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PROACTIVE INFERIOR MEMBER PARTICIPATION MANAGEMENT IN INNOVATION COMMUNITIES

THÈSE EN VUE DE L'OBTENTION DU TITRE DE DOCTEUR EN SCIENCES ÉCONOMIQUES

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Sous la direction de Prof. Dr. Kristof Coussement

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- "Life begins at the end of your comfort zone"
Neale Donald Walsch

RÉSUMÉ GLOBAL

Actuellement, les entreprises ont commencé graduellement à avouer le rôle important que les communautés d'innovation (CI) jouent dans l'intégration de la connaissance externe des consommateurs dans les processus d'innovation. Malgré que les CI possèdent d'innombrables avantages, le fait de garantir leur viabilité soulève deux défis importants. D'une part, les CI sont des environnements big data (de mégadonnées) qui peuvent submerger les animateurs de communauté très vite dès que les membres commencent à communiquer par des publications, générant par la suite un flux énorme de données (volume) qui sont rapidement extensibles (vitesse) et non structurées, pouvant contenir des indices linguistiques et audiovisuels (variété). D'autre part, la majorité des communautés virtuelles n'arrivent pas à produire de bons résultats car elles sont souvent incapables de tirer des avantages des différents membres de la CI à cause de la faible participation des membres. Cette thèse doctorale s'appuie sur des stratégies de gestion de la relation client (GRC) pour faire face à ces défis et ajoute de la valeur en instaurant un cadre proactif de gestion de la faible participation des membres afin de réduire de manière proactive la faible participation des membres tout en gérant efficacement l'environnement de la CI riche en données. Concrétement, cette thèse contribue à la littérature en six façons. Premièrement, elle dévoile l'importance du style rédactionnel orienté vers l'intérêt personnel du modérateur et de la communauté dans l'identification proactive de la faible participation des membres. Deuxièment, elle prouve le pouvoir du style d'écriture émotionnel et positif d'un membre, d'un modérateur et d'une communauté dans la découverte de la faible participation subséquente du membre. Troisièmement, elle démontre l'aptitude de la méthode de classification multi-label à obtenir des performances prédictives plus importantes en matière d'identification proactive de la faible participation des membres contrairement au fait de dresser des modèles indépendants pour chaque label de la participation des individus. Cette augmentation des performances prédictives peut être obtenue par les méthodes de transformation du problème ainsi que les méthodes d'adaptation de l'algorithme. Quatrièmement, une étude de cas montre qu'un e-mail de motivation non ciblé et proactif augmente la faible participation des membres, tandis qu'un e-mail de motivation ciblé et proactif la réduit. Cinquièmement, elle révèle la nécessité pour les animateurs de communauté d'inclure un message de motivation qui anticipe le bénéfice cognitif attendu des membres en participant à la communauté par des campagnes de motivation par courriel pour réduire au maximum la faible participation des membres. Sixièmement, elle démontre le rôle important

du style rédactionnel émotionnel positif d'un membre de la communauté pour indiquer si le membre peut être influencé positivement par un courriel de motivation.

GENERAL ABSTRACT

Nowadays, companies increasingly recognize the benefits of innovation communities (ICs) to inject external consumer knowledge into innovation processes. Despite the advantages of ICs, guaranteeing the viability poses two important challenges. First, ICs are big data environments that can quickly overwhelm community managers as members communicate through posts, thereby creating substantial (volume), rapidly expanding (velocity), and unstructured data that might encompass combinations of linguistic, video, image, and audio cues (variety). Second, most online communities fail to generate successful outcomes as they are often unable to derive value from individual IC members owing to members' inferior participation. This doctoral dissertation leverages customer relationship management strategies to tackle these challenges and adds value by introducing a proactive inferior member participation management framework for community managers to proactively reduce inferior member participation, while effectively dealing with the data-rich IC environment. Concretely, this dissertation contributes to literature both on a theoretical, methodological and empirical level. On a theoretical level, it contributes to innovation literature on innovation communities and sustained member participation by providing a framework for community managers to proactively identify, predict and prevent inferior member participation. First, it extends innovation research on the usage of communication in ICs by revealing the signaling role of community actors' linguistic style for member engagement. In particular, it indicates that a self-interest oriented- and positive emotional writing style of the moderator and community allow to proactively identify member's subsequent inferior participation. Second, it answers the call for research in innovation literature for advanced insights into the use of big data for innovation-management processes by revealing the benefit of exploiting the data-rich IC environment and relying on analytical models to predict inferior member participation. Third, it extends research on motivational tactics in ICs by revealing the optimal characteristics of an e-mail campaign. In particular, it shows that an untargeted e-mail campaign is not viable strategy anymore as it stimulates inferior member participation as opposed to the positive participation effect of a proactive targeted e-mail campaign using cognitive message. Moreover, it extends literature on communication in ICs by indicating the signaling role of a member's positive emotional writing style for an email campaign's influenceability. On a methodological level, it contributes to research streams of the key methods used in this dissertation by introducing a novel business application for the method to be applicable. First, it extends multi-label literature by revealing the ability of problem transformation and algorithm adaptation methods to predict future inferior member participation. Second, it contributes to the uplift modeling research stream by showing the motivational impact of a proactive targeted e-mail campaign to prevent inferior member participation. On an experimental level, it extends innovation literature by using empirical evidence to support the findings of inferior member participation identification, prediction and prevention. First, it builds on previous findings in IC research by revealing value of automatically analyzing real member's community behavior to understand IC habits and influence participation. Second, it extends literature on motivational community campaigns by using a real-life experiment and a business case to demonstrate how to proactively reduce inferior member participation.

Keywords: innovation communities; inferior member participation; big data; linguistic style use; inferior member participation identification; multi-label classification; inferior member participation reduction; motivational e-mail campaign

RÉSUMÉ DÉTAILLÉ

1. COMMUNAUTÉS D'INNOVATION

Le succès, la survie et le renouvellement des entreprises est tributaire de la conception de produit (Brown & Eisenhardt, 1995). Ce sont les entreprises qui lancent de nouveaux produits que les clients sont impatients d'acheter qui ont de fortes chances de réussir, contrairement aux entreprises qui lancent de mauvais produits et qui sont susceptibles de perdre. Les entreprises se renouvellent en développant de nouveaux produits pour s'adapter à l'évolution des conditions du marché et au développement de la technologie (Schoonhoven, Eisenhardt et Lyman, 1990). Au début du 21ème siècle, le modèle traditionnel de la conception du produit selon lequel les entreprises tentent de trouver de nouvelles idées de produits ou décident quels produits doivent être commercialisés en restant à l'intérieur de leurs limites, est de plus en plus remis en question par un nouveau modèle selon lequel le client joue également un rôle plus actif (Fuchs et Schreier, 2011 ; von Hippel, 2005). Les clients peuvent jouer plusieurs rôles et générer, évaluer, rassembler et tester des concepts de produits (Füller, 2006). En fin de compte, le consommateur utilisera le produit, donc l'intégration de la voix du consommateur dans le processus de conception du produit s'avère une démarche très recommandée (Abbie Griffin et Hauser, 1993).

Grâce à Internet, on peut obtenir les participations des consommateurs dans le processus de conception du produit rapidement et à un faible coût (Dahan et Hauser, 2002). Lorsque les entreprises encouragent l'intégration des clients dans les processus de conception de produit, elles bénéficient des communautés en ligne (Nambisan, 2002). Dans ces communautés, les consommateurs peuvent se rassembler en partageant un même intérêt pour des produits ou des services. Ces communautés garantissent l'interaction directe des consommateurs à un faible coût (Hoffman et Novak, 1996), elles couvrent toutes les phases de l'innovation (par exemple, la création d'idées, l'évaluation des idées ; (von Hippel, 2005)), elles s'appliquent à toute les formes de collaboration (par exemple dans l'entreprise, ouverte ; (Jeppesen et Frederiksen, 2006; West & Bogers, 2014)), et elles peuvent s'adapter à plusieurs niveaux d'intensité (de la consultation sporadique à la co-création à forte intensité (Nambisan, 2002)). Quand ces communautés sont créées par des entreprises pour intégrer la voix du consommateur dans la conception du produit, nous les appelons communautés d'innovation (CI).

De nombreuses entreprises adoptent le concept des communautés d'innovation dont la brasserie hollandaise Heineken, l'entreprise agroalimentaire américaine Heinz et la société de télécommunications britannique Vodafone (Troch & De Ruyck, 2014). L'impact de ces CI a été prouvé par plusieurs success stories. Par exemple, Air France KLM, une compagnie aérienne française, a contacté 90 voyageurs fréquents dans le cadre d'un projet de 6 semaines pour co-créer l'avenir des expériences de correspondance (Troch & De Ruyck, 2014). Ils ont découvert 32 nouvelles idées conceptuelles qui ont contribué à la réalisation des futures innovations de service, comme une nouvelle vidéo de vol en correspondance et une application mobile de gestion de correspondance avec une communication en temps réel sur les déplacements à effectuer. Des rapports industriels récents indiquent que plus de la moitié des entreprises ont recours à des communautés en ligne (Murphy, Pospichal & Kosar, 2016) dont la popularité ne fera qu'augmenter à l'avenir selon les experts de l'industrie.

Cependant, quand les entreprises cherchent à tirer parti de ces CI, les animateurs de communautés doivent s'attendre à deux défis importants qui menacent leur viabilité et dont ils doivent faire face :

- (i) Les CI sont des environnements basés « dans le nuage » et riches en données, ce qui peut rapidement submerger les différents animateurs de communauté. En particulier, leurs *caractéristiques relatives aux 3V du Big Data* signifient que les membres communiquent et partagent leurs opinions à travers des messages, créant ainsi des flux énormes de données substantielles (volume), en expansion rapide (vitesse) et non structurées qui peuvent inclure du texte, des vidéos, des images et des fichiers audio (variété). Lorsque les animateurs de communauté commencent à analyser l'ensemble de ces données afin d'extraire des renseignements sur la conception du produit, les caractéristiques relatives aux 3V rendent ces analyses encore plus difficiles et accentuent la pression sur les moyens de ces animateurs.
- (ii) La plupart des communautés en ligne ne parviennent pas à générer des résultats positifs (Sarner, 2008). Plus spécifiquement, les communautés en ligne sont souvent incapables de tirer de la valeur des différents membres de la CI en raison du taux de la *faible participation des membres* en plus de la qualité de cette participation (Ludwig et al., 2014). Lorsque les membres ne sont pas assez nombreux (quantité) à fournir des déclarations et des opinions bien fondées (qualité), les conditions de viabilité peuvent être compromises (Ludwig et al., 2014) et la CI peut être incapable de fournir un sol fertile pour des idées novatrices. Par

exemple, suite à une baisse significative de l'activité des membres dans l'une des CI italiennes de boissons non alcoolisées de Nestlé, l'entreprise l'a arrêtée complètement (Gambetti & Graffigna, 2015). InnovationWorld, une CI d'un opérateur télécom, a subi une réorganisation radicale juste un an après son lancement car la communauté avait été inondée de postes de mauvaise qualité (Bengtsson & Ryzhkova, 2013).

2. GESTION DE LA RELATION CLIENT

Le marketing est une fonction fondamentale de la gestion d'entreprise qui vise à bien comprendre le client pour que le produit présenté par l'entreprise lui convient et soit vendu tout seul (Drucker, 1954). Traditionnellement, le marketing était considéré comme la planification et l'application des éléments du mix marketing tels que le produit, le prix, la promotion et la place (distribution) afin de créer des échanges qui satisferont les objectifs individuels et organisationnels (American Marketing Association, 1985). Cependant, à la fin du XXe siècle, cette vision était considérée comme dépassée et le changement de paradigme du marketing transactionnel vers le marketing relationnel a poussé les entreprises à valoriser les relations avec la clientèle (Brodie, Coviello, Brookes et Little, 1997). Lorsque les entreprises se focalisent sur des transactions de vente uniques, un client devra être acquis de nouveau avant chaque transaction et les coûts d'acquisition seront encourus chaque fois, cependant, quand elles deviennent orientées client et établissent des liens entre ces différentes transactions, elles peuvent réduire considérablement les coûts grâce à la fidélisation des clients et augmentent ainsi la valeur pour toutes les parties prenantes (Osarenkhoe & Bennani, 2007).

Dans ce contexte, soutenue par l'émergence des nouvelles technologies et des différentes solutions de bases de données, la gestion de la relation client (GRC) a émergé comme une sorte de « marketing relationnel informationnel » (Ryals & Payne, 2001), Payne and Frow (2005, p. 168) définissent la GRC comme suit :

« La GRC est une approche stratégique qui vise à créer de la valeur ajoutée pour les actionnaires grâce au développement de bonnes relations avec les clients et les segments de clientèle clés. La GRC associe la force des stratégies de marketing relationnel et des technologies d'information pour créer des relations mutuellement avantageuses à long terme avec les consommateurs et les autres parties prenantes clés. La GRC offre de meilleures possibilités d'utilisation des données et des informations pour comprendre les consomateurs et créer de la valeur avec eux. Cela nécessite une intégration interfonctionnelle des

processus, des personnes, des opérations et des capacités de marketing grâce à l'information, à la technologie et aux applications ».

La GRC analytique utilise des données sur les clients en plus des outils d'analyse dans le but d'extraire de telles données (Teo, Devadoss, & Pan, 2006). Les informations sur les clients et leurs interactions peuvent désormais être stockées à faible coût dans les bases de données de l'entreprise en raison de la baisse des coûts d'entreposage des données (« data warehouse »). Et c'est grâce aux techniques d'exploration de données (« Data mining ») qu'une grande quantité de données peut facilement être transformée en données utiles pour soutenir les stratégies de marketing (Ngai, Xiu, & Chau, 2009). Comme les techniques d'exploration de données sont très répandues et que la puissance de calcul ne cesse d'augmenter (Moore, 1965), les entreprises ont des conditions favorables pour adopter l'ensemble de ces stratégies axées sur les données.

Comme les relations clientèle passent par trois phases importantes, à savoir la prospection, le maintien et la perte des clients, les activités GRC se concentrent respectivement sur l'acquisition, le développement et la fidélisation des clients (Reinartz, Krafft et Hoyer, 2004). L'acquisition de clients consiste à repérer et attirer des clients rentables. Le développement de la clientèle vise à augmenter l'intensité des transactions client, la valeur de ces transitions ainsi que la rentabilité. La fidélisation de la clientèle, quant à elle, vise à améliorer la satisfaction de la clientèle et à renforcer la relation avec l'entreprise.

