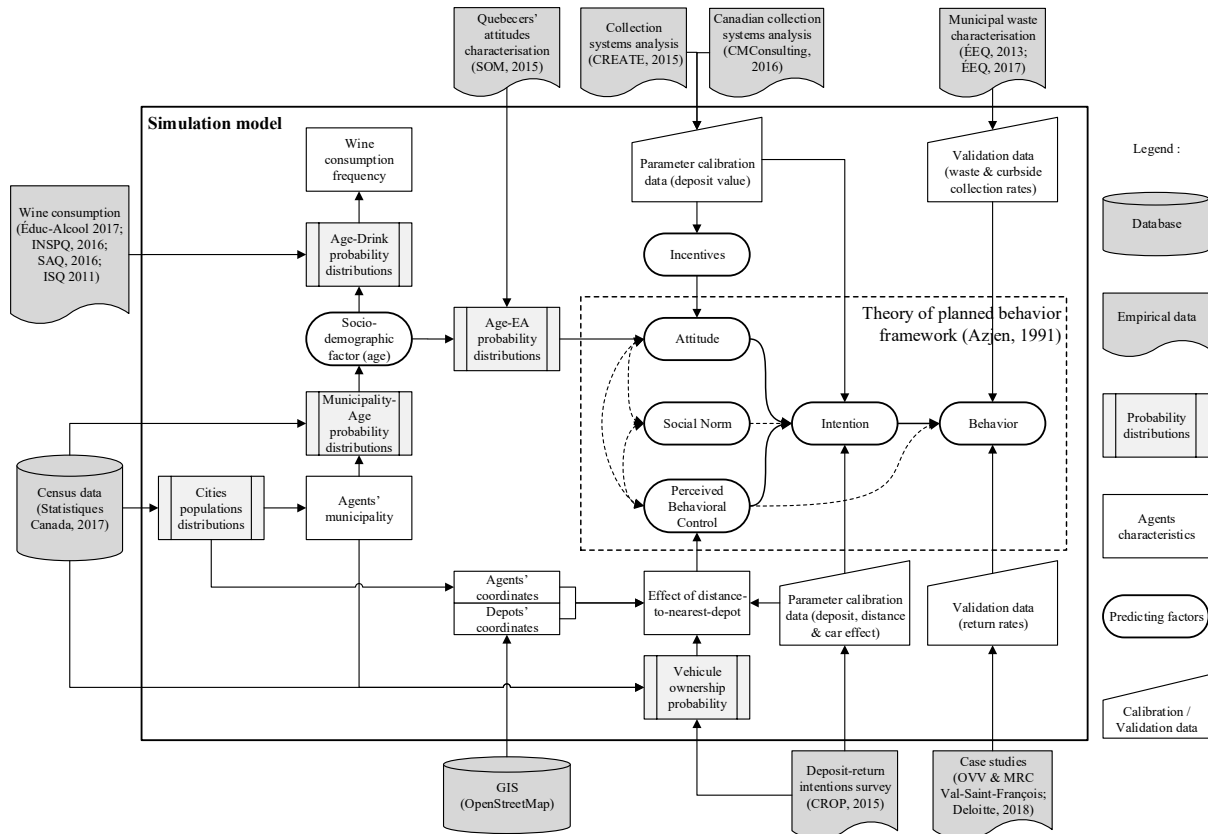


Figure 5.1 Simulation model overview

5.3.3 Mathematical framework

As shown in Figure 2, for each bottle consumed, each agent cycles through its own state diagram and systematically evaluates all possible EoL options using the TPB framework. Equations 1 to 6, taken directly from Labelle & Frayret (2018), represent this evaluation process. The option with the highest value of its Behavior variable (Equation 1) is implemented by the agent. The three options are BringBack, RecycleBin or TrashCan. The Intention variable (Equation 2) is calculated using the Attitude variable (Equations 3 and 4) and the Perceived Behavioral Control (PBC) variable (Equations 5 and 6). If two behavioral variables are equal, one option is chosen at random.

At the beginning of each simulation, all agents are initialized with individual basic characteristics: a position in the GIS environment, an age, and a mode of transportation. After this initialization, the agents enter their own state diagram, provided that it is 12 years old or older.

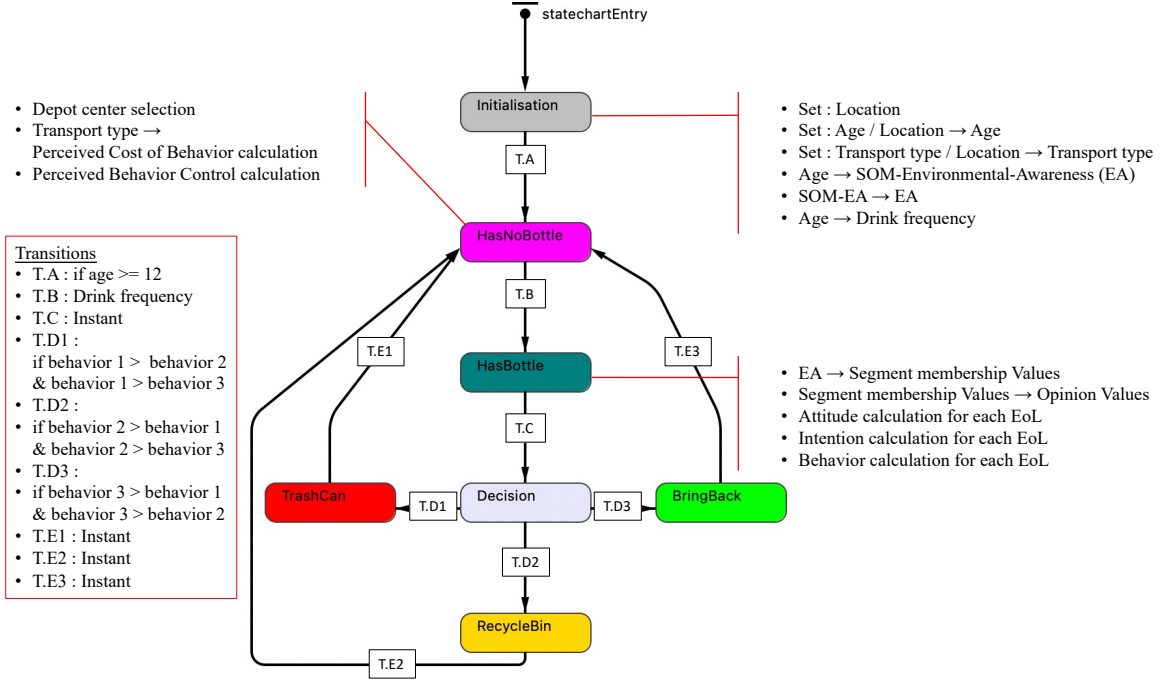


Figure 5.2: Consumer agent statechart diagram (*AnyLogic*).

Next, the Attitude variable for each of the 3 EoL options is calculated using the Opinion Value variable ($OV_{i,t,b}$), which is specific to the agent, and the Incentive Value variable (IV_b), which is specific to the case study. The relative importance of these two variables is set by the parameter γ , which is used to modulate the impact of the opinion and the incentive on the attitude (Equation (3)). In this model, this parameter is specific to the population studied and its value ranges from 0 to 1. When $\gamma=0$, only the incentive is considered by the agents; conversely, when $\gamma=1$, only the opinion is considered. In the first version of this model, the unit used for the incentive was money (\$). In other words, for an incentive of \$0.20, the value of IV would be 0.2. In the Le-Val-Saint-François case study, even if there is no monetary incentive, we can assume that part of the population may still need an incentive to participate in the collect program. Therefore, we cannot assume $\gamma=1$ without studying its impact on the simulation results.

The Opinion Value ($OV_{i,t,b}$) of an agent i for a behaviour b is calculated based on the agent Environmental-Awareness (EA), noted ($x_{i,t}$), which is a parameter that is specific to each consumer agents. The value of EA ranges between 0 (no EA) and 100 (maximum EA). To map the EA parameter to eco-awareness segments defined in the empirical study by (SOM, 2015), we used fuzzy logic. In other words, to calculate the Opinion Value, we use fuzzy numbers that define each

segment over the range of EA (**Error! Reference source not found.**). Therefore, for a given agent i , its Opinion Value for each EoL option is a function (Equation 4) of its specific segments membership values ($\mu V_{i,s,t}$), and the calibrated segments' opinion values ($SOV_{b,s}$). As shown in **Error! Reference source not found.**, this fuzzy logic model is composed of 3 EA segments. Thus, three segments membership values are calculated. Since these segments are overlapping fuzzy numbers, an agent can simultaneously belong to two segments.

$$Behaviour_{i,t,b} = Intention_{i,t,b} \quad \forall i \in I, t \in T, b \in B \quad (5.1)$$

$$Intention_{i,t,b} = Attitude_{i,t,b} + PBC_{i,t,b} \quad \forall i \in I, t \in T, b \in B \quad (5.2)$$

$$Attitude_{i,t,b} = \gamma \times OV_{i,t,b} + (1 - \gamma) \times IV_b \quad \forall i \in I, t \in T, b \in B \quad (5.3)$$

$$OV_{i,t,b} = \sum_{s \in S} [\mu V_{i,t,s} \times SOV_{b,s}] \quad \forall i \in I, t \in T, b \in B \quad (5.4)$$

$$PBC_{i,b} = -PCB_{i,b} \quad \forall i \in I, b \in B \quad (5.5)$$

$$PCB_{i,b} = a_{c_i,b} \times d_i + b_{c_i,b} \quad \forall i \in I, b \in B \quad (5.6)$$

with

Indexes:

$i \in I$	consumer agent, $i \in [0, 30686]$;
$t \in T$	time period (in weeks), $t \in [0, 13]$;
$b \in B$	EoL behaviours, $b \in [\text{RecycleBin}; \text{BringBack}; \text{TrashCan}]$;
$s \in S$	Eco-Awareness segments, $s \in [1, 3]$.

Variables:

$OV_{i,t,b}$,	Opinion value of agent i for behaviour b , $= OV_{i,t,b} \in [0, 100]$;
IV_b ,	Incentive value of behaviour b (in \$), $IV_b \in [0, 1]$;
$\mu V_{i,t,s}$,	Fuzzy membership value of agent i , at time t , and segment s , $\mu V_{i,t,s} \in [0, 1]$.
$PCB_{i,c,b}$	Perceived Cost of Behaviour for agent i , car possession status of agent i , for behavior b ;
$PBC_{i,c,b}$	Perceived Behavioral Control for agent i , car possession status of agent i , for behavior b .

Random parameters based on empirical distribution:

$x_{i,t}$	Environmental-Awareness of agent i at time t , $x_{i,t} \in [0, 100]$, see Error! Reference source not found. ;
c_i	car possession status of agent i , $c_i \in [0; 1]$;
d_i	distance (in km) between agent i and its chosen drop-off depot, $d_i \in [0, 15]$, based on GIS address data.

Calibrated parameters:

$SOV_{b,s}$	Segment Opinion Values for behavior b and segment s , $SOV_{b,s} \in [0, 100]$;
γ	Population's relative importance of opinion versus incentive, $\gamma \in [0, 1]$;
$a_{c_i,b}$; $b_{c_i,b}$	linear parameters of the PCB functions for agent i and behaviour b .

In the first version of this model, EA was randomly defined using data specific to the province of Québec. To improve this, as shown in the next section, the extensions of this model use age as a precursor of environmental awareness. In other words, we use the distribution of EA segments presented in SOM (2015) and their respective probability distributions for each age group. The study presented in SOM (2015) is a province-wide survey ($N = 2068$) that analyzes the environmental attitudes and engagement of the Quebec population. Note that in this original study, the SOM-EA segments do not overlap. However, their distribution is used to define the probability of an agent being in one of these specific segments (A to G). Once an agent's SOM-EA segment is determined, its EA value is chosen randomly using a uniform distribution within the corresponding range of values of this specific SOM-EA segment, as shown in Figure 3.