L'adoption des projets GRC met les entreprises devant un grand défi (Rigby, Reichheld, & Schefter, 2002), mais malgrè ceci, la GRC reste largement utilisée dans l'industrie et de nombreuses applications à succès existent. Selon Gartner, une entreprise américaine de conseil et de recherche, le marché mondial des logiciels de GRC a connu une nette évolution en passant de 23,4 milliards de dollars en 2014 à 26,3 milliards de dollars en 2015 (Woods & Van Der Meulen, 2016). Par exemple, l'implémentation de GRC dans le secteur bancaire commercial augmente l'efficience des bénéfices (Krasnikov, Jayachandran, & Kumar, 2009) et double les bénéfices dans les efforts de fidélisation de la clientèle dans une société de la télévision payante (Burez & Van den Poel, 2007).

3. GESTION PROACTIVE DE LA FAIBLE PARTICIPATION DES MEMBRES

Cette thèse adopte des stratégies GRC au sein des CI dans l'objectif de réduire le problème de la faible participation des membres, tout en gérant efficacement l'environnement riche en données. Il y a plusieurs raisons pour lesquelles nous le faisons :

- (i) Alors que le consommateur demeure la ressource la plus précieuse pour une entreprise, un membre de la communauté demeure la ressource la plus précieuse pour la communauté d'innovation.
- (ii) La GRC est une approche axée sur les données qui repose sur les informations client pour soutenir les stratégies de commercialisation. Puisque les CI sont des environnements big data et que la participation des membres est stockée dans les bases de données de l'entreprise, l'environnement communautaire riche en données pourrait être un terrain fertile pour exécuter les stratégies GRC et soutenir des stratégies de gestion communautaire rentables.
- (iii) Du point de vue du cycle de vie du consommateur, la faible participation des membres peut être comparée au mieux avec la perte des clients. Alors que la perte des clients représente une perte pour l'entreprise, la faible participation des membres représente une perte pour la communauté. Comme la documentation relative à la GRC a étudié plusieurs stratégies de fidélisation pour réduire efficacement la perte (par exemple, Neslin, Gupta, Kamakura, Junxiang et Mason, 2006), les mêmes idées pourraient être appliquées pour réduire la faible participation des membres.

Cette thèse ajoute de la valeur en introduisant un cadre proactif de gestion de la faible participation des membres aux CI. La gestion proactive de la faible participation des membres peut être définie comme suit :

« La gestion proactive de la faible participation des membres est une pratique de gestion communautaire dans les CI où l'animateur de la communauté réduit proactivement la faible participation des membres »

Dans le but de construire le cadre d'une gestion proactive de la faible participation des membres, nous suivons le cadre de gestion proactive de l'attrition (« Churn managment ») en quatre étapes de Blattberg et Neslin (2010) pour réduire la perte des clients. La figure 1 montre les quatre étapes du cadre de la gestion proactive de la faible participation des membres : 1) identifier la faible participation potentielle des membres, 2) comprendre pourquoi ils participent moins, 3) concevoir une stratégie de communication appropriée, 4) surveiller et évaluer les résultats.

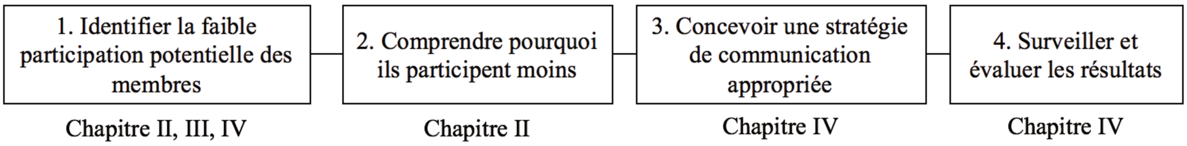

Figure 1 Gestion proactive de la faible participation des membres

Puisque le corps principal de ce travail explique chaque étape en détails au niveau des différents chapitres, ce paragraphe se limite à une description concise de ces différentes étapes. Les résultats des deux premières étapes peuvent être obtenus à l'aide d'un modèle prédictif qui avertit l'animateur de communauté des membres qui montreront une faible participation dans l'avenir et en indiquera la cause. Ensuite, il faut créer une stratégie de communication qui permettra au modérateur de réduire proactivement la faible participation des membres. Enfin, la pérennité de la stratégie de communication qui vise à réduire proactivement la faible participation des membres peut être évaluée en utilisant une expérience sur le terrain.

Cette thèse est composée de cinq chapitres et le corps principal de ce travail se concentre sur une ou plusieurs étapes du cadre de gestion proactive de la faible participation des membres. Après cette introduction générale, les chapitres II à IV forment le corps principal de cet ouvrage. Ces chapitres correspondent à trois études indépendantes. La Figure 1 explique quel chapitre se concentre sur quelle étape du cadre de gestion proactive de la faible participation des membres. Le chapitre II se concentre sur les deux premières étapes, le chapitre III traite de la première étape et le chapitre IV détaille les première, deuxième et quatrième étapes. La section suivante de cette introduction donne un résumé des objectifs et des questions de la recherche. Enfin, le chapitre V présente la fin de cette thèse et étale les conclusions importantes et les orientations pour la recherche future.

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4. OBJECTIFS ET QUESTIONS DE RECHERCHE

Comme les différentes recherches sur le sujet de l'innovation ont montré le défi que pose la gestion de la faible participation des membres et de l'environnement CI riche en données, alors que les stratégies de GRC basées sur les données et qui sont orientées vers les relations clients présentent d'énormes avantages potentiels, cette recherche exploite ces stratégies GRC pour réduire efficacement la faible participation des membres dans les CI. En introduisant le cadre de la gestion proactive de la faible participation des membres dans la littérature, cette thèse augmente la compréhension parmi les chercheurs et les praticiens de la façon dont les animateurs des communautés peuvent réduire de manière proactive la faible participation des membres dans les CI, tout en traitant efficacement l'environnement CI riche en données. Le corps de cet ouvrage, à savoir du chapitre II jusqu'au chapitre IV, consiste en trois études indépendantes. La figure 1 montre les quatre étapes du cadre de gestion proactive de la faible participation des membres et indique quel chapitre correspond à quelle étape. Le reste de cette section explique pour chaque chapitre l'objectif de la recherche et énumère les différentes questions y afférentes.

<u>Chapitre II :</u> Identification de la faible participation des membres dans les communautés d'innovation : le rôle important de l'utilisation du style linguistique

Le chapitre II se concentre sur le rôle important que joue l'utilisation du style linguistique dans l'identification de la faible participation des membres. En règle générale, les modérateurs utilisent leurs propres jugements ou auto-évaluations, des entrevues ou des sondages auprès des membres pour sélectionner les bons membres à subir un traitement correctif. Cependant, dans un environnement dynamique et riche en données, ces méthodes sont irréalisables, longues et coûteuses, et elles détournent l'attention des modérateurs et des membres de la tâche principale d'innovation. Les progrès récents dans la littérature par Ludwig et al. (2014) ont utilisé l'analyse automatisée de texte dans un environnement big data pour montrer l'avantage de l'analyse de style linguistique dans la participation subséquente des membres. Cependant, la surface des avantages potentiels a été à peine effleurée. Puisque les concepts de l'intérêt personnel et de l'émotion positive contribuent d'une manière considérable dans le processus de collaboration et d'innovation, et alors que les recherches en psychologie linguistique indiquent que ces concepts peuvent être analysés par le style d'écriture, les indicateurs linguistiques pourraient révéler la faible participation potentielle des membres. En outre, cette participation est affectée par plusieurs facteurs dont les différentes particularités de chaque individu ainsi que les influences externes. La communauté, qui comprend tous les autres membres qui interagissent avec le membre en question, représente un environnement capable de fournir des gratifications sociales, telles que l'approbation ou le statut. Le modérateur gère la communauté, joue un rôle de leadership et impose le respect en adoptant un comportement exemplaire. Malgré l'importance de ces rôles sociaux, aucune étude n'a examiné l'approche integrative de leur lien avec la faible participation des membres en se basant sur l'utilisation du langage.

Compte tenu de tout ce qui précède, l'objectif de cette recherche est de montrer comment les styles d'écriture émotionnels, positifs et orientés vers l'intérêt personnel des acteurs communautaires (membre, modérateur et communauté) extraits des publications de la communauté en utilisant l'analyse automatisée de texte peuvent aider les animateurs de communauté à identifier la faible participation potentielle des membres. Les questions de recherche suivantes concrétisent ces objectifs de recherche:

- QR1: l'utilisation d'un style d'écriture orienté vers l'intérêt personnel au niveau d'un membre (a), d'un modérateur (b) et d'une communauté (c) révèle-t-elle une faible participation subséquente du membre (en termes de quantité et de qualité)?
- QR2: l'utilisation d'un style d'écriture orienté vers les émotions positives au niveau d'un membre (a), d'un modérateur (b) et d'une communauté (c) révèle -t-elle une faible participation subséquente du membre (en termes de quantité et de qualité)?

<u>Chapitre III</u> : la classification multi-label de la participation des membres dans les communautés d'innovation

Le chapitre III continue d'étudier le sujet de l'identification de la faible participation des membres et étudie l'avantage potentiel de la classification multi-label pour augmenter les performances de prédiction. Une campagne de traitement proactif pour réduire les faibles participations des membres consiste en une approche en deux étapes dans laquelle le modérateur : i) identifie les membres qui démontreront probablement une faible participation future et ii) cible ces personnes pour empêcher que le comportement affecte le reste de la communauté. Puisque la réussite de l'approche de traitement consistant à réduire la faible participation des membres dépend de la capacité à cibler les bons individus, comme l'indiquent directement les résultats des modèles de prédiction, la performance prédictive des modèles de classification est très importante. Le moyen le plus simple de résoudre ce problème consiste à créer des modèles de prédiction indépendants, un pour chaque type de comportement montrant une faible participation et à regrouper les prédictions des comportements individuels. Cette stratégie est caractérisée par la méthode de la pertinence binaire (BR) (« Binary Relevance »). Cependant, dans des publications spécialisées, ce type de problème est décrit comme un problème de classification multi-label (ML) qui est résolu en utilisant la méthode de classification ML qui se concentre particulièrement sur plusieurs stratégies afin de traiter les données ML. En particulier, cette méthode montre l'avantage de l'information du label pour améliorer la performance prédictive. Tsoumakas et al. (2007) identifient deux catégories importantes de méthodes d'apprentissage ML : les méthodes de transformation des problèmes (PT) (ou « Problem Transformation ») et l'adaptation des algorithmes (AA) (ou « Algorithm Adaptation »). La première catégorie transforme les problèmes ML en plusieurs problèmes mono-label (SL) (ou « Single label ») et utilise la méthodologie de classification SL traditionnelle pour résoudre chaque problème SL, tandis que la seconde adapte les méthodes SL pour résoudre les problèmes ML. Lorsque ces méthodes PT et SL sont utilisées dans une approche globale qui prend plusieurs classifieurs en entrée, nous les appelons respectivement : ensemble de transformation de problème (EPT) (ou « Ensemble of Problem Transformation ») et ensemble d'ataptation des algorithmes (EAA) (ou « Ensemble of Algorithm Adaptation »). Le but de cette recherche est d'étudier les algorithmes ML les plus récents et d'en faire une étude comparative à titre expérimental, en plus d'étudier les avantages potentiels de la méthode de classification ML pour obtenir une performance prédictive plus élevée pour une identification proactive de la participation des membres contrairement à l'approche BR. Les questions de recherche peuvent être clarifiées plus en détail comme suit:

- QR1: peut-on augmenter les performances de prédiction de la faible participation des membres en utilisant des méthodes PT au lieu d'une approche BR?
- QR2: peut-on augmenter les performances de prédiction de la faible participation des membres en utilisant des méthodes AA au lieu d'une approche BR?
- QR3: peut-on augmenter les performances de prédiction de la faible participation des membres en utilisant les méthodes PT dans un ensemble de méthodes PT?
- QR4: peut-on augmenter les performances de prédiction de la faible participation des membres en utilisant des méthodes AA dans une méthode Ensemble de AA?
- QR5: comment les méthodes PT, AA, EPT et EAA se comparent-elles?

Chapitre IV : réduire la faible participation des membres de la communauté à l'aide d'une campagne de mailing proactif et motivationnel : les preuves à partir d'une expérience sur le terrain

Le chapitre IV met l'accent sur une stratégie de communication visant à réduire de manière proactive la faible participation des membres. Les campagnes de mailing sont largement utilisées dans le but d'encourager la participation des membres, elles sont utiles dans le sens où elles permettent de communiquer avec les membres en dehors de la plate-forme communautaire, où les membres qui montrent une faible participation peuvent se localiser. Cependant, en raison des faibles coûts de distribution, il est difficile de comprendre les avantages des campagnes de mailing car les e-mails sont largement utilisés et manquent souvent d'utilité. Ceci pousse les modérateurs à mettre en place des campagnes de mailing efficaces et à bien étudier les caractéristiques d'un traitement adéquat. Premièrement, la portée d'une campagne de traitement pourrait être non ciblée ou ciblée (Blattberg et al., 2010). Une stratégie non ciblée vise à traiter chaque membre de la CI, tandis que le ciblage vise à identifier et à traiter uniquement des membres désignés en se basant sur la condition d'une faible participation à la CI. Deuxièmement, la campagne doit livrer un message qui correspond au comportement de l'individu que l'on veut influencer. Quand on désire réduire la faible participation des membres à l'aide d'une campagne de mailing, on doit veiller à envoyer un message pertinent qui correspond à la participation d'un membre de la communauté. Des raisons hédoniques, cognitives et sociales ont été identifiées pour expliquer la participation des membres et se référer aux bénéfices que les membres anticipent de recevoir respectivement de l'expérience agréable, de l'apprentissage lié au produit et des liens relationnels au fil de temps (Nambisan & Baron, 2009). Troisièmement, comprendre le profil et les particularités des membres de la communauté qui peuvent être traités correctement aide les modérateurs à mieux comprendre quels membres doivent être traités pour quelle raison. En particulier, un style émotionnel positif et orienté vers l'intérêt personnel a été identifié comme étant un indicateur pertinent de la faible participation des membres, mais pourrait être également un indicateur très précieux de persuasion par le biais d'une campagne de mailing. Le but de cette recherche est d'étudier la viabilité d'une campagne de motivation par e-mail proactif pour réduire la faible participation des membres dans les communautés d'innovation en ligne en termes de ces trois caractéristiques de courrier électronique. La viabilité de la campagne de motivation par courriel est évaluée en étudiant les questions de recherche suivantes:

- QR1: un e-mail de motivation non ciblé peut-il réduire la faible participation des membres?
- QR2: un e-mail de motivation ciblé peut-il réduire la faible participation des membres?
- QR3: quel message de motivation fonctionne le mieux dans une campagne de motivation par e-mail?
- QR4: quel profil de membre peut être motivé?

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LIST OF PUBLICATIONS

This dissertation is based on three individual studies:

Debaere. S, Coussement. K., De Ruyck, T., Inferior member participation identification in innovation communities: The signaling role of linguistic style use, published in the *Journal of Product Innovation Management (2017), 34 (5): 559–713* (CNRS Cat. 1).

- The preliminary results of this study were presented at the 22nd Innovation Product Development Management Conference (2015), Copenhagen, Denmark
- The results of this study were presented at the Journal of Product Innovation Management/Marketing Science Institute Research Workshop (2016), Knoxville, USA

Debaere. S, Coussement. K., De Ruyck, T., Multi-label classification of member participation in online innovation communities, published in the *European Journal of Operational Research (2018), Forthcoming* (CNRS Cat. 1).

- The preliminary results of this study were presented at the 2nd Business Analytics in Finance and Industry Conference (2015), Santiago, Chile
- The results of this study were presented at the 28th European Conference on Operational Research (2016), Poznan, Poland

Debaere. S, Coussement. K, De Ruyck, T., Reducing inferior member participation in innovation communities: evidence from a field experiment, working paper to be submitted.

- The preliminary results of this study were presented at the 21st Conference of the International Federation of Operational Research Societies (2017), Quebec, Canada

Other communications:

- Debaere S., De Ruyck T., Van Neck S., Coussement K.(2017), Minority Report in Research Communities: The 'Participant' Future Can Be Seen, General Online Research Conference, Berlin, Germany
- Debaere S., De Ruyck T., (2017), Artificial Intelligence in market research - Discussing 2 case studies, QUAL360, Amsterdam, Netherlands
- Debaere S., De Ruyck T., Coussement K., (2017), Minority Report in Research Communities: The “Participant” Future Can Be Seen Insight, Innovation Exchange 2017, Amsterdam, Netherlands

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CHAPTER I:
GENERAL INTRODUCTION

GENERAL INTRODUCTION

1. INNOVATION COMMUNITIES

New product development (NPD) is essential for success, survival and renewal of companies (Brown & Eisenhardt, 1995). Companies that are likely to win come up with new products that customers are anxious to buy as opposed to companies that are likely to lose because they introduce “off-the-mark” products. Companies reinvent themselves as new products are developed to match evolving market and technological conditions (Schoonhoven, Eisenhardt, & Lyman, 1990). At the beginning of the 21st century, the traditional model of NPD in which companies stay within company boundaries to come up with new product ideas or decide which products should be marketed, has become increasingly challenged by a new model in which the customer takes a more active role (Fuchs & Schreier, 2011; von Hippel, 2005). Customers can take up several roles and generate, evaluate, select and experience product ideas (Füller, 2006). As in the end, the consumer will actually use the product, integrating the voice of the consumer in the NPD process is a recommended strategy (Abbie Griffin & Hauser, 1993).

Due to the internet, consumer input for the NPD process can be gathered inexpensively and rapidly (Dahan & Hauser, 2002). When companies pursue customer integration in NPD activities, they benefit from online communities (Nambisan, 2002). In these communities customers can group together among a shared interest in products or services. These communities enable direct consumer interaction at a low cost (Hoffman & Novak, 1996), they span all innovation phases (e.g., idea generation, idea evaluation; (von Hippel, 2005)), they apply to any type of collaboration (e.g., firm-hosted, open; (Jeppesen & Frederiksen, 2006; West & Bogers, 2014)), and they can adapt to various levels of intensity (from sporadic consultation to intense co-creation; (Nambisan, 2002)). When these communities are set-up by companies to inject the voice of the consumer into NPD, we refer to them as innovation communities (IC). As the idea-generation phase is often uncertain and difficult to manage (van den Ende, Frederiksen, and Prencipe, 2015) due to its highly informal, knowledge-intensive, and erratic nature (Lingo and O’Mahony, 2010; Frishammar, Floren, and Wincent, 2011), companies can introduce ICs to positively affect innovation outcomes (Bertels, Kleinschmidt, and Koen, 2011).

Many companies widely adopt ICs such as the Dutch brewing company Heineken, the American food processing company Heinz and the British telecommunications company

Vodafone (Troch & De Ruyck, 2014). The impact of these ICs have been proven by many success stories. For example, Air France KLM, a French airline company, connected with 90 frequent flyers in a 6-week project to co-create the future of transfer experiences (Troch & De Ruyck, 2014). They found 32 new concept ideas that laid the blueprint for future service innovations, such as a new in-flight transfer video and a mobile transfer application with real-time travel detail communication. Recent industry reports dictate that more than half of companies use online communities (Murphy, Pospichal, & Kosar, 2016) and expectations among industry experts are that popularity will only increase in the future.

However, when companies aim to reap the full benefits of these ICs, community managers need to deal with two important challenges as they threaten their viability:

- (i) ICs are data-rich, cloud-based environments that can quickly overwhelm individual community managers. In particular, their *3V big data characteristics* mean that members communicate and share their opinions through posts, thereby creating substantial (volume), rapidly expanding (velocity), and unstructured data that might encompass combinations of linguistic, video, image, and audio cues (variety). When community managers sift through the data set to gather NPD insights, the 3V characteristics make analyses more difficult and increases pressure on managers' resources.
- (ii) Most online communities fail to generate successful outcomes (Sarner, 2008). More specifically, online communities are often unable to derive value from individual IC members due to *inferior member participation* quantity and participation quality (Ludwig et al., 2014). When not enough members (quantity) contribute well-developed statements and opinions (quality), viability conditions may be harmed (Ludwig et al., 2014) and the IC may be unable to provide fertile soil for innovative ideas. For example, following a significant decline in member activity in one of Nestlé's Italian soft-drink ICs, the company shut it down completely (Gambetti & Graffigna, 2015). InnovationWorld, a telecom operator's IC, underwent a radical reorganization just one year after its launch because the community had been flooded with low quality posts (Bengtsson & Ryzhkova, 2013).

2. CUSTOMER RELATIONSHIP MANAGEMENT

Marketing is a fundamental business management function and aims to understand the customer so well that a company product fits him and sells itself (Drucker, 1954). Traditionally, marketing was viewed as the planning and execution of the marketing mix elements such as product, pricing, promotion and distribution to create exchanges that satisfy individual and organizational objectives (American Marketing Association, 1985). However, at the end of the 20th century, this view was considered to be outdated and a paradigm shift from transactional marketing towards relationship marketing urged companies to value customer relationships (Brodie, Coviello, Brookes, & Little, 1997). When companies focus on single transactions, a customer will have to be re-acquired prior to each transaction and acquisition costs will be incurred each time, however, when they become customer oriented and link these transactions, companies can save costs due to customer retention and increase value for all stakeholders (Osarenkhoe & Bennani, 2007).

In this context and supported by arise of technology and database solutions, customer relationship management (CRM) emerged as "information-enabled relationship marketing" (Ryals & Payne, 2001), Payne and Frow (2005, p. 168) define CRM as follows:

"CRM is a strategic approach that is concerned with creating improved shareholder value through the development of appropriate relationships with key customers and customer segments. CRM unites the potential of relationship marketing strategies and IT to create profitable, long-term relationships with customers and other key stakeholders. CRM provides enhanced opportunities to use data and information to both understand customers and cocreate value with them. This requires a cross-functional integration of processes, people, operations, and marketing capabilities that is enabled through information, technology, and applications."

Analytical CRM uses data about customers and analytical tools to mine such data (Teo, Devadoss, & Pan, 2006). Due to the drop in warehousing costs, information about customers and their interactions can be cost effectively stored in company databases. Through data mining techniques, a large amount of data can be easily transformed into valuable knowledge to support marketing tactics (Ngai, Xiu, & Chau, 2009). As there is a widespread availability of data mining techniques and due to the increase in computational power (Moore, 1965), companies have favorable conditions to adopt these data-driven strategies.

As customer relationships consist of three important phases, i.e. customer initiation, maintenance and churn, CRM activities focus on customer acquisition, development and retention, respectively (Reinartz, Krafft, & Hoyer, 2004). Customer acquisition refers to identifying and attracting profitable customers. Customer development aims to increase the customer transaction intensity, transaction value and profitability. Customer retention pursues to improve customer satisfaction and prolong the relationship with the company.

Despite the challenge to adopt CRM projects within companies (Rigby, Reichheld, & Schefter, 2002), CRM is widely used in the industry and many success applications exist. The research company Gartner indicates that the global CRM software market grew from $23.4 billion in 2014 to $26.3 billion in 2015 (Woods & Van Der Meulen, 2016). For example, a CRM implementation in the commercial banking industry increases profit efficiencies (Krasnikov, Jayachandran, & Kumar, 2009) and doubles the profits in customer retention efforts at a pay-tv company (Burez & Van den Poel, 2007).

3. PROACTIVE INFERIOR MEMBER PARTICIPATION MANAGEMENT

This dissertation adopts CRM strategies within ICs to reduce the problem of inferior member participation, while effectively dealing with the data-rich environment. There are a few reasons why we do so:

- (i) Whereas the customer is the most valuable resource for a company, a community member is the most valuable resource for the innovation community.
- (ii) CRM is a data-driven approach that relies on customer information to support marketing tactics. As ICs are big data environments and member participation is stored in company databases, the data-rich community environment could be a fertile ground to pursue CRM strategies and support cost effective community management tactics.
- (iii) From the perspective of the customer's lifecycle, inferior member participation can be compared the best with customer churn. Whereas customer churn represents a loss for the company, inferior member participation represents a loss for the community. As CRM literature has been exploring several retention strategies to effectively reduce churn (e.g., Neslin, Gupta, Kamakura, Junxiang, & Mason, 2006), the same ideas could be applied to reduce inferior member participation.

In literature, CRM has been described as a valuable strategy in the context of online communities and ICs to stimulate member participation. Nambisan and Baron (2007) argue that most firms fail to recognize the importance of member interaction beyond the context of innovation and that they would be able to overcome it by focusing on improving the relationship with community members through CRM activities. Nambisan and Baron (2009) state that CRM helps firms to directly work on members' anticipated benefits to participate in the community.

Because CRM aims to build relationships, while inferior member participation in essence emerges from a relationship problem and CRM thrives on data, while the IC is a data-rich environment, CRM should be a potential viable strategy to reduce inferior member participation, while effectively dealing with the data-rich environment.

This dissertation adds value by introducing a proactive inferior member participation management framework to ICs. Proactive inferior member participation management can be defined as follows:

"Proactive inferior member participation management is a community management practice in ICs where the community manager proactively reduces inferior member participation"

To construct the framework for proactive inferior member participation management, we follow the four-step proactive churn management framework of Blattberg and Neslin (2010) to reduce customer churn. Figure 2 visualizes the four steps of the proactive inferior member participation management framework: 1) identify potential inferior member participation, 2) understand why they participate inferiorly, 3) design an appropriate contact strategy, 4) monitor and evaluate the results.

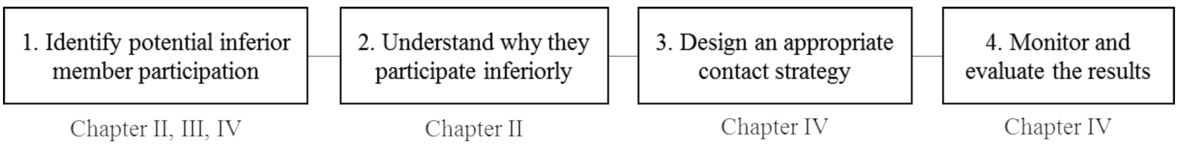

Figure 2 Proactive inferior member participation management

As the main body of this work, through the different chapters, explains each step into detail, this paragraph limits itself to a short description of the different steps. The results of the first two steps can be obtained by a predictive model that alerts the community manager of members who will demonstrate inferior member participation in the future and indicate why they will do so. Next, a contact strategy must be created that allows the moderator to proactively reduce inferior member participation. Finally, the viability of the contact strategy to proactively reduce inferior member participation can be evaluated using a field experiment.

This dissertation is composed out of five chapters and the main body of this work focuses on one or several steps of the proactive inferior member participation management framework. After this general introduction, Chapters II until IV construct the main body of this work. These chapters correspond to three independent studies. Figure 2 explains which chapter focuses on which step of the proactive inferior member participation management framework. Chapter II focuses on the first two steps, Chapter III deals with the first step and Chapter IV goes into detail on the first, second and fourth step. The following two sections in this introduction give a summary of the research objectives, research questions and list main findings, respectively. Finally, Chapter V concludes this dissertation and makes the important conclusions and directions for future research.

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4. RESEARCH OBJECTIVES AND RESEARCH QUESTIONS

As innovation literature has expressed the challenge of dealing with inferior member participation and the data-rich IC environment, while there are huge potential benefits of data-driven CRM strategies for customer relationships, this study leverages these CRM strategies to effectively reduce inferior member participation in ICs. By introducing the framework of proactive inferior member participation management to literature, this dissertation increases understanding among scholars and practitioners of how community managers can proactively reduce inferior member participation in ICs, while dealing effectively with the data-rich IC environment. The body of this work, Chapter II until Chapter IV, consist of three independent studies. Figure 2 visualizes the four different steps of proactive inferior member participation management framework and indicates which chapter that corresponds to which step. The remainder of this section explains for each chapter the research objective and lists the research questions.