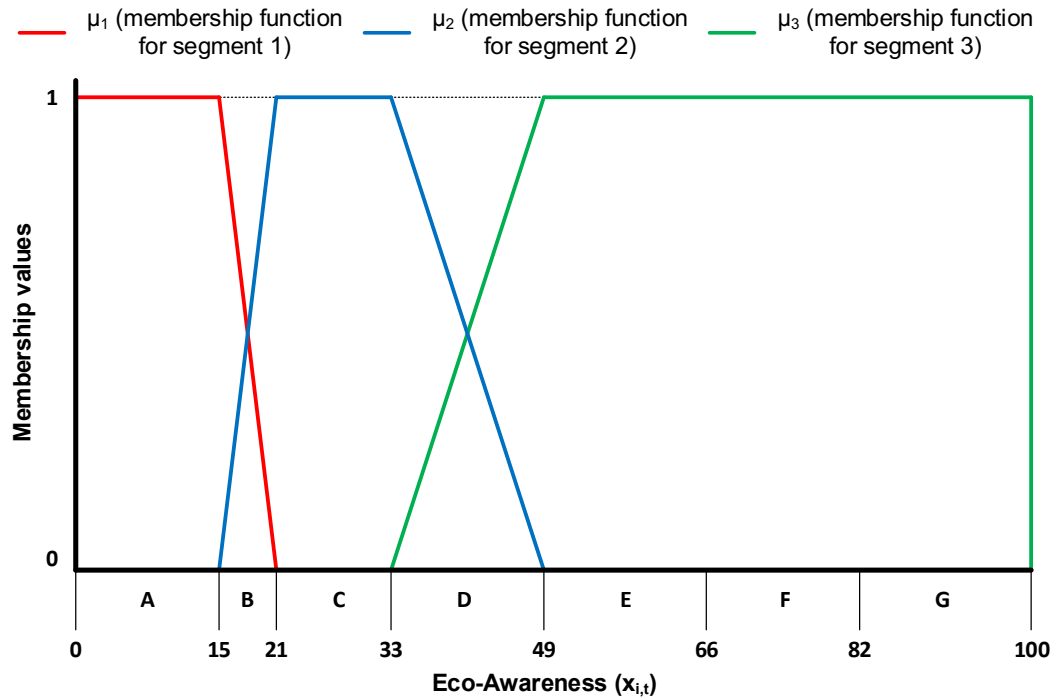


Figure 5.3 Fuzzy logic model for Eco-Awareness with SOM-EA segments (A to G)

Next, the Perceived Cost of Behavior (PCB) was configured to account for the effect of distance to a drop-off depot on the intention to return a bottle. To do so, two piecewise linear functions were calibrated in Labelle & Frayret (2018) to represent the PCB in the context of returning wine bottles to drop-off depots in the province of Quebec. This PCB depends on two factors: the Euclidean distance between the agent and the selected drop-off point, and the ownership of a vehicle. As shown in Figure 4, in the extended versions of the model, the PBC has been changed to linear functions to allow the PBC value to increase beyond the 15 km threshold (Equation 6). The PBC is the inverse of the PCB (Equation 5).

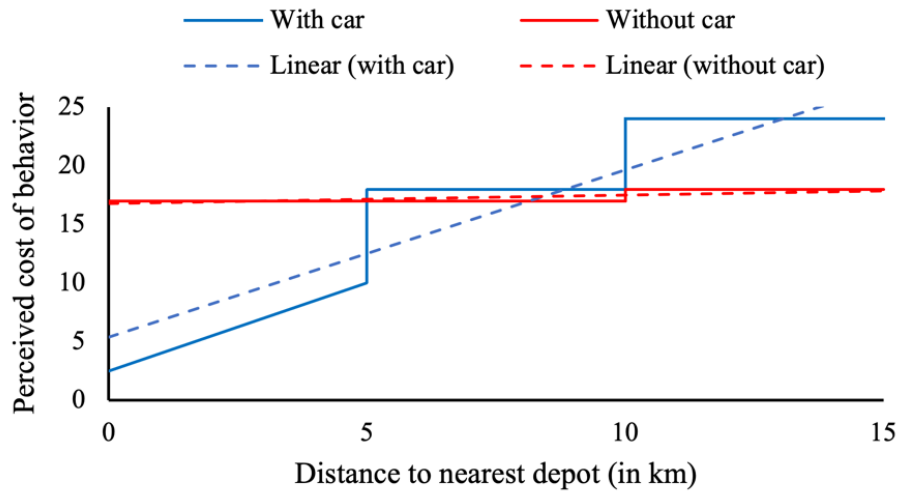


Figure 5.4 Perceived Cost of Behaviour (PCB)

The next section introduces the context of the case study, and presents the various extensions made to this initial model.

5.4 Case study

As mentioned above, this model was adapted and calibrated to a context of voluntary glass depots in the RCM Le-Val-Saint-François (population: 30 686). The coordinates of the actual drop-off depots used in these municipalities are integrated into the *AnyLogic* GIS environment (*OpenStreetMap*) to measure the path (Euclidean) distances between agents coordinates and drop-off locations. The following sections present new assumptions made to create the extended models, and how these new models were configured and calibrated using a practical case study.

5.4.1 Model supplementary assumptions

The various extensions of the model presented in Section 3 use the same initial assumptions as well as new ones. First, unless otherwise stated, we assume that consumers choose the closest depots. However, in the last extension of the model, we introduce the notion of attractiveness. In other words, consumer agents search for all drop-off depots within a 15 km radius of their homes, and then randomly select one of these depots based on its attractiveness. For example, if an agent has two depots within reach with attractiveness scores of 2 and 1, the most attractive depot is twice as likely to be selected by the agent. Finally, the last assumption is that each consumer agent is aware

of the drop-off depot program in the RCM. Because the program was progressively introduced in 2015, and extended in 2019, it would take some time for this information to spread to each citizen. In a future version of the model, we will address this limitation.

5.4.2 Model configurations

As for the first model shown in Figure 1, the configuration of the simulation model for the Val-Saint-François case study required several data sources. In order to assess the gain in precision associated with the use of these data sets, four levels of model configuration (Table 2) were developed, calibrated and tested. The gray cells in Table 3 represent a difference from the previous level. The experiments carried out in Labelle & Frayret (2018) are considered as configuration level 0. The main difference between level 0 and level 1 is the integration of a GIS environment in the simulation model instead of a simple 2D Cartesian coordinate system. In configuration level 2, we use region-specific demographic data and age-specific probability distributions to characterize each agent. Next, level 3 uses the specific GIS location of household addresses in the area to configure the model. Prior to this extension, agents were randomly located in the territory regardless of the actual population density. Finally, configuration level 4 introduces the notion of drop-off depot attractiveness to better represent consumer behavior in terms of where they choose to return their empty bottles. This parameter is used as a proxy to aggregate various factors that could represent how each depot benefits from its location, other points of interest in the area, or other more complex implicit consumer habits. This parameter, which is unique to each drop-off depot, was calibrated to best match their individual simulated return rates to their empirical return rates.

Table 3 presents how the different characteristics of the agents were generated for each model configuration.

Table 5.2 Design of experiments overview

Level 1	• Average Quebec population (General Québec demographics) (S. Canada, 2017); • Consumers are randomly positioned in the RCM territory; • Wine consumption habits are based on Québec average (Éduc-Alcool, 2017; INSPQ, 2016; ISQ, 2011; SAQ, 2016).
Level 2	• Consumers are positioned randomly in one of the 19 municipalities of the RCM based on the number of inhabitants per municipality (S. Canada, 2017); • Consumers' eco-awareness (SOM, 2015) and wine consumption habits are based on Québec population age-group distributions (Éduc-Alcool, 2017; INSPQ, 2016; ISQ, 2011; SAQ, 2016).
Level 3	• Consumers are positioned based on Québec's residential address coordinates (latitude & longitude) from a non-published database produced by the Québec Ministère de l'Énergie et des Ressources naturelles (MERN).
Level 4	• Drop-off depots have an attractiveness value (calibrated) to represent factors, such as proximity to other points of interest (e.g. liquor stores, groceries, etc.) or the popularity/seniority of the depot centre.

It must be noted that some parameters are left unchanged in all four configuration levels. Firstly, the Segment Opinion Values ($SOV_{b,s}$ shown in Equations 7) were initially calibrated using the average Québec population in (Labelle & Frayret, 2018). Secondly, the parameter for the Incentive Values (IV_b) is set to 0 for all behaviours because there is no monetary incentive in the studied voluntary glass deposit program. Thirdly, the configuration of PCB is the same for all experiments.

$$\text{Calibrated } SOV_{b,s} = \begin{bmatrix} 100 & 10 & 5 \\ 95 & 100 & 20 \\ 70 & 90 & 100 \end{bmatrix} \quad (5.7)$$

Table 5.3 Detailed design of experiments for configuration levels 1 to 4

			Level 1	Level 2	Level 3	Level 4
Number of agents			26309*	30686	30686	30686
Agent's position (GIS)			Random inside RCM	Random inside city	Residential addresses	Residential addresses
Age range			12 -100*	0-100	0-100	0-100
Age			n/a	city-specific distribution	city-specific distribution	city-specific distributions
Car possession			Based on RCM average	city-specific distribution	city-specific probability	city-specific probability
Eco-Awareness			Generic Québec average	age-specific distribution	age-specific distribution	age-specific distributions
Wine Drinking Frequency		Generic Québec average		age-specific distribution	age-specific distribution	age-specific distributions
Drop-off	depots	n/a		n/a	n/a	Calibrated to best fit actual return rate
Attractiveness						

From level 2 to level 4, a consumer agent's age group determines the probability distributions used to define its EA and wine consumption. In addition, each municipality has its own age distribution based on census data (S. Canada, 2017). Also, the probability of agents using a vehicle to return their bottles is estimated from their primary mode of commuting from census data (S. Canada, 2017). The empirical probability distributions of wine consumption for each age group were adapted from (Éduc-Alcool, 2017; INSPQ, 2016; ISQ, 2011; SAQ, 2016). According to these data, agents under 12 years of age do not consume wine. Finally, some agents do not produce waste (wine bottles) because they do not consume wine (18% of agents).

5.4.3 GIS data and empirical observations mapping

For agent location, the entire RCM territory was configured using OpenStreetMap GIS, which is seamlessly integrated with AnyLogic. For level 1, agents were randomly positioned within this area. For the second level, the boundaries of the 13 municipalities involved in the study were added. For the last two levels, the coordinates and number of units per residential address were obtained from an unpublished database created by the Québec Ministère de l'Énergie et des Ressources naturelles (MERN) and used under license. The 30,686 agents were thus distributed over 13,262 residential addresses.

Figure 5 shows the GIS simulation environment with the residential addresses used to locate the consumer agents (black dots) and the actual return program depots (green dots). The white dots are addresses from the city of Brompton, which is not part of the Val-Saint-François territory. They were not included in the simulation because Brompton is not included in the return program and its citizens were not officially informed about the program. However, they may partly explain why the Saint-Denis-de-Brompton (SDDDB) depot has the best return rates (see target for SDDDB in Table 5). In fact, this could be due to the fact that some Brompton residents occasionally return their bottles to this depot because it is the closest one and provides an external flow of waste bottles into the Val-Saint-François area.

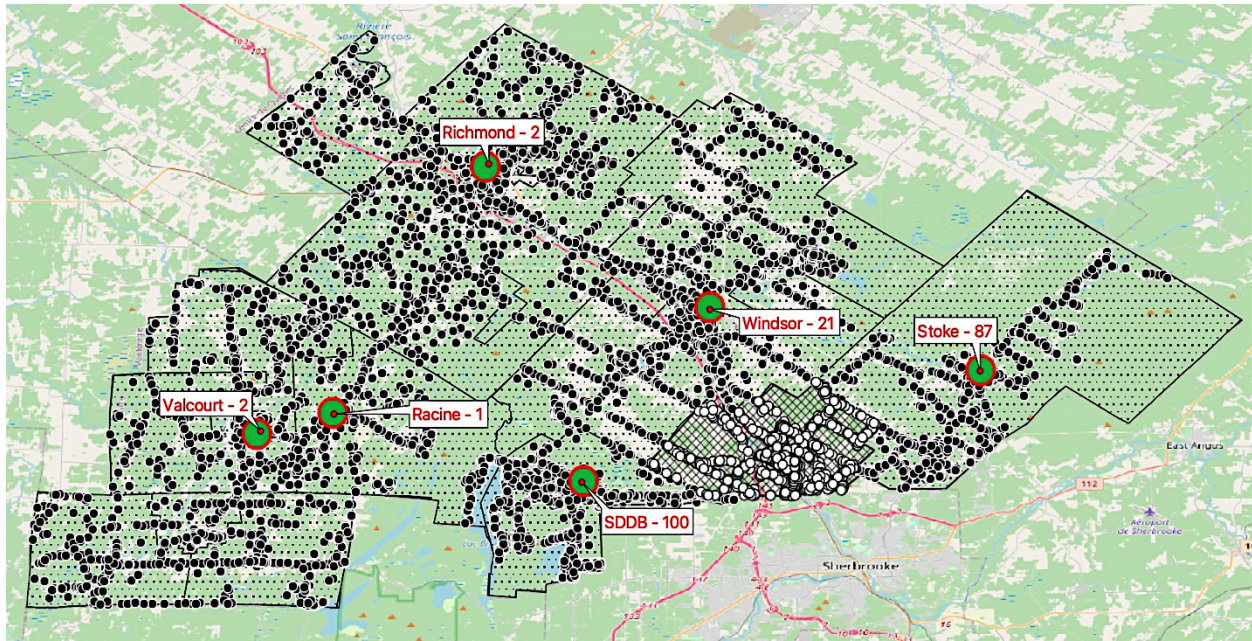


Figure 5.5 GIS configuration for level 4 and attractiveness levels of drop-off depots

In addition, the Saint-Denis-de-Brompton depot was the first to be inaugurated in 2015, while the others were created in July 2019. Therefore, residents of other communities in the area who have access to a closer drop-off depot may bring their bottles to that depot out of habit or convenience. This behavior seems plausible, given that the program is still being implemented.

This illustrates one of the major challenges of mapping empirical observations from an open system to a specific area in a GIS. In other words, the boundaries of the actual territory contributing to the observed volumes of returned bottles cannot be easily mapped. Assumptions must be made that introduce noise or error into the results.