Chapter II: Inferior member participation identification in innovation communities: The signaling role of linguistic style use

Chapter II focuses on the signaling role of linguistic style use to identify inferior member participation. Typically, moderators use their own judgments or self-reports, interviews, or surveys of members to select the correct members for corrective treatment. However, in a dynamic, data-rich environment, these methods are infeasible, time-consuming, and expensive, and they shift moderator’s and members’ focus from the innovation task. Recent advances in literature by Ludwig et al. (2014) used automated text analysis in a big data environment to show the beneficial impact of linguistic-style analysis on subsequent member participation. However, only the surface has been scratched of the potential benefits. There exist many opportunities in exploring underlying psychological and motivational process for community participation. As self-interest and positive emotionality are important concepts in collaboration and innovation, while the linguistic psychology literature indicates that these concepts can be explored through writing style, the corresponding linguistic indicators could be valuable indicators of future inferior member participation. Furthermore, in addition to individual characteristics, external influences are known to affect participation. The community, which consists of all other members interacting with the focal member, represents an environment that can provide social rewards, such as approval or status. The moderator manages the community, plays a leadership role, and enforces respect through exemplary behavior. Despite the importance of these social roles, no study has explored an integrative framework and their link with inferior member participation based on language use. Therefore, the objective of this study is to explore how the self-interest-oriented and positive emotional writing styles of community actors (member, moderator, and the community) extracted from community posts using automated text analysis effectively can help community managers to identify likely future inferior member participation. The following research questions concretize these research objectives:

- RQ1: Does the use of a self-interest oriented writing style of a member (a), moderator (b) and community level (c) signal member's subsequent inferior participation (quantity and quality).
- RQ2: Does the use of a positive emotional oriented writing style of a member (a), moderator (b) and community level (c) signal member's subsequent inferior participation (quantity and quality).

<u>Chapter III</u>: Multi-label classification of member participation in innovation communities

Chapter III continues to explore the topic of inferior member participation identification and investigates the potential benefit of multi-label classification to increase prediction performance. A proactive treatment campaign for inferior member participation reductions consists of a two-staged approach in which the moderator i) identifies the members who will most likely demonstrate future inferior member participation and ii) targets those individuals to prevent the behavior from impacting the community. As the success of the treatment campaign for inferior member participation reduction depends on the ability to target the right individuals, as directly indicated by the output of the prediction models, the prediction performance of the classification models is of the uttermost importance. The straightforward way to solve this problem is to create independent prediction models, one for each type of inferior participation behavior and aggregate the individual label predictions. This strategy is characterized as the Binary Relevance (BR) approach. However, in specialized literature, this type of problem is described as a multi-label (ML) classification problem and is solved using the ML classification methodology that especially focuses on strategies to deal with ML data. In particular, it indicates the benefit of label information to improve predictive performance. Tsoumakas et al. (2007) identify two important categories of ML learning methods: Problem Transformation (PT) and Algorithm adaptation (AA) methods. The former transforms ML problems into multiple single-label (SL) problems and uses traditional SL classification methodology to solve the individual SL problems, whereas the latter adapts SL methods to deal with ML problems. When these PT and SL methods are used in an ensemble approach that takes multiple classifiers as an input, we refer to them as Ensemble of Problem Transformation (EPT) and Ensemble of Algorithm Adaptation (EAA), respectively. The purpose of this study is to investigate state-of-the-art ML algorithms in an extensive experimental comparison and explore the potential benefit of ML classification methodology to obtain higher predictive performance for proactive member participation identification as opposed to the binary relevance approach. The research questions can be clarified as follows:

- RQ1: Can we increase inferior member participation prediction performance by using PT methods instead of a BR approach?
- RQ2: Can we increase inferior member participation prediction performance by using AA methods instead of a BR approach?
- RQ3: Can we increase inferior member participation prediction performance by using PT methods in an Ensemble of PT methods?
- RQ4: Can we increase inferior member participation prediction performance by using AA methods in an Ensemble of AA methods?
- RQ5: How do PT, AA, EPT and EAA methods compare?

Chapter IV: Reducing inferior member community participation using a proactive motivational e-mail campaign: evidence from a field experiment

Chapter IV focuses on a contact strategy to proactively reduce inferior member participation. Email campaigns are widely used to encourage member participation and are especially useful as they allow to contact members outside the community platform, where members who show inferior participation could be found. However, due to low distribution costs, it is difficult to realize the benefits of email campaigns as emails are widely used and often lack usefulness. This suggests the need for moderators to set up effective email campaigns and explore favorable treatment characteristics. First, the scope of a treatment campaign could be untargeted or targeted (Blattberg et al., 2010). An untargeted strategy aims to treat every IC member, while targeting aims to identify and treat only specific members based on the condition of inferior IC participation. Second, the campaign must deliver a message that is relevant to an individual's behavior one aims to influence. When aiming to reduce inferior member participation using an e-mail campaign, a message must be sent that is relevant to a member's community participation. Hedonic, cognitive and social motives have been identified to explain member participation and refer to the benefits members anticipate to receive from the pleasurable experience, product-related learning, and relational ties over time, respectively (Nambisan & Baron, 2009). Third, understanding the profile and characteristics of community members that can be properly treated, helps moderators to increase understanding of which members must be treated because of what reason. In particular, a self-interest oriented and positive emotional style have been identified to be relevant indicators of inferior member participation, but could be valuable indicators of persuadability through e-mail campaign. The purpose of this study is to investigate the viability of a proactive motivational e-mail campaign to reduce inferior member participation in online innovation communities in terms of these three e-mail characteristics. The viability of the proactive motivational e-mail campaign is evaluated by exploring the following research questions:

- RQ1a: Does a proactive untargeted motivational email campaign reduce IMP?
- RQ1b: Which motivational message in an untargeted proactive email works best?
- RQ2a: Does a proactive targeted motivational email campaign reduce IMP?
- RQ2b: Which motivational message in a targeted proactive email works best?
- RQ2: Which member profile can be motivated?

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CHAPTER II:
INFERIOR MEMBER PARTICIPATION IDENTIFICATION: THE SIGNALING ROLE OF LINGUISTIC STYLE USE

INFERIOR MEMBER PARTICIPATION IDENTIFICATION IN INNOVATION COMMUNITIES: THE SIGNALING ROLE OF LINGUISTIC STYLE USE

Abstract

Community managers often struggle to ensure the viability of innovation communities (IC) due to their big data characteristics and inferior member participation, which result in minimal activity and low quality input. In response to a recent call in the innovation literature for new approaches to dealing with the challenges of big data, we propose an IC-management strategy that relies on extracting linguistic-style cues from community posts to identify future inferior member participation. When future destructive IC behavior is signaled, the moderator can effectively select the correct member for corrective treatment to prevent negative community impact. This article uses text mining to extract self-interest-oriented and positive emotional writing style cues from 39,387 posts written by 1,611 members of 10 ICs. Two multilevel regression models deliver novel insights into the relationship between these linguistic cues and the likelihood of inferior community participation (quantity and quality). First, a community member's use of a positive emotional writing style signals less inferior participation quantity and quality in the future. Second, a moderator's use of a self-interest-oriented writing style suggests more inferior participation quality, while a self-interest-oriented community indicates less inferior participation quality. Third, community managers should work to build a positive-emotion-driven community, as such communities experience constructive member participation. This article shows that community managers who struggle with their IC must realize that in addition to what people say, how they say it gives insights into the IC's viability. We conclude our study by revealing the theoretical and managerial implications for IC management and community moderators.

Keywords: innovation communities; inferior member participation identification; linguistic style use

1. INTRODUCTION

User communities are defined as internet-based platforms for communication and exchange among users interested in a given product or technology (Autio, Esmt, and Frederiksen, 2013). These communities are social environments in which talent is distributed and the process is collaborative (Dahlander and Frederiksen, 2011). When user communities are established by organizations in an attempt to gather external consumer knowledge to be fed into innovation processes, they are referred to as innovation communities (ICs). As the idea-generation phase is often uncertain and difficult to manage (van den Ende, Frederiksen, and Prencipe, 2015) due to its highly informal, knowledge-intensive, and erratic nature (Lingo and O'Mahony, 2010; Frishammar, Floren, and Wincent, 2011), companies can introduce ICs to positively affect innovation outcomes (Bertels, Kleinschmidt, and Koen, 2011). In the IC process, the moderator guarantees the viability of the IC and initiates multiple innovation-related conversations to which members respond by sharing their knowledge and opinions in posts. The aim is to convert the collected thoughts into innovation knowledge. For example, Air France–KLM used an IC involving 90 frequent flyers to create 32 innovation concepts, such as new in-flight videos and a real-time travel information application (Troch and De Ruyck, 2014).

Despite the advantages of ICs, guaranteeing their viability poses two pertinent challenges. First, ICs are data-rich, cloud-based environments that can quickly overwhelm individual community managers. In particular, their 3V big data and virtual characteristics mean that members communicate and share their opinions through posts, thereby creating substantial (*volume*), rapidly expanding (*velocity*), and unstructured data that might encompass combinations of linguistic, video, image, and audio cues (*variety*) (Dahan and Hauser, 2002). Second, most online communities fail to generate successful outcomes (Sarner, 2008). More specifically, online communities are often unable to derive value from individual IC members owing to members' inferior *participation quantity* and *participation quality* (Ludwig et al., 2014). Member participation is necessary to sustain the flow of ideas for the company's innovation process (Langner and Seidel, 2014). When not enough members (*quantity*) contribute well-developed statements and opinions (*quality*), viability conditions may be harmed (Ludwig et al., 2014) and the IC may be unable to provide fertile soil for innovative ideas. For example, following a significant decline in member activity in one of Nestlé's Italian soft-drink ICs, the company shut it down completely (Gambetti and Graffigna, 2015). InnovationWorld, a telecom operator's IC, underwent a radical reorganization just one year after its launch because the community had been flooded with low quality posts (Bengtsson and Ryzhkova, 2013).

This study contributes to literature by examining the following research gap. Previous research acknowledges the problem of inferior member participation and offers recommendations on how to reduce inferior member participation through socialization (Liao, Huang, and Xiao, 2017) and content-authoring systems (Lazar and Preece, 2002). These reduction practices are often preceded by an identification phase in which the community manager selects the correct members for corrective treatment. Typically, moderators use their own judgments or self-reports, interviews, or surveys of members to identify inferior member participation, as done in the academic literature (Lakhani and von Hippel, 2003; Wasko and Faraj, 2005). However, in a dynamic, data-rich environment, these methods are infeasible, time-consuming, and expensive, and they shift moderator's and members' focus from the innovation task. The innovation literature has recently acknowledged the challenges of big data in innovation contexts and called for research on new approaches to dealing with the 3V characteristics (Bharadwaj and Noble, 2015; Biemans and Langerak, 2015). Recent advances in big data analytics and text analysis (Chen, Chiang, and Storey, 2012) might offer better solutions that can lead to effective, efficient, proactive approaches to identifying inferior member participation. However, to the best of our knowledge, only Ludwig et al. (2014) have applied automated text analysis in a big data environment to show the beneficial impact of linguistic-style analysis on subsequent member participation. Therefore, only the surface has been scratched of the potential benefits of using automated text analysis to investigate members' actual writing styles for data-rich ICs.

Previous research has shown that *self-interest* and *positive emotionality* are important concepts in collaboration and innovation (e.g., Bagozzi and Dholakia, 2006; Madrid et al., 2014; Tsai and Bagozzi, 2014; Hu and Liden, 2015), and the linguistic psychology literature indicates that these concepts can be explored through writing style (Pennebaker, Mehl, and Niederhoffer, 2003). Therefore, the purpose of this article is to answer the following research question: How can the *self-interest-oriented* and *positive emotional* writing styles of community actors (member, moderator, and the community) extracted from community posts using automated text analysis effectively help community managers to identify likely future inferior member participation (in terms of quantity and quality) in data-rich ICs? In the attempt to answer this research question, 39,387 posts written by 1,611 members of 10 firm-hosted Dutch ICs are used to test a framework for identifying community members with intentions to engage in inferior participation (quantity and quality). To do so, self-interest-oriented and positive emotional writing-style cues are extracted from prior text-based posts.

This study contributes to literature in three primary ways. First, while the extant research mainly explores inferior member participation through member-identification approaches that have important disadvantages in big data environments, this article answers the call for research on new approaches to dealing with the 3V characteristics (Bharadwaj and Noble, 2015;

Biemans and Langerak, 2015). In particular, this study relies on language research to effectively analyze members' unconstructive behavior in ICs by means of cues in community actors' writing styles. This article contributes to the innovation management literature by unraveling the subtle signaling role of language-use drivers in ICs and propose an effective mechanism for identifying inferior member participation.

Second, although the extant literature has explored self-interest and positive emotionality, the question of whether the use of self-interest-oriented and positive emotional writing styles in the online identities of the focal member, moderators, and other community members reflects inferior IC participation remains unanswered. On the basis of psychology research, social exchange theory, social identity theory, and broaden-and-build theory, this article explores the link between these writing styles and inferior member participation. It extends the literature on antecedents of member participation by revealing the signaling role of self-interest-oriented and positive emotional writing styles.

Third, in addition to individual characteristics, external influences (i.e., moderator and community) are known to affect participation. The community members' base (Bagozzi and Dholakia, 2002) and the moderator (Sibai et al., 2015) are important actors within this social environment. The community, which consists of all other members interacting with the focal member, represents an environment that can provide social rewards, such as approval or status (Wasko and Faraj, 2005). The moderator manages the community, plays a leadership role, and enforces respect through exemplary behavior (Sibai et al., 2015). However, no study has explored an integrative framework based on language use. By exploiting social dynamics within the IC, this article explores the links between important community actors and inferior member participation. It extends the innovation management literature by revealing the external influence of the moderator and the community on inferior member participation through the use of self-interest-oriented and positive emotional writing styles.

The remainder of this article is organized as follows. In the next section, it presents the conceptual background by contextualizing our proposed indicators of inferior participation and the hypotheses are developed. The methodology is then described in terms of the research setting, data, measures, and data analysis. Thereafter, the results are presented before the conclusion with a discussion of the theoretical and managerial implications, limitations, and directions for future research.

2. CONCEPTUAL BACKGROUND

2.1. Inferior Member Participation

Inferior member participation is a fundamental problem for IC viability. The loss of a single member's participation would be tolerable for the community, but a high degree of non-participation would be destructive. There are two types of inferior member participation, each of which affects the community in different ways. When participation rates are low (*participation quantity*), the shallow ICs that result feature insufficient activity to be successful (Butler, 2001), providing members with little motivation to contribute to such ghost-town communities. However, sufficient participation quantity is not the only condition for IC viability. Innovation entails the development and implementation of well-presented ideas (*participation quality*), such that the quality of members' participation directly affects innovation success (Van de Ven, 1986). Participation quality indicates members' efforts to develop communication, which leads to better group-discussion outcomes (Gouran, 1990). When ICs contain only low quality responses, companies may not be able to derive any useful insights. To effectively tackle inferior member participation, the moderator must be able to correctly identify members who will show inferior participation so that corrective actions can be taken.