5.4.4 Specific calibrations: γ and attractiveness

Two parameters of the model could not be estimated a priori. First, the population's relative importance of opinion versus incentive (i.e., γ) describes how a given population acts according to its opinion. Although this parameter is specific to everyone, in this model it is a population-specific parameter. Since there are no data to justify the use of a specific value for the area studied, it can only be inferred by performing a calibration through a sensitivity analysis and comparing the results of the simulations with the empirical observations. Next, regarding the attractiveness of drop-off depots, it is a set of parameters used in the Level 4 configuration that also needs to be calibrated.

Since both γ and the attractiveness of drop-off depots have a combined effect on the rate of return, we developed a procedure to calibrate these parameters. As γ had previously been calibrated for the average Quebec population in the context of a deposit, an initial calibration of the attractiveness of the drop-offs was performed with $\gamma = 0.09$ (Labelle & Frayret, 2018). Subsequently, a sensitivity analysis was performed to identify the best value of γ for the specific population of the area. The last step consists in recalibrating the attractiveness parameters with the value of γ found in the previous step.

- Step 1: Calibrate attractiveness with $\gamma = 0.09$
- Step 2: Sensitivity analysis to find the γ value for the RCM population
- Step 3: Recalibrate attractiveness with the RCM gamma value from step 2

5.4.4.1 Step 1: Calibrate attractiveness with $\gamma = 0.09$

This calibration process consisted of calibrating the value of 6 attractiveness parameters, one for each drop-off depot, to best match their individual return rate. This calibration was limited to attractiveness values between 1 and 100. The empirical data (target values) for this calibration (i.e., tons of glass collected for each drop-off depot during the first 13 weeks of 2020) were obtained thanks to the collaboration with OVV.

5.4.4.2 Step 2: Sensitivity analysis

Using the attractiveness values calibrated in the previous step, we used the following values for γ : 0.09; 0.2; 0.3; 0.4; 0.5; 1. Five replications were run for each of these scenarios. With a mean standard deviation of 0.1 tons per depot, the model was considered to be sufficiently consistent. Figure 6 shows that the simulation results are closest to the target values for $\gamma=1$. This suggests that the population of the study area has little interest in an incentive. However, if we assume that a small part of the actual population needs an incentive to return their empty bottles, then we must also assume that the simulation results overestimate the average citizen's willingness to return their bottles, as well as the general collection rate.

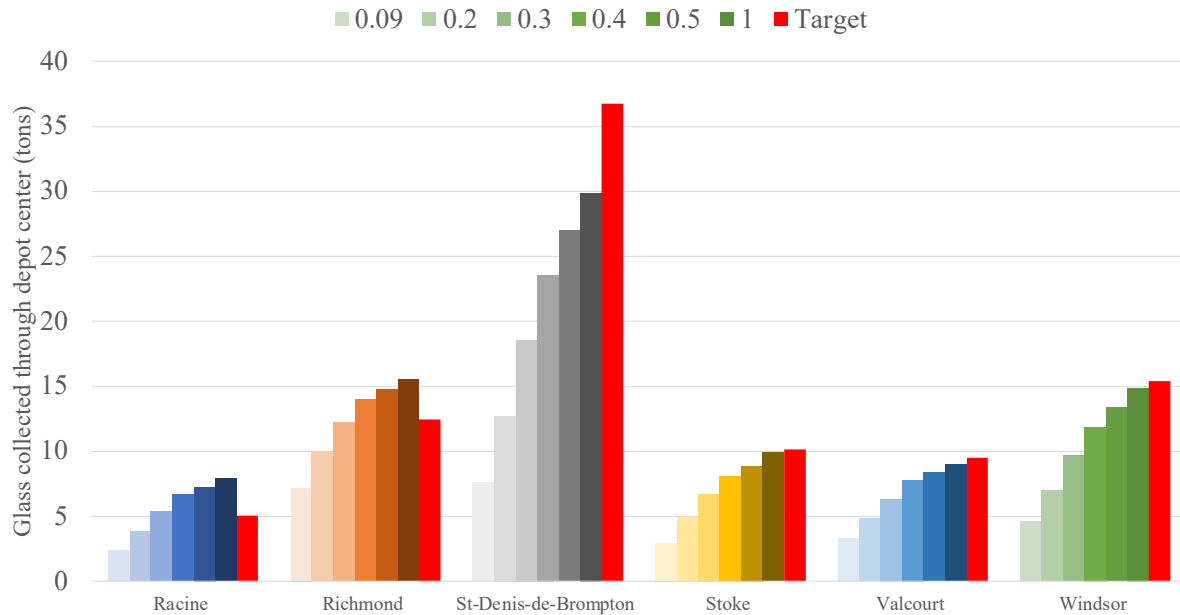


Figure 5.6 Parameter γ 's sensitivity analysis with drop-off target values (tons of glass collected with the voluntary drop-off program from January 2020 to March 2020)

5.4.4.3 Step 3: Recalibrate attractiveness with γ from step 2

Except for the new γ value, the calibration process is identical to the first step. Table 4 shows the values from the final calibrations of steps 1 and 3. Note that the attractiveness values used for the Step 4 experiments are those from the $\gamma = 1$ calibration.

Table 5.4 Attractiveness parameters calibration results

Drop-off depots	Gamma = 0.09	Gamma = 1
Racine	23	1
Richmond	1	2
St-Denis-de-Brompton	95	100
Stoke	80	87
Valcourt	12	2
Windsor	30	21

5.4.5 Data sets contributions to empirical fitting

Table 5, Figure 7, and Figure 8, respectively, show the simulated quantities and gaps to empirical targets of glass collected at each drop-off depot over a 13-week horizon. Given the stochastic nature of the model, 20 simulation replications were performed with all configuration levels to ensure convergence of results. The results for each level also include the standard deviation (SD).

The results indicate that there is an overall increase in model accuracy from configuration level 1 to level 2, suggesting that region-specific population characterization has a positive impact on model accuracy. However, the difference between the simulation results and the target values decreases from level 2 to level 3. In other words, the ability of the model to reproduce the specific volumes of each individual drop-off depot decreases, even though the overall volume improves. Therefore, even though agents are more accurately located in configuration level 3, the assumption that consumers systematically go to their nearest drop-off depot seems to affect the accuracy of the results. Considering that the total quantity of glass collected in both levels 2 and 3 is on target, with a difference of only -1%, it appears that the agents' EoL decisions are well calibrated. However, their choices of drop-off depots are not well modelled, and thus the assumption is incorrect.

Table 5.5 Average tons of glass collected per drop-off depot

Drop-off Depots	Level 1		Level 2		Level 3		Level 4		Target values
	<i>Tons</i>	<i>Diff.(t)</i>	<i>Tons</i>	<i>Diff.(t)</i>	<i>Tons</i>	<i>Diff.(t)</i>	<i>Tons</i>	<i>Diff.(t)</i>	<i>Tons</i>
	<i>(SD)</i>	<i>Diff.(%)</i>	<i>(SD)</i>	<i>Diff.(%)</i>	<i>(SD)</i>	<i>Diff.(%)</i>	<i>(SD)</i>	<i>Diff.(%)</i>	
Racine	12.31	7.27	4.68	-0.36	4.72	-0.32	5.55	0.51	5.04
	(0.35)	(144.17)	(0.17)	(-7.19)	(0.21)	(-6.30)	(0.12)	(10.17)	
Richmond	21.44	8.98	18.03	5.57	20.44	7.98	15.44	2.98	12.46
	(0.47)	(72.05)	(0.38)	(44.68)	(0.49)	(64.07)	(0.32)	(23.94)	
St-Denis-de-	11.04	-25.68	14.89	-21.83	12.18	-24.54	29.84	-6.88	36.72
Brompton	(0.32)	(-69.92)	(0.44)	(-59.44)	(0.35)	(-66.83)	(0.48)	(-18.74)	
Stoke	19.06	8.90	9.07	-1.09	7.41	-2.75	9.91	-0.25	10.16
	(0.34)	(87.62)	(0.36)	(-10.70)	(0.30)	(-27.08)	(0.36)	(-2.49)	
Valcourt	18.29	8.77	15.34	5.82	15.16	5.64	11.89	2.37	9.52
	(0.40)	(92.08)	(0.40)	(61.14)	(0.49)	(59.22)	(0.28)	(24.95)	
Windsor	19.06	3.65	26.38	10.97	28.37	12.96	14.70	-0.71	15.41
	(0.26)	(23.71)	(0.51)	(71.16)	(0.46)	(84.13)	(0.23)	(-4.61)	
Total	101.20	11.89	88.39	-0.92	88.28	-1.03	87.34	-1.97	89.31
	(0.54)	(13.31)	(0.65)	(-1.03)	(0.75)	(-1.15)	(0.75)	(-2.21)	

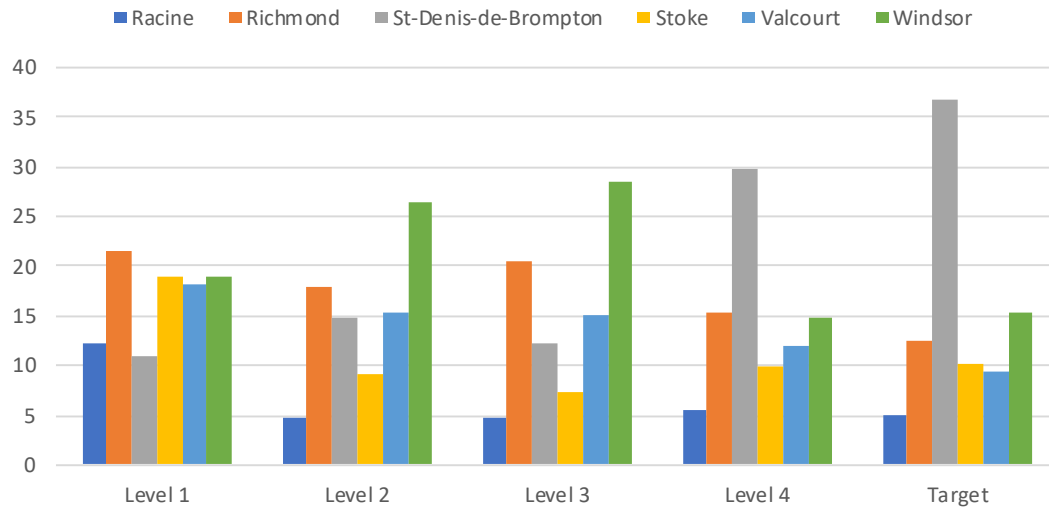


Figure 5.7 Average collected tons per drop-off depot for 13 simulated weeks (20 replications)

Consequently, adding and calibrating the attractiveness characteristic of drop-off depots to match the return rate of the empirical data has a significant impact on the accuracy of the model. In other words, the model with drop-off depot attractiveness can be accurately calibrated to simulate empirical data with relatively small standard deviations.

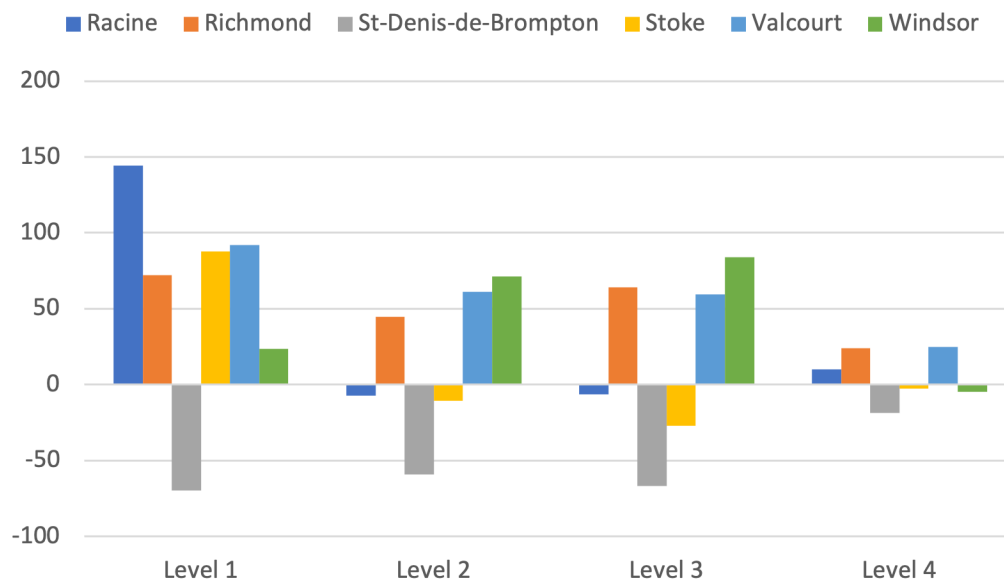


Figure 5.8 Gaps between simulation results & target values (in %)

This important result tells us that consumers who return their EoL products have a non-trivial decision process regarding their choice of a drop-off depot. The act of returning these products

may be linked to other activities or individual habits that need to be better understood in order to improve the logistics of EoL product collection. Nevertheless, the calibrated attractiveness scores of this study can be analyzed with experts (e.g. OVV, stakeholders, politicians) to better understand the factors that influence and explain these attractiveness scores. Complementary studies, such as surveys, could also be conducted for the same purpose.