Prior studies identify several drivers of member participation, including reputation, experience, and integration (Wasko and Faraj, 2005); network position (Dahlander and Frederiksen, 2011); relational social capital (Wiertz and de Ruyter, 2007); hobbyism and firm recognition (Jeppesen and Frederiksen, 2006); and responsibility, self-image, expertise enhancement, and community identification (Nambisan and Baron, 2010). However, the fluidity of online communities suggests that their resources, such as passion, invested time, and identity, change over time (Faraj, Jarvenpaa, and Majchrzak, 2011). This indicates that IC members' motivations change and that anyone can exhibit inferior participation at any time. Thus, there is a clear need for inferior participation identification mechanisms under dynamic contexts.

The monitoring and analyzing of real-time posting behavior is a feasible approach in this big data era because it is fast, simple, inexpensive, and natural (Kozinets, 2002). Therefore, there is a need to automatically identify linguistic-style indicators of community behaviors, as seen in Ludwig et al. (2014). A focus on language style ("how it is said") is preferable to a focus on language content ("what is said") because detection models need to function across all innovation challenges and only language style is independent of the context (Pennebaker, Mehl, and Niederhoffer, 2003). Therefore, the language style of IC members, as expressed in their writing styles, should help us identify patterns in their subsequent behavior. The use of specific words links senders to a specific language style (Pennebaker, Mehl, and Niederhoffer, 2003). More specifically, words relate to word categories, which represent language at a basic linguistic or psychosocial level. For this study, the focus is on pronouns (e.g., "I," "you," "we," "they") and positive/negative words, which are markers of a self-versus-group identity and emotions, respectively (Pennebaker, Mehl, and Niederhoffer, 2003), both of which are closely associated with community participation (Bagozzi and Dholakia, 2006). These important constructs signal *self-interest-oriented* and *positive emotional* writing styles, respectively. As IC dynamics change over time (Faraj, Jarvenpaa, and Majchrzak, 2011), and self-interest and positive emotionality are subject to changes (e.g., Meglino and Korsgaard, 2006; Kuppens, Oravecz, and Tuerlinckx, 2010), the self-interest-oriented and positive emotional writing styles in the IC reflect the current behavior.

According to Bagozzi and Dholakia (2002), community participation reflects the behavior of each individual community member (*individualistic influence*) as well as community influences (*external influences)*. More specifically, both the moderator and the community itself are important influencers. The moderator takes a leadership role in the IC management and shows exemplary behavior that enforces respect (Sibai et al., 2015). The community, which consists of all other members interacting with the focal member, represents the environment that can provide social rewards, such as approval or status (Wasko and Faraj, 2005). Accordingly, similar to the measures of individual members' language styles, this article derives the external impacts of the moderator and community from their corresponding self-interest-oriented and positive emotional writing styles.

2.2. Hypotheses

Self-interest

Many studies in the organizational, social, and behavioral sciences assume that individuals' future actions are aligned with their self-interests (Miller, 1999). Self-interest-oriented individuals are more focused on fulfilling their own needs than the needs of others and on pursuing personal goals (Meglino and Korsgaard, 2004; Meglino and Korsgaard, 2006). Extremely self-focused people tend to seek reputation in order to stand out of the crowd (e.g., Fukushima and Hosoe, 2011). Social network environments (SNEs) are especially attractive for people with high self-interest. Social exchange theory posits that members are motivated to engage in knowledge exchange in SNEs based on the expectation that such exchanges move them closer to their personal goal of enhancing their reputation (Blau, 1964; Wasko and Faraj, 2005). Buffardi and Campbell (2008) highlight the ability of SNEs to satisfy the needs of extremely self-focused members by controlling or boosting their self-presentation, attracting attention, and enlarging their social networks, thereby enhancing their reputation. Thus, those community members who wish to enhance their reputation do so by writing more and better posts (Wasko and Faraj, 2005). In other words, self-focused individuals in SNEs increase their social posting behavior and self-promoting content (Buffardi and Campbell, 2008). Even though social interactions in ICs focus on innovation challenges rather than on social communication, ICs are still essentially social environments (Dahlander and Frederiksen, 2011). In turn, community members with high self-interest-oriented writing styles are expected to regard active, superior participation as a way to enhance their reputations and satisfy their self-interest. Therefore, they should be less likely to demonstrate inferior participation.

Therefore, relying on social exchange theory and the reputational and social enhancement opportunities in ICs, self-interest is expected to be negatively related to inferior member participation, which leads to the following hypothesis:

H1a: A community member's use of a self-interest-oriented writing style is negatively related to that member's subsequent inferior participation (quantity and quality).

The organizational literature suggests that when individuals demonstrate a low self-interest, they are more inclined to consider collective characteristics and success (Meglino and Korsgaard, 2004; Meglino and Korsgaard, 2006). Thus, when moderators and members of ICs demonstrate high self-interest, they may be more focused on pursuing their own interests and goals, and pay little attention to other community members' needs. Social identity theory (Hogg, 2001; Tajfel, 1978) explains that influences on member participation stem from the anticipated social benefits of such participation (Bagozzi and Dholakia, 2002; Dholakia, Bagozzi, and Pearo, 2004), such as approval from the environment or enhanced social status. The most influential roles—including that of the moderator, who manages the community as its formal leader—are implicitly granted to members who best match the group's dynamics and embody its norms (Hogg, 2001). Therefore, high levels of self-interest among the moderator and community members may lead to a self-focused community with little opportunity for a focal member to attain social enhancement because the self-focused group does not really care about what he or she has to say. A moderator who engages in self-interest-oriented behavior fails to adopt an inside-out view, violates collaborative norms (von Hippel, 2005), and is unlikely to motivate members to actively participate. Therefore, relying on the negative association of an individual with self-interest expressed by others and social identity theory as an explanation why individuals reject other's self-interest-oriented behavior, the authors hypothesize:

H1b: A moderator's use of a self-interest-oriented writing style is positively related to a member's subsequent inferior participation (quantity and quality).

H1c: A community's use of a self-interest-oriented writing style is positively related to a member's subsequent inferior participation (quantity and quality).

Positive Emotionality

People who exhibit positive emotionality tend to be positive in their affect, which translates into greater cognitive effort (Sullivan and Conway, 1989), task persistence, creative thinking, interpersonal attraction, and helping behavior (Staw, Sutton, and Pelled, 1994). In the psychology literature, broaden-and-build theory (Fredrickson, 2011) explains how experiencing positive emotions broadens people's attention, cognition, and action, which develops their physical, social, and intellectual resources. However, positivity could be an indicator of being in the broaden-and-build process, which would suggest flourishing future behavior. The link between positive emotionality and creativity is explained by the development of more motivational and cognitive processes, which in turn help produce creative ideas (James, Brodersen, and Eisenberg, 2004; Bjørnebekk, 2008; Nikitin and Freund, 2010). Community members with positive mood may thus be less likely to engage in inferior participation. Individuals high in positive emotionality adopt more approach-oriented achievement goals, as positive emotionality represents an approach temperament. In innovation problem-solving processes, for example, members gain rewards from active participation in terms of outcomes (i.e., the developed product) or in terms of the process itself (i.e., developing the product) (von Hippel, 2005). As people with positive emotionality wish to achieve these goals, they should be less likely to exhibit inferior participation. Therefore, on the basis of the motivational indicators associated with positive emotionality and broaden-and-build theory, a member's positive emotionality is expected to be negatively related to inferior participation. This leads to the next hypothesis:

H2a: A community member's use of a positive emotional writing style is negatively related to that member's subsequent inferior participation (quantity and quality).

Positive emotionality exhibited by external influencers should also have positive impact on a focal member. Broaden-and-build theory (Fredrickson, 2011) explains how an individual who is exposed to positive emotions from others grows and builds skills. A positive experience in the community induces positive emotions among community members and supports constructive participation. Moreover, a positive environment stimulates work behavior (Staw, Sutton, and Pelled, 1994) and engagement in education (Harasim et al., 1995). Amabile et al. (2005) also describe a powerful affect-creativity cycle in which positive affective states resulting from the reception of others' creative ideas initiate a virtuous cycle that stimulates creative thoughts and a constructive environment for solving innovation-related problems. In an entrepreneurial setting, positive affect within a group is positively related to creativity, which in turn positively affects firm-level innovation (Baron and Tang, 2011). In ICs, which are dedicated to solving innovation-related problems (von Hippel, 2005), high positive emotionality among others may start such an affect-creativity cycle and motivate a focal member to continue participating. Furthermore, a leader's positive emotionality is positively related to group performance (George, 1995) and increases pro-social behavior in groups, which also positively influences performance (Chi, Chung, and Tsai, 2011). As this positive emotionality expressed by external influencers should encourage members to participate, members should be less likely to demonstrate inferior participation. Therefore, given the motivational power of others' positive emotionality and broaden-and-build theory, the authors hypothesize:

H2b: A moderator's use of a positive emotional writing style is negatively related to a member's subsequent inferior participation (quantity and quality).

H2c: A community's use of a positive emotional writing style is negatively related to a member's subsequent inferior participation (quantity and quality).

3. METHODOLOGY

3.1. Research Setting

This study uses two separate models because community members might demonstrate inferior participation quantity, inferior participation quality, or both. The model construction and hypotheses tests relied on a sample of 39,387 posts written by 1,611 recruited members from 10 Dutch firm-hosted ICs. The marketing-research agency facilitated the focal firm's innovation process by hosting its online IC platform. The firm carefully selected members and invited them to join the IC on the basis of extensive usage experience, which was traceable in the firm's internal transactional database, or by answers to an intake survey that demonstrated their deep knowledge of the focal topic. Members received a small financial incentive to participate at the start of the IC, but they joined because they were intrinsically motivated. The moderators were responsible for stimulating collaboration in the innovation tasks by introducing questions according to a semi-structured topic guide. Members could reply to each moderator's topic questions, or reply to other members' or the moderator's answers. Table 1 presents the general characteristics of the community and the innovation tasks.

3.2. Data and Measures

Data

To capture inferior member participation within the community, the available dataset is divided into an "initiation" period (T1) and an active participation period (T2) (Ludwig et al., 2014). The initiation period, which is used to calculate the independent and control variables, covers the first eight weeks of each member's membership in the IC, while the participation period gives insight into members' subsequent participation and encompasses the eight weeks of membership following the initiation period.

Writing Style Extraction

To analyze posting behavior, this study utilized the Linguistic Inquiry and Word Count (LIWC) text-analytics software (Tausczik and Pennebaker, 2010), which uses dictionaries to calculate the degree to which each piece of text contains specific category words, such as first-person pronouns or affective processes. The output is the percentage of words within the text that belongs to a specific word category. In the management literature, LIWC is a popular tool for extracting psychological and linguistic constructs from texts (Berger and Milkman, 2012; Ludwig et al., 2013; Barasch and Berger, 2014; Ludwig et al., 2014).

Community	Sector	Duration (Months)	Number of Members	Innovation Task for
1	Media	5	71	New marketing strategy
2	Technology & services	6	106	New shop design and footwear
3	Technology & services	7	75	Consumers' experiences with product
4	FMCG	8	135	Upgrades of existing products
5	Technology & services	8	90	Improvements for online consumer platform
6	FMCG	9	116	New product/marketing strategy
7	FMCG	12	130	New product/marketing strategy
8	Media	16	106	New political strategy
9	Media	32	346	New marketing strategy
10	FMCG	32	436	New food products

Notes: FMCG = fast moving consumer goods.

Table 1 Sector, Duration, and number of members in each community

		Level	M	SD	1	2	3	4	5	6	7	8	9	10	11	12
1	Self-interest	M	3.685	2.405												
2	Positive emotionality	M	1.546	2.484	.029											
3	Average word count per post	M	94.312	62.407	-.188	-.168										
4	Membership length	M	83.565	42.751	.011	-.053	-.041									
5	Participation quantity	M	14.412	31.949	.020	-.036	-.042	-.083								
6	Participation quality	M	8.903	3.465	.212	.022	.105	.023	.027							
7	Self-interest	MO	1.764	1.580	.114	.093	-.278	.098	-.107	.064						
8	Self-interest	C	3.527	0.805	.290	.112	-.253	.046	.018	.119	.625					
9	Positive emotionality	MO	3.192	2.298	.115	.098	.004	-.095	.007	.217	-.206	-.263				
10	Positive emotionality	C	1.884	.921	.230	.234	-.066	-.097	-.060	.154	-.046	.021	.650			
11	Size	C	66.788	36.536	.030	.020	-.147	.017	-.015	-.092	.413	.388	-.374	-.145		
12	Participation quantity	C	2001.650	1384.260	.116	-.056	-.138	-.111	.290	-.039	-.059	.274	-.170	-.152	.287	
13	Participation quality	C	9.262	1.059	.098	.057	.110	.083	-.020	.461	.122	.198	.250	.039	-.098	-.086

Note1: Level: M: member; MO: moderator; C: community

Table 2 Means, standard deviations, and correlation matrix for the independent variables

Dependent Variables

To operationalize the dependent variables, this study builds on definitions provided by Ludwig et al. (2014). Participation quantity is operationalized as a proportion and reflects the ratio of topics with which a member engages to the total active community topics in the active participation period, T2. The mean and standard deviation for this ratio are .253 and .262, respectively. Participation quality is operationalized as a count measure. The average number of cognitive words per post is counted, which indicates the extent to which each contribution is well elaborated in the active participation period, T2. As many different innovation problems are tackled within ICs, a measure is needed that can be used across various problems and is, thus, context independent. Therefore, the *cogmech* language feature in LIWC is applied, which consists of 1,068 terms such as "cause," "know," and "ought." The mean and standard deviation of the average amount of cognitive words per post are 7.33 and 7.40, respectively.

Independent Variables

As a distinct language style develops in the beginning of the member's community participation (Fayard and Desanctis, 2010), the linguistic-style markers for self-interest and positive emotionality are only assessed for the initiation period, T1. The conceptualization of self-interest, i.e. whether an individual's behavior is based on self-concern or egoism versus other-concern or altruism, is a long-lasting debate (e.g., Meglino and Korsgaard, 2004; De Dreu, 2006; Meglino and Korsgaard, 2006). Theoretical work (Meglino and Korsgaard, 2004; Meglino and Korsgaard, 2006) and recent empirical work in collaborative settings like ICs (e.g., Haynes, Josefy, and Hitt, 2015) define self-interest as a bipolar continuum in which high self-focus coupled with low other-focus is found at one end and low self-focus combined with high other-focus is found at the other end. Therefore, the self-interest-oriented writing style is operationalized by considering the percentage of the LIWC categories self-referential words (*self*; first-person pronouns) and other-referential words (*other*; second- and third-person pronoun). Both categories contain 12 words like "I," "me," and "mine" versus "her," "they," and "one." The member's self-interest-oriented writing style is calculated as the average of the difference between the self-referential usage intensity and the other-referential usage intensity across all of that member's posts in the initiation period T1. The usage intensity for a specific word category is calculated as the total word count per post for that word category divided by the total number of words in that post. A similar calculation is used to calculate the moderator's and the other community members' self-interest-oriented writing styles.