Finally, Table 6 shows the simulation results per type of EoL strategy. The target value (gray cells) for trash is taken from (ÉÉQ, 2017). Standard deviations (SD) are also included, as well as differences between empirical targets and simulation values. Based on an estimated return rate of 40% (Deloitte, 2018), the territory of Val-Saint-François initially expected to collect 200 tons of glass in the first year. However, according to published information, this threshold was reached after only 8 months. The collection of such a quantity in 8 months is more likely to represent a return rate of 60%, a rate close to that simulated by our model. Therefore, these results seem to be in line with the empirical data, which show an initial underestimation of the return rate.

Table 5.6 Simulated wine bottles EoL

EoL	Level 1		Level 2		Level 3		Level 4		Target values
<i>units</i>	<i>Tons</i>	<i>%</i>	<i>Tons</i>	<i>%</i>	<i>Tons</i>	<i>%</i>	<i>Tons</i>	<i>%</i>	<i>%</i>
	<i>(SD)</i>	<i>(SD)</i>	<i>(SD)</i>	<i>(SD)</i>	<i>(SD)</i>	<i>(SD)</i>	<i>(SD)</i>	<i>(SD)</i>	
Trash can	24.91 (0.49)	15.34 (0.003)	24.65 (0.59)	17.02 (0.004)	25.11 (0.45)	17.33 (0.003)	25.14 (0.60)	17.35 (0.004)	13
Recycle bin	36.11 (0.56)	22.24 (0.003)	31.66 (0.52)	21.86 (0.003)	31.41 (0.43)	21.68 (0.003)	32.31 (0.60)	22.30 (0.004)	27
Bring back	101.36 (0.53)	62.42 (0.003)	88.49 (0.65)	61.11 (0.005)	88.39 (0.75)	60.99 (0.003)	87.43 (0.75)	60.34 (0.004)	60
Total	162.37 (0.57)	100.00 (0)	144.79 (0.82)	100.00 (0)	144.92 (0.89)	100.00 (0)	144.88 (0.89)	100.00 (0)	100

5.5 Case study: model application for decision support

Once the model was calibrated for the population studied, we analyzed the current logistics strategy. A series of experiments were conducted to demonstrate the ability of the simulation model to support decision-making. The results are presented below.

5.5.1 Design of experiments and results

The current voluntary collection strategy consists of 6 collection points, some of which collect relatively small quantities. The general context of this analysis is to answer the following questions. What would be the impact on EoL product flows and total collected tonnage if one or more of these drop-off points were removed? Which of these drop-off points would be the least punitive to remove? To answer these questions, the design of experiments shown in Table 7 was developed. The Level 4 configuration of the model was used for these experiments (A through D) with 5 replications per scenario. The results shown are the average of these replications.

It is assumed that the attractiveness values remain unchanged regardless of the number of drop-off points. For each proposed scenario (i.e., number of drop-off points), a sensitivity analysis was performed on the standard deviation of the population's relative importance of opinion versus incentive (i.e., γ). We assumed that this parameter follows a normal distribution. In fact, it is not reasonable to assume that all agents in the study area would have the same parameter value of 1, which corresponds to having strictly no interest in incentives.

Table 5.7 Design of experiments with varying number of drop-off points

Depot	Attractiveness	A	B	C	D
Racine	1	X			
Richmond	2	X			
St-Denis-de-Brompton	100	X	X	X	X
Stoke	87	X	X	X	
Valcourt	2	X			
Windsor	21	X	X		
Average distance to depot (in km)	-	5.3	8.7	10.7	11.8

Figures 9 and 10 illustrate the potential impact on the collection system of removing one or a few drop-off depots in terms of loss of tonnage or shifting of tonnage from one depot to another or from the return strategy (return) to the selective collection program (Blue bin). Note that when all agents do not have a γ value of 1 (i.e., when γ standard deviation $>$ than 0), there is a significant negative impact on return rates (Figure 9). In other words, instead of returning their empty bottles, some agents put them in their blue bin. This is to be expected, since there is no incentive used here. Similarly, having fewer drop-off depots reduces the average distance to return empty bottles, which in turn reduces the tonnage of bottles returned (Figure 10). We can also observe the shift of tonnage from one depot to another, which helps to estimate the required capacity of the depot.

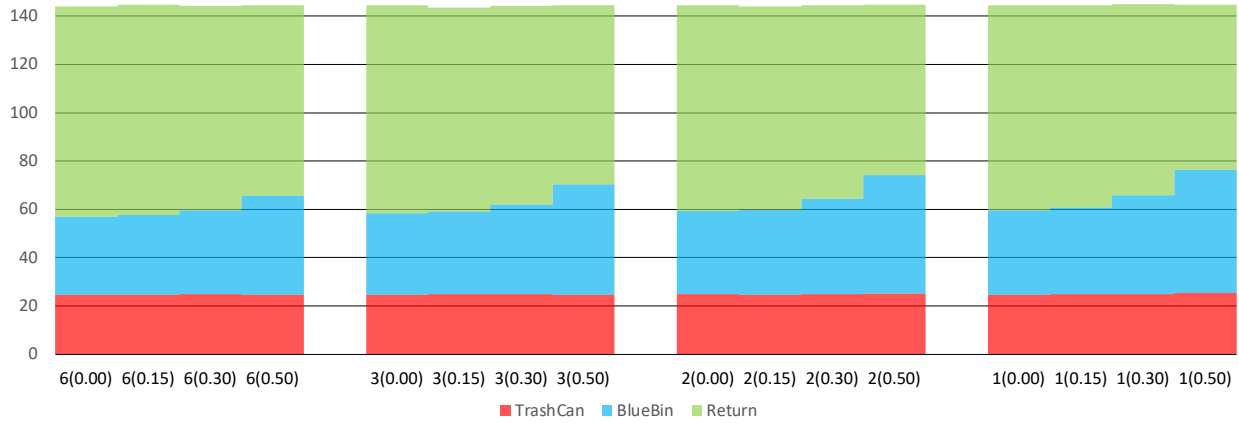


Figure 5.9 Average tons of bottles per type of EoL strategy, with varying numbers of drop-off points (6, 3, 2, 1) and γ standard deviation values (0.00, 0.15, 0.30, 0.50)

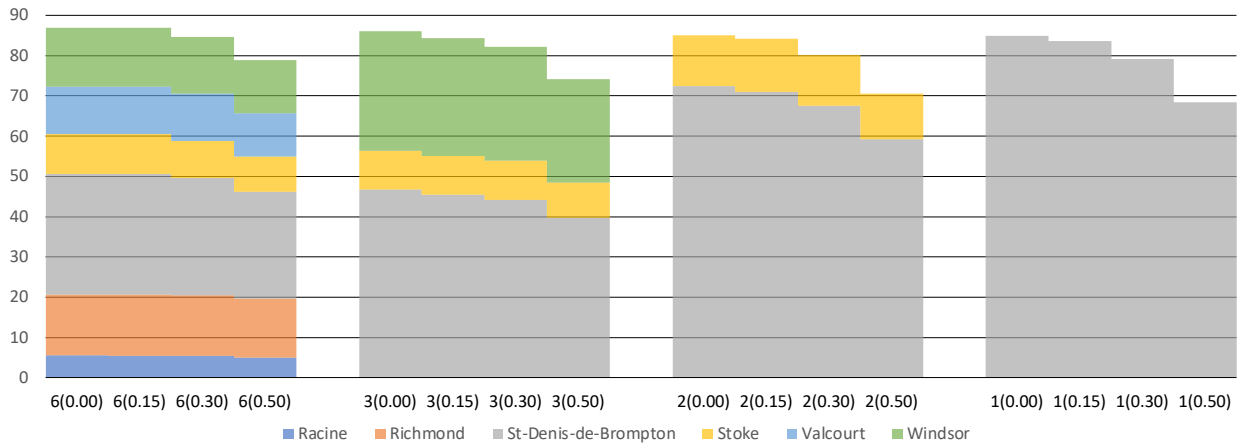


Figure 5.10 Average tons of glass returned to drop-off points, with varying numbers of drop-off points (6, 3, 2, 1) and γ standard deviation values (0.00, 0.15, 0.30, 0.50)

5.6 Discussion

In this section, we discuss two aspects of the model. First, we analyze the model's ability to accurately simulate consumers return behavior. Second, we analyze the model's ability to support decision-making, specifically the design of a collection strategy.

5.6.1 Model capacity to simulate consumer return behaviour

The various models tested in this study propose a general framework and a set of factors that can be used to develop a model that can accurately simulate consumer behavior in terms of what they do with their empty bottles and how they do it. However, some of these factors (i.e., the relative

importance of opinion versus incentive in the population and the attractiveness of the drop-off depot) are difficult to estimate a priori because there is little information available to specify them. Although their contribution to shaping consumer return behavior is reasonably unquestioned, the process of estimating their value needs to be further explored through empirical observation, surveys, or other forms of empirical study.

For example, some people may return their empty bottles while engaged in other activities, such as grocery shopping, or even while returning other EoL products. As a result, the return depot for empty bottles will not necessarily be chosen as the closest, but as the most convenient in terms of these other activities. Therefore, a drop-off depot located near a shopping mall or eco-center may be more popular than others.

Similarly, a population that has used voluntary return programs for many years may be less likely to need incentives than another. The cultural background of a population may also play a role in shaping consumer return behavior.

5.6.2 Model capacity to support decision-making

In terms of the model's ability to support decision-making, the case study presented in Section 5 illustrates how the model can be used to provide new information about potential strategies. For example, the material flows predicted by our model can be used to plan a new strategy and estimate its installation and operating costs (e.g., transporting consolidated materials from collection points to recyclers).

These results also suggest that the simulated consumer return behavior is reasonably accurate. Sensitivity and comparative analyses (Figure 9 and Figure 10) show the impact of adjusting a strategy or comparing several options. Although such a tool cannot prescribe an optimal strategy, it can predict the performance of different alternative strategies or show the impact of adjusting some decision parameters.

However, more research is needed to fully understand consumer choice of drop-off depot. For example, as discussed in the previous section, consumers often prefer to return their bottle to a different depot that is closer to points of interest, such as grocery stores or liquor stores, rather than to the nearest depot. Rhodes et al. (2014) found similar results, noting the importance of

incorporating both proximity and travel planning considerations into household decision-making processes regarding recyclable collection programs (Rhodes et al., 2014).

An aspect that was not studied in this model concerns the transportation of returned bottles to the recycling center. For instance, Idwan, Mahmood, Zubairi, & Matar (2020) used a similar GIS environment as a tool for route optimization of collection trucks. Combined with our return behavior simulation model, this type of optimization tool could be useful for designing efficient collection strategies (Idwan, Mahmood, Zubairi, & Matar, 2020).

Furthermore, as discussed in (Walzberg et al., 2020), agent-based modelling of complex socio-technical systems can also be a useful tool to facilitate the emergence of the circular economy. The ability to simulate product EoL strategies and the return/recycling behavior of a specific population according to its socio-demographic characteristics is an important step towards designing specifically tailored reverse logistics strategies to promote recycling and return.

Finally, due to the stochastic nature of the model, some inconsistencies were expected. However, several other factors may have influenced the performance of the model. These factors could have led to an underestimation or overestimation of the amount of glass collected. For example, Table 8 lists several factors that provide some context for interpreting the results, as well as a possible solution to address these limitations. For example, the volume of glass reported by the OVV initiative does not specify a ratio of wine bottles to total volume. However, based on their observations, wine bottles make up the majority of returned glass containers.

Table 5.8 Potential factors that could affect simulation results

Factors	Potential effect on results (↑/↓)	Data needed to improve
External flows (e.g. Brompton residents bringing back their EoL bottles to the territory's drop-off depots).	External flows can cause the simulation model to overestimate the individual agent's return rate compared to observed data because some consumers are not included in the study. ↑	Surveys on the origins and travel itineraries of consumers bringing back their bottles.
Mixed container types of glass collected.	Other types of glass (e.g., jars) may cause simulation results to overestimate individual return rates compared to empirical data because other types of glass containers are not included in the study. ↑	Materials characterization of collected glass can specify the ratio of wine bottles to total amount of glass.
Agent awareness of the drop-off depots program.	Not all residents of the territory are aware of the voluntary drop-off program. Thus, the simulation model tends to underestimate the individual return rate compared to observational data because too many agents contribute by returning bottles. ↓	Impact analysis of word-of-mouth and communication programs on consumers recycling intentions and behaviours.
Limited empirical data (i.e. data collection is out of sync with actual behaviors).	An additional 5 tons for the Racine drop-off was recorded shortly after the 13th week of 2020 and was not included in the observed data. This could explain why the simulated amount of glass collected for the Racine drop-off is higher than the empirical data. ↑	Real-time data collection of collected glass with the Internet of Things (IoT) technology (Idwan et al., 2020).

5.7 Limits and future work

As discussed above, in addition to the model's ability to reproduce empirical results, several aspects of the model can be improved. For example, the model is not configured to ensure that the age distribution within a single residential address is representative of reality. Thus, during a simulation, it is possible for an agent under the age of 12 to occupy a single residential address. Although this is unrealistic, the impact on the results is negligible given the size of the simulated population and the fact that multiple replications were run per simulation experiment.