For the positive emotional writing style, this article relies on both positive and negative affect (Kowalski, 2000). In line with the linguistic psychology literature (e.g., Cohn, Mehl, and Pennebaker, 2004), the operationalization is similar to the operationalization of the self-interest-oriented writing style, but in this case the LIWC word categories of positive words (*posemo*) and negative words (*negemo*) are used. The LIWC dictionaries contain positive and negative emotional language dimensions that represent 685 positive and 1,332 negative emotion words, respectively (e.g., “love,” “nice,” and “sweet” versus “hurt,” “ugly,” and “nasty”). Table 2 summarizes the means and standard deviations of all of the independent variables by aggregation level (i.e., member, moderator, or community) and presents the correlation matrix.

Control Variables

In addition to the member’s self-interest-oriented and positive emotional writing styles, several *member*-related aspects in the initiation period T1 could affect the quantity and quality of participation in period T2. To capture differences in members’ general disposition to participate in the IC, the models control for each member’s number of posts (participation quantity) and the average number of cognitive words (participation quality). Previous research has suggested a significant positive impact of these variables on participation (Koht al., 2007; Ma, Agarwal, and Meng, 2007; Ludwig et al., 2014). Furthermore, the models control for the member’s average post length because participation quality is a count measure (Ludwig et al., 2014). Moreover, the models control for membership length defined as the number of days since the first post. Previous research suggests a negative effect of membership length in the initial weeks on member participation (Langerak et al., 2003). Also, the models control for *community*-level variables that may affect the member’s future intention to participate. In this regard, the models control for community size, as previous research has shown that it reduces member participation (Butler, 2001). Moreover, as on the member level, a sufficient quantity and quality of participation in the community are necessary conditions for sustaining members’ involvement (Seibold, Lemus, and Kang, 2010; Ransbotham and Kane, 2011; Ludwig et al., 2014).

3.3. Data Analysis

The nature of our dataset is that multiple members are nested in each IC, and that the models have to control appropriately for the possibility that members originating from the same community expose maybe more similar behaviors than members participating in another community. Therefore, two hierarchical linear models (HLMs) are specified that make it possible to estimate relationships that are nested across various levels (Hox, Moerbeek, and van de Schoot, 2010). Both HLMs are intercept models that include the individual-level independent variables (self-interest and positive emotionality of the member), the individual-level control variables (average word count per post, membership length, and the quantity and quality of the member's participation), the group-level independent variables (self-interest and positive emotionality of the moderator and of the community), and the group-level covariates (community size, and the community's participation quantity and quality). In this study, to regress the influence of these independent and control variables at the individual- and group-level at T1 (time-fixed) on member's participation at T2, a Beta HLM is used for participation quantity (Ferrari and Cribari-Neto, 2004), and a Poisson HLM for participation quality (Hox, Moerbeek, and van de Schoot, 2010) given the nature of the dependent variables. Both models are estimated using the maximum likelihood estimation with Laplace approximation (Wolfinger, 1993), rely on a completely unstructured covariance matrix and are implemented in SAS 9.4. The dependent variable, participation quantity, is rescaled according to Smith and Verkuilen (2006) to ensure that it is aligned within the (0,1) interval. The independent and control variables are standardized for both models. None of the HLMs suffer from major multicollinearity issues as indicated by the correlation matrix in Table 2 and the variance inflation factor (VIF) scores (i.e., the maximum of the VIFs equals 2.60).

4. RESULTS

Table 3 contains the standardized parameter estimates and *p*-values for the impact of the independent and control variables on participation quantity and quality. Note that a *positive* (negative) beta indicates a *positive* (negative) relationship with subsequent members' participation and, therefore, a *negative* (positive) relationship with subsequent inferior participation.

4.1. Inferior Participation Quantity

Self-interest expressed in the initiation period, T1, for the member ($\beta = -.007$, $p > .05$), moderator ($\beta = -.132$, $p > .05$) and community ($\beta = .104$, $p > .05$) has no significant impact on inferior participation quantity in the subsequent participation period, T2. Therefore, H1a, H1b, or H1c cannot be confirmed. There is support for H2a, as members' positive emotionality has a significant negative relationship with inferior participation quantity ($\beta = .058$, $p < .05$). The effect of positive emotionality of the moderator ($\beta = .032$, $p > .05$) has no significant impact, so there is no support for H2b. For positive emotionality expressed by the community in T1 ($\beta = .185$, $p < .05$), there is a significant negative relationship with inferior participation quantity in T2, which supports H2c.

4.2. Inferior Participation Quality

There is no support for H1a given that member's self-interest ($\beta = .002$, $p > .05$) does not affect inferior participation quality. However, self-interest-oriented posting behavior of the moderator ($\beta = -.283$, $p < .01$) and community ($\beta = .149$, $p < .01$) in the initiation period, T1, is positively and negatively related, respectively, to inferior participation quality in the active participation period, T2. Therefore, there is support for H1b, while for H1c, the findings indicate a significant, but reverse effect as the community's self-interest has a negative relationship with inferior participation quality. The relationship between positive emotionality of the member expressed in T1 with inferior participation quality in T2 ($\beta = .023$, $p < .05$) is significant and negative, which supports H2a. Positive emotionality of both the moderator ($\beta = .054$, $p < .05$) and community ($\beta = .114$, $p < .01$) have a significant negative relationship with inferior participation quality, which supports H2b and H2c.

4.3. Individual-level Control Variables

Membership length has a significant positive relationship with inferior participation quantity ($\beta = -.155$, $p < .01$) and quality ($\beta = -.208$, $p < .01$). Moreover, there is a significant negative relationship between the quantity of member participation in T1 and inferior participation quantity ($\beta = .955$, $p < .01$) and quality ($\beta = .060$, $p < .01$) in T2. The average quality of the member's contributions, operationalized as the average number of cognitive words per post, has a significant negative relationship with participation quality ($\beta = .188$, $p < .01$). However, no significant impact is found for this variable in relation to inferior participation quantity ($\beta = .010$, $p > .05$).

Variable	Member	Moderator	Community	Participation Type: Quantity			Participation Type: Quality		
Individual-level									
Self-interest	X			-.007	(.07)		.002	(0.03)	
Positive emotionality	X			.058	(4.04)	*	.023	(5.08)	*
Average word count per post	X			-.010	(.10)		.225	(688.92)	**
Membership length	X			-.155	(16.51)	**	-.208	(88.73)	**
Participation quantity	X			.955	(120.57)	**	.060	(129.70)	**
Participation quality	X			.010	(.12)		.188	(241.88)	**
Group-level									
Self-interest		X		-.132	(3.03)		-.283	(81.45)	**
Self-interest			X	.104	(3.28)		.149	(39.49)	**
Positive emotionality		X		.032	(.29)		.054	(5.98)	*
Positive emotionality			X	.185	(4.62)	*	.114	(13.05)	**
Size			X	-.078	(4.05)	*	-.050	(12.39)	**
Participation quantity			X	-.204	(20.03)	**	.135	(90.94)	**
Participation quality			X	-.118	(5.76)	*	.059	(9.94)	**
Intercept				-1.141	**		1.876	**	
Number of members					1611			1611	
Number of communities					10			10	
-2 Log Likelihood					-4948.84		14261.08		

* $p < .05$. ** $p < .01$.

Note1: Standardized regression coefficients are reported with superscripts indicating significance levels.

Note2: A positive (negative) beta indicates a positive (negative) relationship with subsequent members' participation behavior

Table 3 HLM analysis results

4.4. Group-level Control Variables

For community size, there is a significant positive relationship with both inferior participation quantity (β = -.078, $p < .05$) and quality (β = -.050, $p < .01$). Moreover, the number of contributions posted by the community in T1 has a significant positive relationship with inferior participation quantity (β = -.204, $p < .01$) but a significant negative relationship with participation quality (β = .135, $p < .01$). In addition, there is a significant positive relationship between the community's participation quality in the initiation period, T1, and inferior participation quantity in T2 (β = -.118, $p < .05$), and a significant negative relationship between the community's participation quality in T1 with inferior participation quality in T2 (β = .059, $p < .01$).

5. DISCUSSION

Nowadays, an increasing number of firms wish to continuously incorporate consumers' knowledge and feedback in their innovation processes through ICs. Such ICs have several notable benefits: they enable direct consumer interaction at a low cost (Hoffman and Novak, 1996), they span all innovation phases (e.g., idea generation, idea evaluation; von Hippel, 2005), they apply to any type of collaboration (e.g., firm-hosted, open; Jeppesen and Frederiksen, 2006; West and Bogers, 2014), and they can adapt to various levels of intensity (from sporadic consultation to intense co-creation; Nambisan, 2002). However, moderators invest a significant amount of time in guaranteeing the viability of their ICs, which restricts the quality of their innovation-supporting tasks. This study shows that community managers who struggle with their ICs must realize that in addition to *what* people say, *how* they say it gives insights into the IC's viability. By conceptualizing self-interest and positive emotionality at the individual (member) and external (moderator and community) levels, this study offers a clearer understanding of how to assess members' future participation quantity and quality based on linguistic cues that are operationalized using text analysis.

With regard to self-interest, the findings suggest that a community member's self-interest-oriented writing style does not give insight into future inferior participation quantity, nor quality. Therefore, monitoring linguistic style use to investigate whether a member is self-focused is not important for identifying future inferior member participation. However, the results indicate that it is more valuable to closely monitor the linguistic style use of other community actors. This article indicates that moderator's self-interest-oriented writing style signals a higher level of inferior member participation quality, while the community's self-interest-oriented writing style signals less inferior member participation quality. In contrast to the hypotheses, self-interest-oriented writing styles of the moderator and the community do not help in identifying a member's inferior participation quantity. Hence, a self-interest-oriented writing style of other community actors can only be associated with the member's participation quality dimension.

With regard to positive emotionality, the findings indicate that community member's positive emotional writing style signals less inferior member participation quantity and quality. Despite the non-compelling results on the signaling role of a community member's self-interest-oriented writing style, the results suggest that the linguistic style use of the community member should not be neglected due to the important signaling role of a member's positive emotionality. Furthermore, exploring the positive emotionality level of other community actors writing style is valuable. The moderator's positive emotional writing style signals less inferior member participation quality, whereas no significant relationship is found with inferior participation quantity. Furthermore, the community's use of a positive emotional writing style indicates less inferior member participation quantity and quality.

6. THEORETICAL IMPLICATIONS

First, this article responds to the call in the innovation literature for advanced insights into the use of big data for innovation-management processes (Bharadwaj and Noble, 2015; Biemans and Langerak, 2015). Through our focus on language style, it complements extant research on the antecedents of community participation (Wasko and Faraj, 2005; Jeppesen and Frederiksen, 2006; Koh et al., 2007; Ma, Agarwal, and Meng, 2007; Wiertz and de Ruyter, 2007; Nambisan and Baron 2010; Dahlander and Frederiksen, 2011). In particular, it builds on existing findings in IC research (Füller, Jawecki, and Mühlbacher, 2006; Bengtsson and Ryzhkova, 2013; Troch and De Ruyck, 2014; Gambetti and Graffigna, 2015) to extend the growing stream of literature on sustained member participation (Fang and Neufeld, 2009; Faraj, Jarvenpaa, and Majchrzak, 2011; Ransbotham and Kane, 2011; Langner and Seidel, 2014; Ludwig et al., 2014). This is done by providing insight into effective and proactive identification of inferior member participation. This study exploits the data-rich IC environment by using HLM modeling and text analysis to identify the early signals of such inferior member participation. On the one hand, it shows that the proactive identification of members who exhibit inferior participation is a realistic strategy and a valuable input for IC management. In this regard, it complements efforts that look into community-moderation practices, such as content curation (Lazar and Preece, 2002), social control (Sibai et al., 2015), and socialization tactics (Liao, Huang, and Xiao, 2017), by offering community managers a way to identify which members should be prioritized in order to prevent a negative community impact. On the other hand, via the exploration of textual cues, it extends past research emphasizing the importance of language use and the ability of this type of unstructured big data to reveal community behavior (Adjei, Noble, and Noble, 2010; Ludwig et al., 2014). In contrast to previous studies that focused on participation content and consumer ideas to gather innovation insights (Füller, Jawecki, and Mühlbacher, 2006; Mahr and Lievens, 2012), this research suggests that community managers can go beyond language content to determine the sustainability of an IC by paying close attention to language style. While previous innovation literature explores communication in an attempt to unravel co-created knowledge-value dimensions (Mahr, Lievens, and Blazevic, 2014) and knowledge distribution among team members (Tang, Mu, and Thomas, 2015), this study shows that communication style reveals the level of community engagement.

Second, in line with previous studies recognizing the impact of constructs like self-interest and positive emotionality (e.g., Bagozzi and Dholakia, 2006; Madrid et al., 2014; Tsai and Bagozzi, 2014; Hu and Liden, 2015), this article extends the extant research by investigating writing-style cues as antecedents of inferior community participation. In line with broaden-and-build theory (Fredrickson, 2011), our results show that a member's positive emotional writing style signals a lower likelihood of future inferior participation. As an extension of innovation research that looks into community composition (Franke, Von Hippel, and Schreier, 2006), our results offer insight into which community members should be moderated based on their lower use of positive emotions during community participation, with the aim of guaranteeing community viability.

Third, this study extends research into external influences on member participation (Bagozzi and Dholakia, 2002; Dholakia, Bagozzi, and Pearo, 2004) by showing that the use of self-interest-oriented and positive emotional writing styles by external influencers (i.e., the moderator and other community members) affects the focal member's future participation. More specifically, the results indicate that when the moderator avoids a self-interest-oriented writing style, it has a positive impact on the quality but not the quantity of a focal member's posts. Consistent with social identity theory (Tajfel, 1978; Hogg, 2001), this study shows that a moderator who is highly self-focused hinders the focal member in fulfilling social needs

(Bagozzi and Dholakia, 2002; Dholakia, Bagozzi, and Pearo, 2004), which reduces the quality of the member's posts. Hence, it also contributes to the literature on the importance of community leadership (Lazar and Preece, 2002; Koh et al., 2007; Sibai et al., 2015).

Moreover, in contrast to our hypothesis, our results show that a self-interest-oriented community has a positive impact on the quality of focal members' posts. This suggests that when other community members adopt a self-interest-oriented writing style and have a high self-focus rather than an other-focus, the focal member feels competitive pressure to be rewarded and recognized by the community for his or her future contributions. Our results show that the focal members keep up with the community by sharing only high-quality contributions. This tension between collaboration and competition is supported by prior research undertaken in crowdsourcing settings (Franke and Shah, 2003; Boudreau, 2010), where competition helps to motivate individuals putting more effort into their contributions (Boudreau, Lacetera, and Lakhani, 2011).

In line with broaden-and-build theory (Fredrickson, 2001) and consistent with our hypothesis, the use of a positive writing style by the community signals that the community member will exhibit higher participation quantity and higher participation quality. The positive community environment broadens a community member's awareness of the need to engage in constructive community actions through high participation. This article also confirms literature on community management (Lazar and Preece, 2002; Koh et al., 2007; Sibai et al., 2015; Liao, Huang, and Xiao, 2017), which suggests that community managers must strive to ensure a positive community environment in order to avoid inferior member participation. A negative community atmosphere can quickly lead to inferior participation through emotional contagion (Barsade, 2000). Moreover, the moderator can use a positive writing style to motivate the focal members to put more effort into developing higher quality posts, although the moderator's writing style does not boost the amount of participation.

Fourth, our analysis of the control variables on both the member and community levels offers additional insights. Consistent with Langerak et al. (2003), the findings show that the longer members are active in the community, the more inferior member participation quantity and quality is observed. Furthermore, in line with Ludwig et al. (2014) and the perceived identity verification theory, this study indicates that members who write more posts exhibit less inferior participation owing to a perceived congruence between their own views and those of others (Koh et al., 2007; Ma, Agarwal, and Meng, 2007), while members using well-developed arguments during posting envision only lower inferior participation quality. In line with Butler (2001), but in contrast to Koh et al. (2007), this article concludes that larger communities experience more inferior participation due to higher information-processing costs and fewer opportunities to be heard by others. In addition, the findings show that when other community members post more and use more cognitive words in their posts, focal members are less participative. However, when focal members do participate in such situations, their arguments are well constructed. Indeed, in active communities with many high quality posts written by others, the focal member needs to invest significantly more energy to boost his or her number of posts to the required quality level in order to stand out. This means that an increased quantity of information within the community comes at the cost of a significant reduction in post quality, as information-processing costs increase (Resnick et al., 2000; Butler, 2001). Therefore, to keep up with the community, the member focuses on the quality of the posts.

7. MANAGERIAL IMPLICATIONS

First, this study leverages the big data context of ICs by proposing a new, effective community management approach that relies on HLM modeling and text analysis to proactively identify members likely to exhibit inferior participation. When community managers know beforehand whether inferior member participation is expected, preventing the IC from being impacted by destructive behavior by taking proactive, corrective actions becomes extremely valuable. Otherwise, the moderator may have to control damage in the wake of inferior member participation and attempt to reanimate the community if the impact is severe. Community managers unceasingly work to determine whether they have enough, high-quality member interactions to support their innovation pursuits (Mahr and Lievens, 2012). If they can anticipate inferior member participation, they can reduce this effort, because our models alert the moderators automatically to the threat of future unconstructive behavior in their ICs. By alleviating this management burden, this automated approach allows moderators to focus their energy on innovation tasks.

Second, community managers should be aware of moderators using a self-interest-oriented writing style and avoiding a positive writing style, as doing so gives rise to inferior participation quality among members. A dashboard that monitors the self-interest-oriented and positive emotional writing styles of moderators in real time can help managers assess the influence on future member participation. Community managers are encouraged to closely monitor moderators' self-interested-oriented and positive writing styles to fine-tuning and steering the moderation practices within the communities.

Third, community managers can install a dashboard to monitor positive emotionality within their ICs in real time. Leveraging the positive emotionality of individual members and the community is important for avoiding negative influences on member participation. When the positive emotionality within the IC begins to diminish, the moderator should reestablish a positive atmosphere. In this regard, notes of personal thanks, "thumbs up" messages, or general feedback about the positive aspects of the group might provide sufficient signals.

8. LIMITATIONS AND FUTURE RESEARCH

Although this study adds to the extant literature, it is not without limitations, which highlight interesting paths for continued research. In particular, it relies on the writing style used in posts as a signal of likely inferior member participation. This text-analysis approach is widely accepted in the innovation and management literature (Barasch and Berger, 2014; Berger and Milkman, 2012; Ludwig et al., 2013). However, other methodological advances in big data analytics might improve members' participation even further. Several IC frameworks allow members to contribute to innovation tasks in a non-textual way. Members can, for example, post images, videos, or audio snippets. As such content-rich contribution types are becoming increasingly popular, research is encouraged that finds ways to extract relevant meaning from non-textual cues and, thereby, supports innovation processes through image, video, or audio mining.

In addition, this article relies on HLM modeling and text analysis to uncover inferior member participation. However, alternative prediction strategies are relevant for the IC environment, including moderators' individual judgements, members' self-reported behaviors, and managerial heuristics implemented at the community management level. These decision strategies can be compared using the effort/accuracy framework proposed by Payne, Bettman and Johnson (1993). The basic hypothesis of that framework is that the strategy used to make a prediction has the goal of being as accurate as possible with the aim of limiting cognitive efforts. In terms of effort, focusing on moderators' individual judgements or analyzing members' self-reported behaviors are time-consuming and expensive strategies. They are therefore likely to be highly inefficient in a data-rich IC environment. With respect to accuracy, Wübben and Wangenheim (2008) compare managerial heuristics with advanced models in a customer base analysis and find inconclusive results that depend on the prediction application. Therefore, this article leaves the question of a detailed accuracy comparison open for future investigation in an IC context.

Moreover, only firm-hosted online ICs are considered—ICs that are initiated and moderated by the firm. Other types of communities also exist, such as open ICs and user-regulated ICs (Bagozzi and Dholakia, 2006). Therefore, researchers might identify other ways of defining inferior member participation and its antecedents across different types of ICs.

Furthermore, although this article provides a means to proactively identify community members, our findings do not offer concrete recommendations for corrective actions or communication strategies that can improve the viability of the IC. Future studies could build on recent advances in the response modeling literature to define the design characteristics that might improve community management (Feld et al., 2013).

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CHAPTER III:
MULTI-LABEL CLASSIFICATION OF MEMBER PARTICIPATION IN ONLINE INNOVATION COMMUNITIES

MULTI-LABEL CLASSIFICATION OF MEMBER PARTICIPATION IN ONLINE INNOVATION COMMUNITIES

Abstract

Online innovation communities are defined as internet-based platforms for communication and exchange among customers interested in building innovations for a given product or technology. As firms recognize an online innovation community as a valuable resource for integrating external consumer knowledge into innovation processes, they increasingly ignore to build long-term interactions and collaborations. However, in the pursuit of a long-term community, moderators face enormous challenges, especially due to inferior member participation. Inferior member participation, whether in the form of inferior participation quantity, quality and/or emotionality, produces a community with minimal activity, unhelpful content and an unconstructive atmosphere, respectively. Because members can be associated with multiple labels of inferior participation behavior simultaneously, the paradigm of multi-label (ML) classification methodology naturally emerges, which associates each member of interest with a set of labels instead of a single label as known in traditional classification problems. Using 1,407 members of 7 real-life innovation communities, this study explores 10 state-of-the-art ML algorithms in an extensive experimental comparison to explore the benefit of ML classification methodology. We advance literature by demonstrating a novel application for ML classification adoption in the domain of online innovation communities, while comparing ML classifiers in the smallest possible scenario of 3 labels. The results indicate the effectiveness of the ML classification methodology for inferior member participation prediction, gives insights into ML classifiers' performance and discusses paths for future research.

Keywords: analytics, multi-label classification; innovation communities; member participation

1. INTRODUCTION

Nowadays, many companies rely on online innovation communities to collaborate together with consumers and integrate external consumer knowledge within firm boundaries for new product development purposes (Füller, Jawecki, & Mühlbacher, 2006). To obtain potential valuable consumer insights for the company's innovation process, a moderator presents innovation challenges to the community, and members answer them by interacting and sharing their knowledge and opinions with other community members. For example, Air France-KLM connected with 90 frequent flyers in a six-week community and generated 32 concepts that laid the future for new travel experiences such as new in-flight videos and a mobile app to communicate travel experiences (Troch & De Ruyck, 2014). Despite the huge potential benefits, still, more than half of online communities fail to remain viable. The biggest threat comes from inferior member participation that can have severe implications for the community leading to a radical reorganization (Bengtsson & Ryzhkova, 2013) or complete shut down (Gambetti & Graffigna, 2015). We recognize three types of inferior member participation, i.e. members do not participate enough in the community (*quantity*), contribute low quality arguments (*quality*) and show negative sentiment (*emotionality*). Each community member could engage in none, one or multiple types of inferior participation behavior simultaneously. As part of a proactive community management framework, the identification of members that will engage in future inferior participation is crucial. This is solvable in a straightforward way by building separate prediction models for each type of inferior participation behavior using historical member community behavior (Kristof Coussement, Debaere, & De Ruyck, 2017), known in the data analytics literature as a binary classification problem (Baesens, Van Gestel, Viaene, Stepanova, & Suykens, 2003; Lessmann, Baesens, Seow, & Thomas, 2015; Lessmann & Voß, 2009; Verbeke, Dejaeger, Martens, Hur, & Baesens, 2012). However, this classification problem is also solvable using the multi-label (ML) classification methodology. Indeed, the problem characteristics of proactive member participation identification comply with the ML problem prerequisites of Read (2010): a predefined, meaningful and human-interpretable set of labels, a limited number of labels that is not greater than the number of attributes, training observations that are associated with several labels of the label set, a large number of attributes that can be reduced and the number of observations that may be large. The difference between a ML and multi-class problem is that in a ML problem, each member can have assigned more than one label class, while the classes are not mutually exclusive, so that the ML problem is answered by a set of labels instead of one single label class.

This paper contributes to recent advances in the operations and analytics literature of member participation prediction in innovation communities (Coussement et al., 2017) by investigating the beneficial impact of ML classification methodology to increase prediction performance. In addition to the wide variety of ML applications, this paper contributes to the ML research stream by demonstrating a novel application for ML classification in the domain of online communities and inferior member participation classification. Furthermore, this paper contributes to ML literature by unraveling the benefit of ML methods in the smallest scenario possible, i.e. 3 labels.

This study is structured as follows. Section 2 reviews existing work in the field of innovation communities and ML learning. Section 3 defines the ML problem and explains the ML methodology and evaluation metrics used in this study. Section 4 gives insight into the experimental design by describing the dataset characteristics, variable operationalization, benchmark setup, experimental parameters and statistical evaluation framework. Section 5 describes the results, while section 6 concludes this study and gives directions for further research.

2. RELATED WORK

2.1. Inferior member participation

Inferior member participation is a fundamental problem for innovation communities viability. The loss of a single member's participation would be tolerable for the community, but a high degree of non-participation would be destructive. Current practice advises moderators to monitor member participation behavior in real-time. If moderators are suspicious about inferior participation amongst their member base, they can react, target these members and take corrective actions, for instance through socialization (Liao, Huang, & Xiao, 2017) or content-authoring mechanisms (Lazar & Preece, 2002) in an attempt to reduce destructive participation behavior that negatively impacts the community atmosphere and outcomes. However, this approach has several drawbacks. First, the moderators' decisions to take corrective actions are often highly subjective and hard to standardize within and across communities. Second, the moderators react based on the observed behavior of the member base, and thus the member base is already touched with inferior member participation. Third, the online nature of the innovation communities allow members to post and interact with the community 24/7, resulting in an overwhelming amount of textual content on which the moderator has to make a decision to intervene. This is a hard task, and distracts the moderator's attention to what really counts, i.e. shaping innovations.

Due to the big data-rich community characteristics and the potential benefit of data-driven techniques, new analytical solutions recently arise to effectively predict inferior member participation using historical member behavior (Kristof Coussement et al., 2017). By identifying and targeting the most risky members before the destructive behavior has taken place, the community is preserved from bad behavior. It will continue to generate sufficient and qualitative input to derive useful insights and realize a constructive atmosphere to continue participation.

Prior studies in the innovation management literature extensively investigate drivers of member participation, including hobbyism and firm recognition (Jeppesen & Frederiksen, 2006); network position (Dahlander & O'Mahony, 2011); reputation, experience, and integration (Wasko & Faraj, 2005); relational social capital (Wiertz & de Ruyter, 2007); and responsibility, self-image, expertise enhancement, and community identification (Nambisan & Baron, 2010). Most of these drivers are operationalized using survey-based measures and are therefore hard and expensive to employ in a real-time big data context. Contrary, the monitoring and analysis of real-time posting behavior is a feasible approach in this big data era because it is fast, simple, inexpensive, and natural (Kozinets, 2002). Therefore, the prediction of future inferior member participation using historical community behavior is an interesting path for proactive community management (Kristof Coussement et al., 2017).

2.2. Multi-label classification

Recently the ML classification methodology became a hot topic in literature. Many successful applications exist today in several settings (Gibaja & Ventura, 2015) like movie genre prediction (Wehrmann & Barros, 2017), large scale visual search (Xia, Feng, Lin, & Hadid, 2017), patent classification (Cong & Tong, 2008), face verification (Kumar, Berg, Belhumeur, & Nayar, 2009), melanoma diagnosis (Barata, Emre Celebi, & Marques, 2017), and drug discovery (Kawai & Takahashi, 2009). We kindly refer to Madjarov, Kocev, Gjorgjevikj and Džeroski (2012) or Zhang and Zhou (2014) for an extensive review of ML methods. However, the ML applications in a business-oriented context remain scarce, and to the best of our knowledge, this study is the first ML study in the field of innovation management.