Next, with respect to the robustness and validity of this model, our study only demonstrates that this model is flexible enough to accurately fit the observed data. In a simulation context, it is said to be valid if it is used to test scenarios that are relatively similar to the one used for calibration. Thus, simulating drastically different scenarios could lead to poor accuracy, which is the case with all simulation models. Nevertheless, we have shown that it can be calibrated to a specific region. Robustness in this context would be to show that it could be calibrated to another region with similar accuracy. This work remains to be done.

Next, as mentioned above, additional work is being done on social norms. In the TPB model, it is conceptualized that the perception of a behavior by the individual's environment can influence the individual's intention toward that behavior. This is referred to as the subjective norm (Ajzen, 1991), and it has been studied in terms of its effect on recycling behavior, but the results are not unanimous. For example, while (Chan & Bishop, 2013; White & Hyde, 2011) identified subjective norm as an precursor of intention to recycle, (Botetzagias et al., 2015; Rhodes et al., 2014; Tonglet et al., 2004) found no significant relationship. However, as emphasized by (Wood, 2000) and Ajzen (1991), it is also possible to influence individuals' attitudes toward a behavior through social interactions, as opposed to directly influencing intention. For example, two agent-based simulation models of behavior diffusion on the adoption of agricultural practices (Kaufmann et al., 2009) and on the adoption of energy technologies (Rai & Robinson, 2015) have interpreted the influence of social norms in this way. To do so, they have used Deffuant, Amblard, Weisbuch, & Faure's (2002) Relative Agreement Model, which proposes a model that replicates the impact of social interactions on individuals' opinions. Future work will also develop an extension of the model that includes the relative agreement model to model the social influence on opinion, and actual road distances (instead of Euclidian distance) to better model the Perceived Behavioral Control.

Finally, although it is the most commonly used in surveys, age as a precursor to attitude and drinking frequency is also another limitation of the model. According to the available empirical data, other precursors, such as education or annual income, could also be used (SOM, 2015).

5.8 Conclusion

The complex socio-technical system studied in this paper is a "first mile" reverse logistics system that involves voluntary return behavior. It complements Quebec's selective collection program, which does not discriminate between recycled materials, but still requires some level of sorting at home.

To address the lack of an established tool or method in the literature to accurately study such systems and assess the impact of consumer decisions at the intersection of consumption and reverse logistics material flows. The main contribution of this paper is a simulation model capable of accurately predicting the volume of wine bottles voluntarily returned through a distributed system of drop-off depot scattered throughout a community of more than 30 thousand people. This model uses several heterogeneous sources of empirical data (e.g., surveys), statistical census data, and detailed GIS location data. This type of simulation tool can be used to predict the potential performance - in a risk-free environment - of new collection systems and reverse value chains for EoL products, whether in terms of the number of drop-off depots, their locations, their capacities (i.e., container size), the value of the incentive, as well as the target population segments.

The paper also provides some methodological guidelines for data integration, configuration, and calibration of such a complex simulation model. With a large population sample in the study case and empirical data for validation, this paper presents how an agent-based simulation model can be calibrated and configured with various sources of detailed data to develop an accurate model of a complex socio-technical system in the field of reverse logistics and urban-industrial symbiosis.

CHAPITRE 6 ARTICLE 3: WORD-OF-MOUTH IN AGENT-BASED SIMULATION MODEL OF REVERSE LOGISTICS

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Submitted on July 20, 2023

Agent-based modeling and simulation is a method well suited for studying individual behavior and interactions among members of a population connected by social networks. Although the development of such simulation models can be relatively complex, it is even more challenging to develop models that are empirically valid. In the case of reverse logistics, the sophisticated and difficult-to-predict behavior of consumers must be modeled. In this paper, an agent-based simulation model of consumer behavior and interactions was configured to conduct a case study of the voluntary deposit collection program for wine bottles in the Val-Saint-François region of Quebec. As this collection program was officially launched in 2019, two empirical samples were obtained to test the validity of the model and study how social interactions such as word of mouth contributes to the success of the collection program. The first sample represents the amount of glass collected during the last 26 weeks of 2019, while the second sample covers the first 13 weeks of 2020. Having observed an increase in collection rates between 2019 and 2020, word of mouth was introduced into the model to explain this phenomenon. Statistical tests show that the model is indeed valid with the inclusion of diffusion of awareness, as the simulation results are significantly consistent with the empirical data.

6.1 Introduction

logistics networks for the collection of end-of-life products. It is particularly critical for selecting the number, location, and capacity of drop-off points and collection routes. There are many factors to consider when modeling consumer recycling behavior. Individual attitudes, beliefs, socio-economic factors, cultural influences, and the accessibility and convenience of recycling infrastructure all play an important role. Previous studies have assessed the relationship between the location and number of collection points and the amount of recycled material (Labelle & Frayret, 2018, 2023; Tong et al., 2018). In this paper, we propose to assess the impact of certain types of social interactions on the volume of recycled material.

To do so, this paper presents a case study in reverse logistics that aims to study the impact of social interactions on the performance of a collection system, and more specifically on the word-of-mouth effect regarding the spread of awareness of drop-off points. This contribution is an extension of a series of models previously published by the same authors (Labelle & Frayret, 2018, 2023) and briefly outlined in the literature review. The interested reader is referred to the aforementioned published works for more details on the agent-based simulation model used for this research.

The case study, which focuses on the voluntary collection program of glass containers (mainly wine bottles), consists in analysing two samples of data obtained with the valuable collaboration of the Opération Verre-Vert (OVV) committee, founders of the voluntary glass collection program of the Val-Saint-François Regional County Municipality (VSF).

This paper is organized as follows. The next section presents an analysis of the literature related to the impact of social interaction on circular economy initiative and consumer recycling behavior. This section also introduces the simulation model of glass container collection used in previous studies, which is extended in this paper. The following section introduces the case study and proposes a descriptive analysis of the two data sets used to conduct this study. Section 4 then proposes some adjustments of the original simulation model to study the impact of agents' drop-off awareness to justify the change of the collection rates observed in the data. Finally, Section 5 presents the results of an analysis to quantitatively assess the impact of simple social interactions on the volume of glass containers collected. Section 6 discusses these results and Section 7 concludes.

6.2 Literature review

It's been several years since the application of simulation for studying reverse logistics has gained in interest (Kara, Rugrungruang, & Kaebernick, 2007), but with the advent of agent-based modeling and simulation (ABMS), which is particularly well-suited for reverse logistics problems (Abid et al., 2019) and waste management, (Alonso-Betanzos et al., 2017) several researchers have chosen this approach to study these problems (Tong et al., 2023; Walzberg et al.). However, in their systematic review of simulation and optimization methods applied to the context of reverse logistics (Abid & Mhada, 2021), the authors note that ABMS, while offering many advantages, is used much less frequently than other more popular methods such as Monte Carlo simulation, discrete-event simulation and numerical simulation. (Agnusdei, Gnoni, & Tornese, 2019) report similar findings in their review of modeling and simulation tools used in the integration of forward and reverse logistics, leaving plenty of room for new contributions in the field of ABMS in reverse logistics. According to (Peres, Muller, & Mahajan, 2010), agent-based models are not trivial to develop, as they have to satisfy the balance between specificity and applicability, and typically have a large number of parameters and degrees of freedom. As a result, calibration and validation of these models is a recurring challenge with this method (Walzberg et al., 2023).

6.2.1 Agent-based models of glass container collection and consumer recycling behavior

This subsection briefly outlines the simulation model of glass container collection and consumer behavior used in this study, published in (Labelle & Frayret, 2018, 2023). The model is mainly based on the Theory of planned behavior (Ajzen, 1991), commonly used to model pro-environmental behaviors (Yuriev, Dahmen, Paillé, Boiral, & Guillaumie, 2020). Because of its intrinsic ability to model the behaviors of autonomous entities, researchers often integrate the TPB into the ABMS in order to have a solid conceptual base on which to build their behavior simulation models. This approach has been applied to study the emergence of industrial symbioses (Ghali et al., 2017), reuse and recycling of solar panels (Walzberg et al., 2021), agricultural practices to manage water quality (Bourceret, Amblard, & Mathias, 2022), the circularity of hard-disks drives (Walzberg, Burton, et al., 2022) and post-consumer recycling (Tong et al., 2018; Tong et al., 2023).

In this paper's model, agents have a choice of three end-of-life options for their wine bottles: the garbage disposal, curbside recycling, or taking the bottle to a voluntary drop-off point. To decide,

the agent calculates a score for each end-of-life and performs the behavior that obtains the highest score. The score is mainly determined by attitude and the perceived behavior control (influenced by the distance between the agent and the drop-off point). It is important to mention that these calculation parameters are almost entirely based and calibrated from empirical data; they are also different for each possible end-of-life and unique for each agent. (Dugundji & Gulyás, 2008). For this paper, a network of connections has been added, enabling the exchange and diffusion of information between agents, specifically awareness of the existence of voluntary drop-off points.

6.2.2 Impacts of social interactions on circular economy initiatives

A number of authors have examined the impact of the social aspect in circular economy initiatives using ABMS. Although not always modeled in the same manner, the findings are relatively unanimous: the social impact on behavior is non-negligible in the performance of circular initiatives. While the majority of authors represent the social aspect as a consideration of the share of circular behavior adopters in their networks, (Bourceret et al., 2022; Byrka, Jędrzejewski, Sznajd-Weron, & Weron, 2016; Tong et al., 2018; Walzberg, Burton, et al., 2022; Walzberg et al., 2021) other studies integrate social impact through the perceived opinion of other network members (Tong et al., 2023).

Equally important in the field of innovation diffusion, the social aspect is also often modeled as the diffusion of awareness, the impact (positive or negative) of word-of-mouth and the proportion of adopters in a stakeholder's network (Kiesling et al., 2012). In this paper, the social aspect will be integrated into the model from the point of view of innovation diffusion, where it is the impact on the collection system of the diffusion of awareness by word-of-mouth (Huete-Alcocer, 2017) which will be investigated. Future work could focus on integrating the social norm into the model, see section 6 for more details.

6.3 Case study

province of Quebec, VSF's voluntary collection program was launched on a larger scale in 2019 with its 6 drop-off points in Racine, Richmond, Saint-Denis-de-Brompton, Stoke, Valcourt and Windsor. Initially, VSF planned to collect around 200 tons of glass per year, which Deloitte estimated to be a return rate of around 40% (Deloitte 2018). However, 183 tons of glass were collected in just 8 months, significantly exceeding expectations and representing a 60% return rate.

It should be noted that two of these collection points, Racine and Saint-Denis-de-Brompton, had been active for several years before the official launch of the program. In fact, the first voluntary drop-off point in the province was inaugurated in Racine in 2015. Since then, the initiative has grown in popularity in Quebec, and there are now more than 75 glass drop-off points managed directly by municipalities, in parallel with the province's regular residual materials collection system. All collected glass is processed locally; the 7650 tons of glass collected annually are first conditioned at 2M Resources and then 95% recycled at Owen Illinois, a glass container manufacturer.

For this paper, two samples of empirical data on the quantities of glass collected at each of VSF's depots were obtained with the valuable assistance of OVV. Table 1 shows the quantities, in tons of glass, collected for the last 26 weeks of 2019 and the first 13 weeks of 2020.

Table 6.1 Tons of glass collected via OVV's voluntary drop-off program

<i>Drop-off</i>	<i>2019 (26 weeks)</i>		<i>2020 (13 weeks)</i>		<i>Total (39 weeks)</i>
	<i>Tons</i>	<i>%</i>	<i>Tons</i>	<i>%</i>	<i>Tons</i>
Racine	10.86	12	5.04	6	15.90
Richmond	8.56	9	12.46	14	21.02
St-Denis-de-Brompton	44.55	49	36.72	41	81.27
Stoke	4.21	5	10.16	11	14.37
Valcourt	8.16	9	9.52	11	17.68
Windsor	14.26	16	15.41	17	29.67
<i>Total</i>	<i>90.60</i>	<i>100</i>	<i>89.31</i>	<i>100</i>	<i>179.91</i>

6.3.1 Statistical analysis of the 2019 and 2020 samples

While in (Labelle, 2023) we used only one data set, the 2020 sample, the addition of a second sample allows us to study and analyze the evolution of the reverse logistics collection system over time. Two statistical tests (t-test: paired two-sample for means) were therefore carried out to qualify the relationship between the two empirical samples. In other words, the following two questions were answered:

- Is there a significant difference in the distribution of returned bottles between the depots?

The results of the t-test in Table 2 indicate that we can accept the hypothesis that the percentage of glass collected per depot is similar from 2019 to 2020 with a p-value > 0.05 .

Table 6.2 Paired t-tests results for the distribution of glass across drop-off points in percentages.

<i>(6 observations, df=5)</i>	<i>sample 2019</i>	<i>sample 2020</i>
Mean	16.67	16.67
Variance	266.93	158.21
Pearson Correlation	0.95	
t Stat	0	
p-value	1.00	

- Is the amount of glass collected constant?

The results of the t-test in Table 3 show that there is a significant difference in the number of bottles collected per week between 2019 and 2020 with a p-value < 0.05 . In fact, the average number of tons collected per week in 2020 is much higher than in 2019, with approximately double the amount (3.48 tons per week in 2019 compared to 6.87 tons per week in 2020).

Table 6.3 Paired t-tests results for the rate of collection (tons/week) glass across drop-off points

	<i>(6 observations, df=5)</i>	<i>(2019)</i>	<i>(2020)</i>
Mean		0.58	1.15
Variance		0.32	0.75
Pearson Correlation		0.95	
t Stat		-3.73	
p-value		0.01	

Increase in rates of collection between 2019 and 2020

What could explain this significant increase in weekly glass collection? According to Recyc-Québec's annual reports on the management of residual materials in Quebec, there was indeed a 40% increase in glass generated by Quebecers between 2015 and 2021, from 158,000 tons to 220,000 tons generated annually (Recyc-Québec, 2020, 2023). However, the increase in Quebec's volume could not account for all of the variation between the two samples.

A change in citizens' attitudes could also have been an explanatory factor, but the second edition of *Portrait des comportements et attitudes des citoyens québécois à l'égard des 3RV* (SOM, 2021) does not mention of such a change in behavior. Instead, the study notes a province-wide increase of almost ten percent in the use of authorized collection points (e.g., voluntary drop-off centers and eco-centers), as well as an increase in access to residual materials management services.

Another important point to consider is that the first sample for 2019 represents the official launch of the voluntary collection program. It is therefore reasonable to assume that not all citizens were aware of the existence of the program. The effect of word-of-mouth and, although very limited, advertising (posters, local newspapers, local radio) may have had an impact on the dissemination of information about the locations of the containers (drop-off points) placed in the VSF area. It is therefore reasonable to assume that awareness of the drop-off points could be a factor explaining the increase in weekly glass collection. Therefore, to assess the impact of awareness on the

performance of the collection system in its start-up phase, the parameter of awareness was added to the simulation model proposed in (Labelle, 2023).

6.4 Implementing awareness in the simulation model

The concept of awareness introduced in this article removes a previous limitation of the model, which assumed that all agents are aware of the existence and location of collection points. In practical terms, this would mean that such systems are fully mature in terms of awareness. Adding this parameter is critical to assess the need to ramp up the capacity of the reverse logistics network and manage capital expenditure. The inclusion of awareness in the model is illustrated in Figure 1.

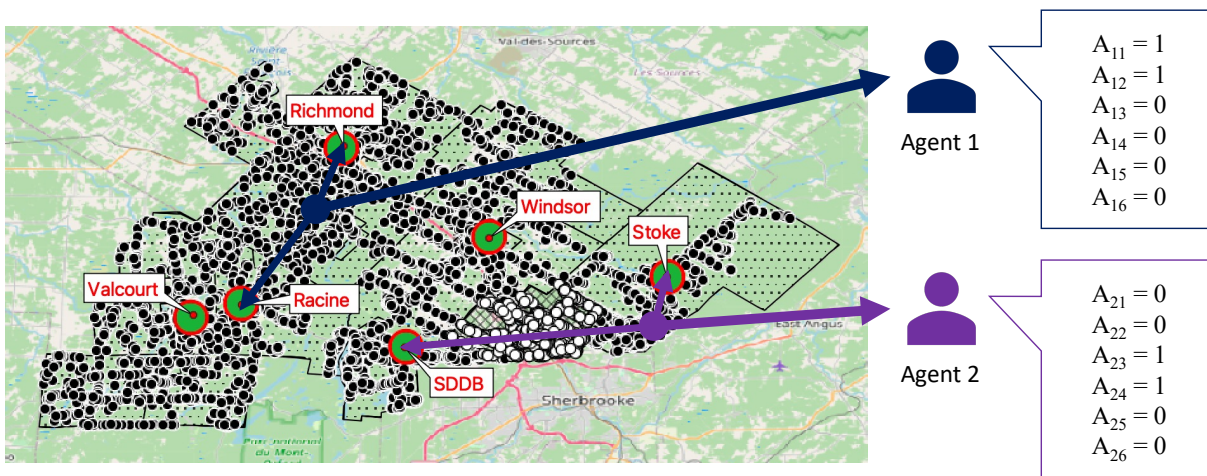


Figure 6.1 An example of two agents being aware of two drop-off points each

As shown in Figure 1, each agent has a vector of 6 binary variables (A_{id} , where i is the agent and d is the drop-off) representing its awareness of each drop-off point. If the value of A_{id} is 0, the agent i is not aware of the drop-off point d and therefore cannot return bottles to it. Conversely, if the value is 1, the agent i can consider returning his bottles to d .

The drop-off point selection process is performed for each bottle. The agent randomly selects a drop-off point from its list of known drop-offs based on their attractiveness. The higher the drop-off's attractiveness, the more likely it will be selected, and vice versa.

Considering that two drop-off points (Racine & Saint-Denis-de-Brompton) were inaugurated a few years before the official launch of the program, an initial awareness parameter was also introduced into the model to represent the heterogeneity in the degree of awareness for each drop-off point. In this way, it is possible to model drop-off points that are more popular than others from the

beginning of the simulation. The value of these parameters (i.e. Awareness & Initial Awareness) lies between 0 and 1, where a value of 1 means that the entire population is aware of the existence of this drop-off point. Thus, at the start of the simulation, all agents are assigned an awareness value of 0 or 1 for each drop-off point, depending on their respective initial awareness values.

Given the complexity of measuring, or even estimating, the level of awareness of the 30,000 inhabitants of VSF, in order to assess the impact of this aspect on the performance of the voluntary collection system, this paper presents an exploratory analysis of awareness through the calibration of this parameter in different social scenarios.

6.4.1 Impact of awareness on attractiveness

In preparation for the awareness calibration that is presented in section 5, an analysis of the relationship between attractiveness and awareness was performed to justify this case study experimental design assumption that the attractiveness of drop-off points is independent of the level of awareness. In the tourism and branding literature, where the aim is to understand the motivations behind choices of travel destinations or brand purchases, researchers are proposing measurement scales for awareness (Sophonsiri & Polyorat, 2009; Yoo, Donthu, & Lee, 2000) and attractiveness (Kim, Han, & Park, 2001). Generally, these two parameters are independent and evaluated on the basis of 3 to 6 items, which are scored on a Likert scale (Ye, 2012).

However, in the model presented in this paper, attractiveness was instead calculated through reverse engineering with calibrations against empirical data. It would therefore be interesting to investigate further, with surveys, what might explain the attractiveness values obtained for each drop-off. As far as awareness is concerned, there is very little to know about a drop-off point, apart from its location, unlike a travel destination. It was therefore considered reasonable for the awareness parameter to be binary for agents.

While the attractiveness calibrated in (Labelle, 2023) was calculated with 100% population awareness for all drop-off points, a sensitivity analysis of the attractiveness calibration was performed for 4 different levels (25%, 50%, 75%, and 100%) of awareness for the entire population. Thus, in the experiments presented in section 4, all agents have the same probability of being aware of a drop-off point. For example, an agent would have a 25% probability of being aware of each drop-off point individually. The results are shown in Table 4.

First, attractiveness calibration results were obtained with OptQuest using the attractiveness values calculated in (Labelle, 2023) as a starting point and the same empirical sample, namely the first 13 weeks of 2020. As shown in Equation (1), the goal of the calibrations was to minimize the sum of the absolute differences between the simulation results and the empirical data for the percentages of total glass collected via the various drop-off points. The simulation results used for these calibrations were the average of 5 to 50 repetitions per iteration to obtain a 99% confidence interval and 0.1% error.

$$\text{Min } Z = \sum_{d \in D} \text{absolute}(\% \text{simulations}_d - \% \text{empirical}_d) \quad (6.1)$$

Where

$$d \in D [\text{Racine, Richmond, SDDb, Stoke, Valcourt, Windsor}]$$

Next, the calibrated attractiveness scores were normalized to ensure that they could be properly compared according to their relative attractiveness. Thus, attractiveness values calibrated at 25%, 50%, and 75% awareness were compared to attractiveness values at 100% awareness using paired t-tests. The attractiveness calibration results are shown in Table 4 and the t-test results are shown in Table 5. This statistical test allows us to accept the hypothesis that the attractiveness calibration is independent of the general awareness level of the population.

Table 6.4 Attractiveness calibration results for awareness levels of 25%, 50%, 75% and 100%

<i>Drop-off</i>	<i>Calibrated Attractiveness (2020)</i> <i>[0-100]</i>				<i>Calibrated Attractiveness (2020)</i> <i>(normalized)</i>			
	<i>25%</i>	<i>50%</i>	<i>75%</i>	<i>100%</i>	<i>25%</i>	<i>50%</i>	<i>75%</i>	<i>100%</i>
	<i>aware</i>	<i>aware</i>	<i>aware</i>	<i>aware</i>	<i>aware</i>	<i>aware</i>	<i>aware</i>	<i>aware</i>
Racine	6	7	11	13	3	3	5	5
Richmond	24	30	32	33	12	14	14	14
St-Denis-de-Brompton	100	100	100	99	48	46	43	41
Stoke	13	23	25	28	6	11	11	12
Valcourt	34	18	23	26	16	8	10	11
Windsor	30	39	40	41	14	18	17	17
<i>Total</i>	<i>207</i>	<i>217</i>	<i>231</i>	<i>240</i>	<i>100</i>	<i>100</i>	<i>100</i>	<i>100</i>

Table 6.5 Paired t-tests results for attractiveness calibration with normalized values

<i>(6 observations, df=5)</i>	<i>25% aware</i>	<i>50% aware</i>	<i>75% aware</i>	<i>100% aware</i>
Mean	16.67	16.67	16.67	16.67
Variance	265.84	232.53	187.61	159.72
Pearson Correlation	0.97	1.00	1.00	
t Stat	0.00	0.00	0.00	
p-value	1.00	1.00	1.00	

Whatever the awareness value of the population tested, i.e. 25%, 50% or 75%, the attractiveness values calibrated for each drop-off points are always statistically similar to the values calibrated with 100% awareness. However, there is an increase in variance and a decrease in the correlation coefficient as awareness decreases, which is justified by the fact that the stochastic component is more prominent in these cases. What's interesting is that Valcourt's attractiveness is higher than that of Stoke and Windsor at an awareness level of 25%, whereas this is not the case at other awareness levels.

6.5 Potential impact of word-of-mouth effect on collected glass containers

To study the impact of awareness on reverse logistics flows, simple social networks were introduced in the model proposed by (Labelle, 2023). By randomly connecting agents at the beginning of the simulation, agents can interact and exchange information (Erdős & Rényi, 1960; Gilbert, 1959). The choice to connect agents randomly rather than in small-world (Travers & Milgram, 1977; Watts & Strogatz, 1998), scale-free (Barabási & Albert, 1999), or other types of networks provides a baseline scenario and limits the degrees of freedom required to calibrate the model. As highlighted by (Bohlmann, Calantone, & Zhao, 2010) in their study, the authors conclude that random networks produce less variable results than other types of networks, which is important when calibrating a model efficiently. Although real-world networks are generally more clustered than random generated networks, the latter often have small diameters, which is a characteristic that real networks generally have as well. (Travers & Milgram, 1977). Random networks are also prevalently used in the study of innovation diffusion via agent-based simulation. (Kiesling et al., 2012).

Therefore, a word-of-mouth information diffusion mechanism is introduced into the simulation model. Periodically, agents meet and discuss drop-off points with another agent randomly selected from their network of contacts, and these agents interact with each other to inform each other of their knowledge of the existence and location of drop-off points. For example, an agent with knowledge of two of the six drop points could interact with an agent who knew of two others, and so after the interaction each agent would have knowledge of 4 of the 6 drop points.

6.5.1 Experiments

The experimental design described in this paper to study awareness consists of 2 steps. The first step is to calibrate initial awareness of drop-off points for a series of social interaction scenarios. In this step, only the 2019 sample is used, representing 26 weeks. A total of 11 calibrations were performed, representing 5 interaction frequencies and 2 network sizes. The interaction frequency indicates the duration in weeks between two interactions (2, 4, 6, 8, and 10 weeks), while the network size indicates the number of connections (10 or 20 connections) that each agent has. The eleventh scenario is the case where there is no interaction between agents. Table 6 shows the results of these calibrations. The objective of the calibrations was to minimize the sum of the absolute differences between the simulation results and the empirical data for the percentages of the total glass collected through the different redemption points, but this time; the difference between what is simulated and the empirical data for the total number of tons collected at the redemption points was also included in the objective function, as shown in Equation (2).

$$\begin{aligned}
 \text{Min } Z = & \sum_{d \in D} \text{absolute}(\% \text{simulations}_d - \% \text{empirical}_d) \\
 & + \text{absolute}(\text{total collected simulation} - \text{total collected empirical})
 \end{aligned} \tag{6.2}$$

Table 6.6 Calibrated initial awareness values for varying social interaction scenarios

<i>Drop-off</i>	<i>Frequency of interactions (number of weeks between interactions)</i>					
	<i>2</i>	<i>4</i>	<i>6</i>	<i>8</i>	<i>10</i>	<i>-</i>
<i>10 connections per agents</i>						
Racine	0.0003	0.004	0.007	0.009	0.02	0.11
Richmond	0.00009	0.0007	0.003	0.007	0.01	0.06
St-Denis-de-Brompton	0.0004	0.005	0.02	0.03	0.04	0.3
Stoke	0.00001	0.0004	0.0009	0.0008	0.0009	0.05
Valcourt	0.0001	0.002	0.005	0.009	0.01	0.08
Windsor	0.00006	0.002	0.006	0.01	0.02	0.11
<i>average Z value</i>	<i>38.03</i>	<i>16.70</i>	<i>22.06</i>	<i>17.61</i>	<i>17.22</i>	<i>9.07</i>
<i>20 connections per agents</i>						
Racine	0.0001	0.002	0.008	0.007	0.02	0.11
Richmond	0.0001	0.0007	0.004	0.009	0.01	0.06
St-Denis-de-Brompton	0.0003	0.005	0.01	0.002	0.03	0.3
Stoke	0.0001	0.0002	0.0009	0.0007	0.0006	0.05
Valcourt	0.0001	0.0008	0.004	0.008	0.008	0.08
Windsor	0.00005	0.002	0.006	0.01	0.01	0.11
<i>average Z value</i>	<i>47.71</i>	<i>20.47</i>	<i>19.30</i>	<i>23.48</i>	<i>19.98</i>	<i>9.07</i>

Calibrations were performed using the OptQuest module built into AnyLogic. From 5 to 50 repetitions were performed per iteration to obtain a confidence interval of 99% and a percentage error of 0.1%. The average Z-values calculated for the objective function are shown in Table 6. It can be seen that the results between 10 and 20 connections per agent are very similar, but that the average Z values for the case of 10 connections per agent are lower, indicating that the simulation results are closer to the empirical values. For this reason, only the 10-connection case is kept for the next step.

In the second step, simulations were run for the different social interaction scenarios, using the initial awareness values found in the previous step. The duration of the simulations in this case was 39 weeks, corresponding to the duration of the two samples, i.e. the last 26 weeks of 2019 and the first 13 weeks of 2020. Therefore, the goal of these experiments is to assess whether the awareness calibration using only the first sample (26 weeks) produces simulation results (i.e., tons of glass collected at collection points) that remain valid when simulated for 39 weeks. Valid results would indicate that the inclusion of awareness and social interactions in the simulation model can approximate the evolutionary dynamics of the system as observed with the first and second samples.

For these experiments, 10 replications were performed, which was sufficient to obtain results where the standard deviations of the percentages for the different behaviors are less than 1%. The average results for the 10 replications of the number of tons going to the three possible end-of-life behaviors are presented in Table 7. The disaggregated results for the collection behavior, i.e. the number of tons collected at each collection point for each period (2019 & 2020), are presented in Table 8, and the differences between these simulation results and the empirical data are shown in Figure 2.

Table 6.7 Simulation results for 6 social interactions scenarios with 10 connections per agents

<i>End-of-life choice</i>	<i>Social scenarios (weeks between interactions)</i>																	
	<i>2</i>			<i>4</i>			<i>6</i>			<i>8</i>			<i>10</i>			<i>-</i>		
	<i>Tons</i>	<i>%</i>	<i>S.D.</i> <i>(%)</i>	<i>Tons</i>	<i>%</i>	<i>S.D.</i> <i>(%)</i>	<i>Tons</i>	<i>%</i>	<i>S.D.</i> <i>(%)</i>	<i>Tons</i>	<i>%</i>	<i>S.D.</i> <i>(%)</i>	<i>Tons</i>	<i>%</i>	<i>S.D.</i> <i>(%)</i>	<i>Tons</i>	<i>%</i>	<i>S.D.</i> <i>(%)</i>
Waste	74.51	17.17	0.33	74.27	17.17	0.28	74.04	17.12	0.36	74.01	17.12	0.30	74.49	17.23	0.21	73.85	17.12	0.38
Curbside	177.53	40.92	0.76	180.54	41.74	0.48	180.90	41.82	0.41	185.82	42.98	0.28	183.17	42.38	0.42	219.71	50.94	0.64
Bring Back	181.78	41.90	0.74	177.76	41.09	0.47	177.62	41.06	0.38	172.53	39.90	0.44	174.56	40.39	0.37	137.72	31.93	0.42
Total	<i>433.82</i>	<i>100.00</i>		<i>432.56</i>	<i>100.00</i>		<i>432.56</i>	<i>100.00</i>		<i>432.36</i>	<i>100.00</i>		<i>432.22</i>	<i>100.00</i>		<i>431.28</i>	<i>100.00</i>	

Table 6.8 Simulation results of glass collected at each depot center for 6 social interactions scenarios with 10 connections per agents.

<i>Drop-off</i>	<i>Collected glass in tons (simulation)</i>			<i>Difference in tons (simulation-empirical)</i>		
	<i>2019</i>	<i>2020</i>	<i>Total</i>	<i>2019</i>	<i>2020</i>	<i>Total</i>
<i>2 weeks</i>						
Racine	9.47	4.88	14.35	-1.39	-0.16	-1.55
Richmond	11.63	11.08	22.71	3.07	-1.38	1.69
St-Denis-de-Brompton	46.74	37.45	84.18	2.19	0.73	2.91
Stoke	5.61	5.91	11.52	1.40	-4.25	-2.85
Valcourt	9.26	9.68	18.93	1.10	0.16	1.25
Windsor	14.49	15.60	30.09	0.23	0.19	0.42
<i>Total</i>	<i>97.19</i>	<i>84.59</i>	<i>181.78</i>	<i>6.59</i>	<i>-4.72</i>	<i>1.87</i>
<i>4 weeks</i>						
Racine	12.13	4.67	16.80	1.27	-0.37	0.90
Richmond	6.49	11.26	17.75	-2.07	-1.20	-3.27
St-Denis-de-Brompton	45.56	35.61	81.18	1.01	-1.11	-0.09
Stoke	3.46	8.73	12.20	-0.75	-1.43	-2.17
Valcourt	10.51	9.13	19.64	2.35	-0.39	1.96
Windsor	15.49	14.71	30.20	1.23	-0.70	0.53
<i>Total</i>	<i>93.65</i>	<i>84.11</i>	<i>177.76</i>	<i>3.05</i>	<i>-5.20</i>	<i>-2.15</i>
<i>6 weeks</i>						
Racine	9.25	4.95	14.21	-1.61	-0.09	-1.69
Richmond	6.57	10.28	16.85	-1.99	-2.18	-4.17
St-Denis-de-Brompton	53.09	39.46	92.55	8.54	2.74	11.28
Stoke	1.84	5.37	7.20	-2.37	-4.79	-7.17
Valcourt	8.87	9.03	17.90	0.71	-0.49	0.22

Table 6.9 (continued and end)

Windsor	14.01	14.90	28.91	-0.25	-0.51	-0.76
<i>Total</i>	<i>93.64</i>	<i>83.99</i>	<i>177.62</i>	<i>3.04</i>	<i>-5.32</i>	<i>-2.29</i>
<i>8 weeks</i>						
Racine	7.76	4.90	12.66	-3.10	-0.14	-3.24
Richmond	8.87	10.33	19.20	0.31	-2.13	-1.82
St-Denis-de-Brompton	49.26	43.65	92.91	4.71	6.93	11.64
Stoke	0.13	0.32	0.45	-4.08	-9.84	-13.92
Valcourt	9.86	8.99	18.85	1.70	-0.53	1.17
Windsor	13.71	14.76	28.46	-0.55	-0.65	-1.21
<i>Total</i>	<i>89.59</i>	<i>82.94</i>	<i>172.53</i>	<i>4.15</i>	<i>-8.25</i>	<i>-4.10</i>
<i>10 weeks</i>						
Racine	11.97	5.99	17.96	1.11	0.95	2.06
Richmond	8.70	8.78	17.47	0.14	-3.68	-3.55
St-Denis-de-Brompton	46.40	42.58	88.97	1.85	5.86	7.70
Stoke	0.74	0.99	1.73	-3.47	-9.17	-12.64
Valcourt	7.59	7.00	14.59	-0.57	-2.52	-3.09
Windsor	18.24	15.60	33.84	3.98	0.19	4.17
<i>Total</i>	<i>93.63</i>	<i>80.93</i>	<i>174.56</i>	<i>3.03</i>	<i>-8.38</i>	<i>-5.35</i>
<i>No interactions</i>						
Racine	10.87	5.47	16.34	0.01	0.43	0.44
Richmond	6.78	3.39	10.18	-1.78	-9.07	-10.84
St-Denis-de-Brompton	46.61	23.28	69.89	2.06	-13.44	-11.38
Stoke	5.27	2.65	7.92	1.06	-7.51	-6.45
Valcourt	8.81	4.43	13.24	0.65	-5.09	-4.44
Windsor	13.44	6.71	20.15	-0.82	-8.70	-9.52
<i>Total</i>	<i>91.79</i>	<i>45.94</i>	<i>137.72</i>	<i>1.19</i>	<i>-43.37</i>	<i>-42.19</i>

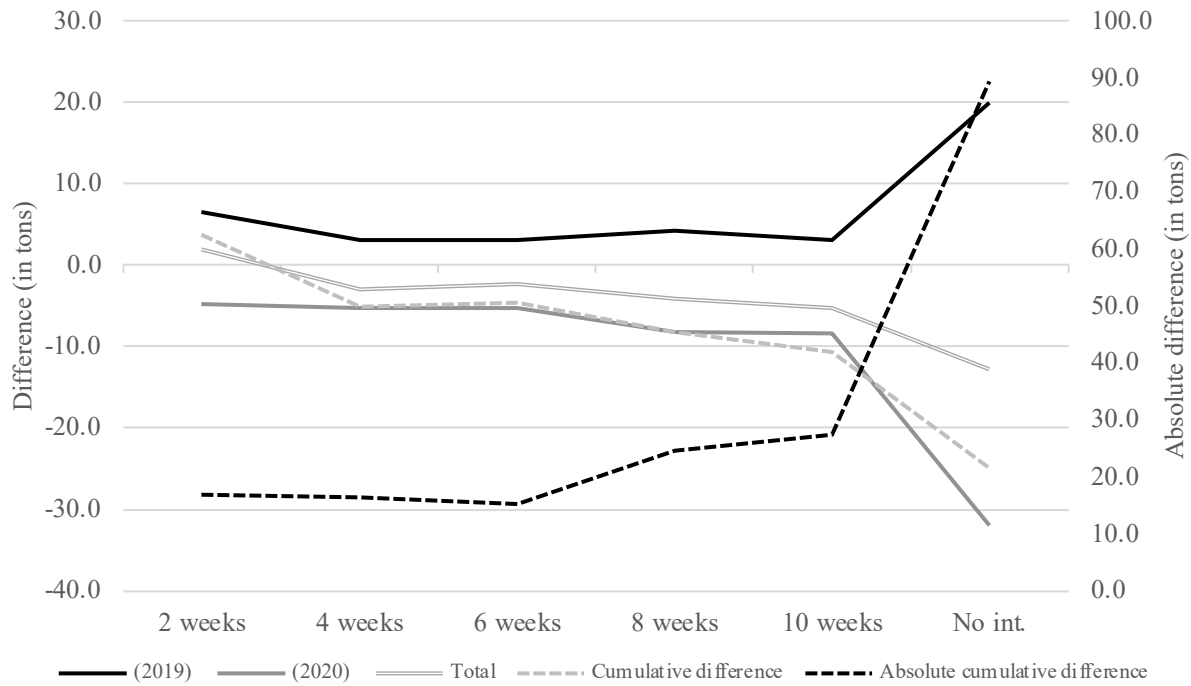


Figure 6.2 Difference between simulation results and empirical data for the tons of glass collected through drop-offs per social interactions scenarios.

6.5.2 Results analysis

While the aim of this paper is to study the collection phenomenon quantitatively using an agent-based simulation model to gain a better understanding of consumer behavior and possibly facilitate the design of collection networks, the results are very encouraging. Indeed, the analysis of simulation results enabled the rejection of social scenarios that were not statistically significant when compared with empirical data. On the other hand, it was possible to identify scenarios that are quite comparable to the phenomenon observed in reality.

6.5.2.1 Unsuccessful model validations

As shown in table 9, which presents the statistical results of the comparison between the simulation results and the empirical values for the distribution of tons collected at the drop-off points, three statistical tests (paired t-tests) have a p-value < 0.05 . This means that scenarios with at least one of their p-values lower than 0.05 are not combinations of parameters that accurately reflect the observed phenomenon. For these specific scenarios, the hypothesis that the simulation results are

similar to the empirical data is rejected. These scenarios are: interactions every 4 weeks and the scenario without interactions.

For the 2020 results with 4-weekly interactions, it is the only case where the number of tons collected is lower than the empirical data for all depots. Considering that the calibrations minimize the absolute deviations, it is possible that the initial awareness values calibrated with the 2019 sample are a combination of values that on the one hand optimize the objective function, but which do not satisfy the level of representativeness of the reality of the system dynamics when the 2020 period is included in the simulation. The fact that the total amount collected at the drop-off points is also included in the objective function could make it possible to obtain such a result (i.e. where the accuracy of the total would be prioritized over the accuracy of the distribution of the tons collected at the various drop-off points and vice versa).

For the results of the scenario without interactions, we note that over a period of 26 weeks, the initial awareness seems sufficient to support a number of tons collected comparable to what is observed empirically. However, from 2020 onwards, there is an increase in the rate of glass returned to depots that is clearly not captured in the simulations, as shown by the low total amount of glass returned to the collection points.

Table 6.10 Paired t-test comparing simulations results to empirical data for the tons of glass collected at each drop-off location

<i>(6 observations, df=5)</i>	<i>2019 (26 weeks)</i>		<i>2020 (13 weeks)</i>		<i>Total (39 weeks)</i>	
	<i>empirical</i>	<i>simulation</i>	<i>empirical</i>	<i>simulation</i>	<i>empirical</i>	<i>simulation</i>
<i>2 weeks</i>						
Mean	15.10	16.20	14.89	14.10	29.99	30.30
Variance	219.10	232.38	126.19	145.61	660.85	739.48
Pearson Correlation	1.00		0.99		1.00	
t Stat	-1.73		1.05		-0.36	
p-value	0.14		0.34		0.74	
<i>4 weeks</i>						
Mean	15.10	15.61	14.89	14.02	29.99	29.63
Variance	219.10	233.20	126.19	122.74	660.85	673.35
Pearson Correlation	0.99		1.00		1.00	
t Stat	-0.77		4.80		0.44	
p-value	0.47		0.00		0.68	
<i>6 weeks</i>						
Mean	15.10	15.61	14.89	14.00	29.99	29.60
Variance	219.10	352.97	126.19	168.79	660.85	1000.35
Pearson Correlation	1.00		0.99		1.00	
t Stat	-0.30		0.87		0.15	
p-value	0.77		0.42		0.89	

Table 6.11 (continued and end)

<i>8 weeks</i>						
Mean	15.10	14.93	14.89	13.82	29.99	28.75
Variance	219.10	302.57	126.19	237.57	660.85	1073.01
Pearson Correlation	0.99		0.97		0.99	
t Stat	0.13		0.49		0.37	
p-value	0.90		0.65		0.73	
<i>10 weeks</i>						
Mean	15.10	15.61	14.89	13.49	29.99	29.09
Variance	219.10	260.25	126.19	225.46	660.85	965.23
Pearson Correlation	0.99		0.97		0.99	
t Stat	-0.49		0.68		0.30	
p-value	0.64		0.53		0.77	
<i>No interactions</i>						
Mean	15.10	15.30	14.89	7.66	29.99	22.95
Variance	219.10	243.79	126.19	60.66	660.85	547.66
Pearson Correlation	1.00		0.94		0.99	
t Stat	-0.35		3.82		3.80	
p-value	0.74		0.01		0.01	

6.5.2.2 Successful model validations

Overall, the simulation model is able to produce results that are comparable to what is observed in reality. However, the simulation results seem to be valid only in cases where social interaction actually takes place, i.e., when the p-value is greater than 0.05. This finding suggests that the word-of-mouth phenomenon, combined with the basis that knowledge of the existence of drop-off points is heterogeneously distributed, could explain some of the growth in weekly return rates observed when comparing the two empirical data samples (see Section 3.1).

According to the results in Figure 2 and Tables 8 and 9, the scenario that best represents the real situation is the one with interactions between agents every 6 weeks. This is the case with the smallest absolute cumulative difference between the simulation results and the empirical data, and it is also the case with the highest p-value for the total collected after 39 weeks.

6.5.2.3 Model inaccuracies

It's worth noting that for all scenarios, the number of tons collected in 2020 is systematically lower than the actual volume. On the other hand, the opposite is true for 2019, where the collected tons are overestimated. These results may suggest an overestimation of initial awareness and an underestimation of awareness diffusion, which could potentially be counterbalanced by the introduction of an additional diffusion vector: advertising (posters, newspapers, radio, etc.). The structure of the social network could also be responsible. Indeed, as (Delre, Jager, & Janssen, 2007), innovation seems to spread more rapidly in more regular networks than in random ones.

6.6 Discussion

Given that the case study collection system is based on a voluntary citizen initiative, the OVV program did not really have a budget for advertising. According to OVV experts, word-of-mouth was indeed the main vector for spreading information, so from a qualitative point of view, the qualitative validation of the simulation model in terms of its ability to reproduce expected observable behavior is achieved.

Of course, like any simulation model, the one presented in this paper has certain limitations. The principle that the initial perception is general for the whole population and independent of the agents' location is a blatant simplification of the real situation. To obtain a more accurate model, it would have been interesting to ensure that agents living close to a drop-off point are more likely

to be aware of its availability. Testing more types of social networks could also have added a degree of finesse to the experiments, but it would have also added degrees of freedom that would have had to be managed. The random network with a fixed number of connections was therefore the option that provided the necessary level of stability to the results, given the exploratory nature of the analysis.

Other models of social interactions that are commonly used in ABMS could have been considered, see section 2.2. Nonetheless, as pointed out by (Wood, 2000), it is possible to influence and even change the attitude of individuals towards a behavior through social interactions, as opposed to influencing the intention to perform a behavior. Two agent-based simulation models have used this concept to include the influence of the social aspect (Kaufmann et al., 2009; Rai & Robinson, 2015). To do so, they used the Relative Agreement Model of (Deffuant et al., 2002), which proposes a model to reproduce the impact of social interactions on the opinions of individuals. Given the continuous opinion spectrum of the agents in this paper's model, it would be interesting to see how the Relative Agreement Model could be used to integrate the TPB's social norm into the model (Chen, Su, Mei, & Bullo, 2020).

6.6.1 How is this research useful?

From the outset, the paper presents to researchers, experts or anyone interested in the field of reverse logistics simulation; an approach for the calibration, experimentation and validation of a complex agent-based simulation of a reverse logistics collection system. The peculiarity of the model is that it requires a significant amount of data to be parameterized, including behavioral studies, empirical studies for calibration and validation, socio-demographic studies (census), non-public databases on residential address geolocation, and more. On the other hand, this makes it a very malleable, consistent and accurate model.

The model can also be used to estimate dynamic logistics requirements for reverse logistics systems. That is, to try to answer questions such as: how often do materials need to be moved from depots to packers and/or recyclers?

The model could be adapted to include another information dissemination channel, such as the media, to better estimate the need for advertising campaigns to match investments with potential gains in tons collected. It is also possible to reverse-engineer the calibration of initial awareness, possibly in combination with attractiveness, to assess which drop-off points would merit some form

of investment in either awareness or attractiveness, and then use the simulation to evaluate potential gains and returns on investment.

6.7 Conclusion

Although the model cannot determine which word-of-mouth scenario actually occurred in the VSF, it can show that word-of-mouth would be a reasonable explanation for the growth and stabilization of the return rates. However, there are certainly other factors that could explain this phenomenon, such as an increase in the volume of residual materials produced by the Quebec population or changes in citizens' attitudes.

The rigorous approach outlined in the article clearly demonstrates the ability of agent-based models to be configured to complex socio-technological reverse logistics systems. The particularity of these systems is that human decisions play a crucial role in the distribution of material flows in the economy. To produce simulation models that are valid and sufficiently accurate to support decision making, it is therefore important to understand consumer behavior and to be able to model it correctly.

CHAPITRE 7 DISCUSSION GÉNÉRALE

Pour faire suite aux discussions des sections précédentes, cette section présente certains constats qui émergent des trois chapitres précédents, une discussion sur les limites du modèle de simulation développé dans la présente thèse en plus d'identifier des avenues de recherche intéressantes.

Les résultats du chapitre 4 soulignent l'importance de considérer l'impact des incitatifs dans la décision des consommateurs. Effectivement, la calibration de la valeur du paramètre gamma, soit l'importance relative de l'incitatif par rapport à l'opinion, suggère que le québécois moyen est d'avantage influencé par la valeur de l'incitatif que par son opinion lors de sa prise de décision. Les expériences réalisées dans les chapitres 4 et 5 démontrent également la capacité d'un modèle de simulation basé sur le TPB sans l'utilisation de SEM à reproduire des comportements observés.

Les expériences réalisées dans le chapitre 5 démontrent que l'implantation de l'aspect géographique améliore la précision des résultats par rapport aux données empiriques, mais il semblerait qu'aller au-delà d'une modélisation des consommateurs aléatoirement placés dans une municipalité, contrairement à géolocaliser ces derniers avec des adresses résidentielles, n'augmente pas considérablement la précision du modèle quant à la distribution des bouteilles retournées aux points de dépôts. Cependant, ce qui semble être crucial dans la modélisation du comportement étudié est l'aspect du choix du point de dépôt par les consommateurs, qui a été modélisé dans cette thèse à travers « *attractiveness* ». Malgré que cette thèse fasse ressortir l'importance d'inclure cet élément dans le modèle, il n'en reste que ce qui définit ou caractérise ces « *attractiveness* » n'a pas été investigué.

Les résultats des calibrations effectuées au chapitre 6 illustrent que l'effet du bouche-à-oreille peut effectivement potentiellement expliquer une partie de la croissance dans les taux de retours qui est observée entre les deux échantillons de données empiriques. Par contre, d'avantage de recherche doit être effectué afin de mieux comprendre comment correctement modéliser cet aspect dans des contextes où le modèle serait utilisé pour faire de la prédiction. Il est aussi important de faire ressortir que le modèle présenté dans cette thèse n'inclus pas la norme sociale du TPB, ce qui est une limite considérable du modèle (Tong et al., 2023). Il serait intéressant d'investiguer comment planter cet aspect dans le modèle.

Bien que le modèle soit capable de reproduire le comportement d'une population de plusieurs dizaines de milliers de personnes, il n'en reste que ce n'est qu'une représentation simplifiée du comportement réel des consommateurs. D'ailleurs, considérant la complexité du contexte étudié, un modèle de simulation du comportement ne sera jamais parfaitement juste. En effet, des simplifications doivent être effectuées, tel qu'avec TPB par exemple, pour être en mesure de l'intégrer dans un logiciel de simulation (Scalco et al., 2017). Il ne faut pas oublier que plus un modèle est complexe, il peut souvent être plus précis et s'adapter à plus de situations, mais il nécessitera plus de données et de temps pour le calibrer et le valider (Labelle, 2023). Dans leur revue de littérature sur l'utilisation de la simulation à base d'agent pour étudier l'économie circulaire, les auteurs font ressortir que la calibration et la validation des modèles est bien reconnus comme un des enjeux principal de modèles de simulation à base d'agent (Walzberg et al., 2023). Il serait donc intéressant que d'avantages d'auteurs indiquent clairement la contribution des données et des sous-modèles qui sont utilisés quant aux gains en précision qu'ils apportent. Par exemple, des auteurs ont récemment utilisé une matrice de pedigree pour caractériser la qualité des données qui ont été utilisés dans leurs modèles (Walzberg, Burton, et al., 2022).

Il est important de rappeler que malgré que le modèle a été validé dans un certain cas spécifique, soit le programme de dépôt volontaire de la MRC du Val-Saint-François; il faudrait tester la robustesse du modèle avec une étude de cas sur d'autres populations. Le modèle étant configurable pour d'autres produits, il serait également intéressant de tester la capacité du modèle à s'adapter à d'autres produits comme les canettes d'aluminium ou les bouteilles de plastique.

CHAPITRE 8 CONCLUSION

Le déploiement efficace de l'économie circulaire passe par une connaissance précise de comment les matières circulent dans la biosphère et la technosphère. Dans le cas des produits de consommation, comme les bouteilles de vin par exemple, le consommateur se doit de prendre une décision envers sa bouteille lorsque celle-ci atteint sa fin de vie. Le choix est pourtant simple : poubelle, recyclage ou retour à un point de collecte. Cependant, ce simple choix, à l'échelle d'une population, a des conséquences considérables sur la circularité des bouteilles de vin. Ainsi, la compréhension du comportement des consommateurs est critique pour anticiper les flux de matières dans la chaîne de logistique inverse du verre.

La simulation à base d'agents est une méthode particulièrement bien adaptée à l'étude du comportement des consommateurs à l'égard de leurs produits en fin de vie par sa capacité à modéliser des entités qui interagissent et prennent des décisions de manière autonome. Toutefois, il y a encore très peu de modèles à base d'agents appliqués à ce contexte dans la littérature et encore moins qui sont calibrés et validés avec des données empiriques. L'anticipation précise de la performance d'une stratégie de logistique inverse, tel que la consigne sur les bouteilles de vin est donc particulièrement complexe et difficile.

Au travers de cette thèse, un modèle de simulation qui reproduit l'impact des consommateurs sur les flux de matières de produits en fin de vie a été développé et appliqué aux bouteilles de vin au Québec. Le modèle a été principalement configuré et calibré avec des données empiriques et a aussi été validé à l'aide de deux échantillons empiriques. La contribution de cette thèse réside dans :

- Le développement d'un modèle de simulation à base d'agent du comportement des consommateurs à l'égard de leurs produits en fin de vie qui est configurable à des produits et des populations spécifiques;
- L'identification et l'évaluation des données nécessaires pour configurer le modèle;
- La démonstration de la validité du modèle à travers une étude de cas.

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