One of the main ideas in ML learning is that if label dependencies exist, extra information can be found and exploited to improve classification performance. For example, a picture with the label desert is more likely to be associated with the label camel than the label dolphin. Dembczynski, Waegeman, Cheng, & Hüllermeier (2012) distinguish two types of label dependencies, i.e.

unconditional and conditional dependence. The difference between both types of dependencies is that conditional dependence captures the dependence among labels given a particular observation, whereas unconditional dependence is a kind of global dependence independent of any concrete observation. For example, it is very likely that labels La Liga and Real Madrid appear frequently together as tags for some videos of a sports website, because there is a strong relationship between both labels. It seems that the dependence between labels Real Madrid and La Liga is mostly unconditional. No matter the actual content of the video, if it is related to Real Madrid, it is also related to La Liga because the former is a franchise of the latter.

Tsoumakas and Katakis (2007) identify two important categories of ML learning methods, i.e. problem transformation (PT) and algorithm adaptation (AA) methods. The former transforms ML problems into multiple single-label (SL) problems and uses traditional SL classification methodology to solve the individual SL problems, whereas the latter adapts existing SL classification methods to deal with ML problems. Furthermore, previous literature has shown that the performance of PT and AA methods could be improved by including them into a ML ensemble (Madjarov et al., 2012). As the ML ensembles take previous PT and AA methods into account, we refer to them as ensemble of problem transformation (EPT) and ensemble of algorithm adaptation (EAA) methods, respectively. In detail, these ensemble methods split up the ML problem into multiple smaller sub problems that are easier to learn by the PT or AA method. These methods are thus conceptually different than the SL ensemble methods that learn a SL problem by combining the outputs of multiple SL classifiers which are built on slightly different versions of the training data. We kindly refer you to section 3 for a detailed overview of the PT, AA, EPT and EAA methods used in this benchmark study.

2.3. Study overview

Because the success of the prevention campaign for proactive community management depends on the ability to target the correct members as directly indicated by the output of the prediction models, the prediction performance of the classification models is of the uttermost importance. Until now, only the scenario has been explored of training a SL classifier for each label and independently from the other labels (Coussement et al., 2017). In ML literature, this strategy is characterized as the Binary Relevance (BR) approach, and represents the baseline method in this study. As the ML classification methodology is identified as a promising approach to improve prediction performance in a ML context, this paper explores the potential benefit of ML classification methodology to increase the performance of inferior member participation prediction in online innovation communities. In concrete, we first investigate whether we can achieve higher prediction performance by choosing PT or AA methods instead of the baseline BR approach. Second, we investigate whether prediction performance of these PT and AA methods can be improved by using them in ML ensembles. Third, we compare the overall performance of all PT, AA, EPT and EAA methods. Hence, we explore the following research questions:

Can we increase inferior member participation prediction performance by using:

- R1: PT methods instead of a BR approach?
- R2: AA methods instead of a BR approach?
- R3: PT methods in an ensemble of PT methods?
- R4: AA methods in an ensemble of AA methods?

and

- how do PT, AA, EPT and EAA methods compare?

3. METHODOLOGY

This section introduces the ML learning methodology to online innovation communities by describing the ML classification task for inferior member participation and the ML classifiers that we focus upon in this study.

3.1. Multi-label classification task of member participation

Relying on the definition of Madjarov et al. (2012), we define the ML classification task of member participation in online innovation communities as follows:

- $\mathcal{X}$ the d-dimensional input space of discrete or continuous values that reflect member or community characteristics, i.e. $\forall x_i \in \mathcal{X}, x_i = \{x_{i_1}, x_{i_2}, \dots, x_{i_d}\}$

- $\mathcal{L} = \{\lambda_1, \lambda_2, \lambda_3\}$, the *3*-dimensional participation label output space of boolean values that reflect the level of inferior member participation quantity (λ_1), quality (λ_2) and emotionality (λ_3), respectively ($\lambda_j = 1$ if an inferior level for the *j*th participation label is observed, otherwise $\lambda_j = 0$).
- $E = \{(x_i, Y_i) | x_i \in \mathcal{X}, Y_i \in \mathcal{L}, 1 \leq i \leq N\}$, the set of *N* member observations that are 2-tuples from the input space and participation label output space
- a quality criterion *c* to evaluate models

The goal of the ML classification task is to find a function $h: \mathcal{X} \rightarrow 2^{\mathcal{L}}$ such that *h* maximizes *c*. For any member observation $\tilde{x}$, $\hat{Y} = h(\tilde{x})$ is the participation ML prediction of classifier h.

3.2. Multi-label classifiers

In ML classification, the members are associated with a set of labels, while traditional SL classification is concerned with learning from a set of members that are associated with a single label λ_j. Figure 3 displays the conceptual framework for this ML study that uses the k-Nearest Neighbor (kNN) and AdaBoost algorithm as the SL base classifiers for the ML methods.

ML methods can be categorized into two distinct groups (Tsoumakas & Katakis, 2007), i.e. PT and AA methods. This study takes into account three PT methods, i.e. Binary Relevance (BR), Classifier Chain (CC) and Stacking, two AA methods inspired from the kNN algorithm, i.e. ML-kNN and IBLR, and one AA method derived from the AdaBoost algorithm, i.e. AdaBoost.MH.

Following (Madjarov et al., 2012), the prediction performance of PT and AA methods could be improved by considering PT and AA methods in an ensemble approach, i.e. EPT and EAA methods, respectively. This study uses the hierarchy of multi-label classifiers (HOMER), clustering based multi-label classification (CBMLC) and random k-label sets (RAkEL) methods to break down the ML problem into smaller sub problems that are then learned by the PT (i.e. CC and Stacking) or AA (i.e. ML-kNN, IBLR, and AdaBoost.MH) methods using kNN or AdaBoost as SL base classifier. Additionally we do consider an additional ensemble version of the PT method CC, i.e. ensemble of classifier chains (ECC), into our benchmark study.

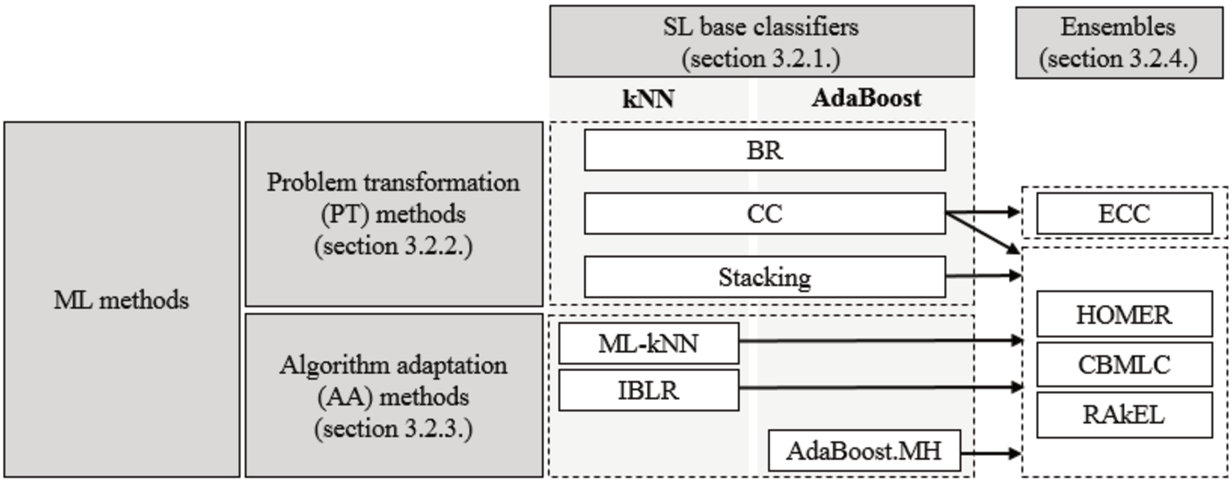

Figure 3 Conceptual framework

Single-label methods as ML base classifiers

kNN. The kNN algorithm identifies for a new observation the *k* most-similar training instances and determines the prediction class by using the known class of these nearest examples (Blattberg, Kim, & Neslin, 2010). kNN uses a distance function to determine the nearest observations and an aggregation function to determine the predicted class. kNN is simple and easy to learn, trains fast and is robust to noisy data. However, it is biased by the value of *k*, and is limited by memory to load training data (Bhatia & Vandana, 2010).

AdaBoost. AdaBoost builds on the boosting concept proposed by Schapire (1990) to generate a strong from a weak classifier. Given, a weak classifier and training set that associates equal weights to all examples, *t* times, AdaBoost learns a weak classifier from the training set and increases weights for incorrectly classified examples, resulting in a training set with updated weights that the classifier in the next iteration adapts to. The final model is a weighted sum of all *t* weak classifiers. AdaBoost is fast, simple and effective through the combination of many weak decision rules. It requires no parameter tuning or prior knowledge about weak learner, but is sensitive to noisy data and outliers, depends on the classifier choice (which results in overfitting when too complex or under fitting when too weak) (R. Schapire, 2012).

Problem Transformation (PT) methods

Binary Relevance. BR transforms a ML problem in *q* binary problems, one for each label, and solves each one independently (Tsoumakas & Katakis, 2007). For a new observation $\tilde{x}$, BR predicts $\hat{Y} = (h_1(\tilde{x}), \dots, h_3(\tilde{x}))$ with h_j the SL classifier for y_j. BR may challenge the ML learning task in two particular ways. First, by splitting up the ML problem in q binary problems, there is information loss as the dependency of the labels is ignored. Second, by splitting up the ML problem in q binary problems, a risk exists that the negative class dominates the positive class in the new label, i.e. known as the class imbalance problem. The risk exists that the classification performance is harmed, as the classifier focuses too much on the negative class, while the positive class is seen as noise (Zhou, Tao, & Wu, 2012). More information on learning from imbalanced datasets is available in Chawla (2009) and Weiss and Provost (2003). Nevertheless, BR is theoretically simple because labels can be edited without affecting other models and it has low computational complexity compared with other models because it scales linearly with the number of labels (Read, 2010).

Classifier Chain. CC follows the BR transformation, but introduces predictions of previous labels to the attribute space (Read, Pfahringer, Holmes, & Frank, 2011). For a new observation $\tilde{x}$, CC predicts $\hat{Y} = (h_1(\tilde{x}), h_2(\tilde{x}, \hat{y}_1), h_3(\tilde{x}, \hat{y}_1, \hat{y}_2))$ with h_j the SL classifier for y_j and $\hat{y}_k$ the *0/1* predictions of previous labels ($k \in [1, \dots, j-1]$). CC exploits label correlation through shared label information among the classifier chain, but is sensitive to the label ordering and loses the opportunity for parallel implementation due to dependencies on previous labels (Zhang & Zhou, 2014).

Stacking. Stacking applies BR twice as it builds a BR learner during the first step and introduces the output predictions to a meta-learning BR stage (Godbole & Sarawagi, 2004). For a new observation $\tilde{x}$, stacking predicts $\hat{Y} = (h_1^2(h^1(\tilde{x})), .., h_3^2(h^1(\tilde{x})))$, with h_j^2 the SL meta-classifier for y_j and $h^1(\tilde{x})$ the output of the first BR phase. Following the stacking philosophy proposed by Wolpert (1992), stacking overcomes the label independence assumption of BR through the stacked approach and shares the low computational complexity.

Algorithm Adaptation (AA) methods

Multi-Label k-Nearest Neighbors. ML-kNN adapts kNN using Bayesian Inference (Zhang & Zhou, 2007). It follows the classical nearest neighbor determination procedure and determines the relevant label set using prior and posterior probabilities of label occurrences within the neighborhood (maximum a posteriori (MAP) principle). For a new observation $\tilde{x}$, ML-kNN predicts $\hat{Y} = (h_1(\tilde{x}), .., h_3(\tilde{x}))$, using the MAP principle $h_j(\tilde{x}) = \backslash argmax_{b \in \{0,1\}} P(c_j | y_j = b) P(y_j = b)$ for label j with c_j the number of y_j occurrences within the neighborhood $N(\tilde{x})$. ML-kNN is actually a BR learner but adopts the benefits of both lazy learning through kNN and Bayesian inference: decision boundary for label classification can be adjusted through varying neighbors and class-imbalance issue can be mitigated due to prior probabilities estimated for each class label (Zhang & Zhou, 2014).

Instance-Based Logistic Regression. IBLR builds on kNN by considering labels of neighboring instances as features in a meta logistic regression scheme (Cheng & Hüllermeier, 2009). For a new observation $\tilde{x}$, IBLR predicts $\hat{Y} = (h_1(\tilde{x}), .., h_3(\tilde{x}))$, where $h_j(\tilde{x}) = \omega_j + \sum_{k=1}^{q} \alpha_j^k \omega_j^k(\tilde{x})$, with ω_j the bias term and for all three labels, α_j^k the extent to which y_k in the neighborhood of $\tilde{x}$ increases the probability that y_j is relevant, i.e. $\omega_j^k(\tilde{x})$. IBLR automatically optimizes the balance between global and local inference through fitting a logistic regression function. Interdependencies between labels are estimated through regression coefficients α_j^k.

AdaBoost.MH. AdaBoost.MH adapts AdaBoost by not only maintaining a set of weights over training examples, but also over labels. Adaboost.MH carries out a reduction of ML data into a binary dataset, by mapping each example (x, Y) to three examples of the form $([x, i], y_i)$ for all three labels y_i. Then, AdaBoost is applied to the binary data and increases in each iteration the weights of misclassified example-label pairs. $[x_i, i]$ represents the *(d+1)* dimensional attribute vector that concatenates the example *x* with the class label *i*. Adaboost.MH considers label dependencies through the shared instance *x* after the transformation phase. Furthermore, it is generalizable to other base classifiers than AdaBoost, but can suffer from class-imbalance when label density is low (Zhang & Zhou, 2014).

Ensemble Methods

Hierarchy of Multi-Label Classifiers. HOMER follows the divide-and-conquer paradigm by recursively creating a tree, starting with a root node containing all labels, and distributing labels of nodes using a clustering algorithm into disjoint subsets, one for each child node. A ML classifier h^c is trained on each non-leaf child node's c meta-label μ_c, the disjunction of all labels contained in that node. For a new observation $\tilde{x}$, predict $\hat{Y} = (h_1(\tilde{x}), \cdots, h_3(\tilde{x}))$, with $h_j(\tilde{x}) = h_j^v(\tilde{x})$ the ML classifier for label j corresponding with μ_v, obtained through a recursive process, starting with h_{root} and forwarding $\tilde{x}$ to h_c of a child node if μ_c is among the predictions of $h_{parent(c)}$.

Clustering Based Multi-Label Classification. Clustering Based Multi Label Classification (CBMLC) breaks the training set into k disjoint data clusters and trains a ML classifier on each cluster (Nasierding, Tsoumakas, & Kouzani, 2009). For a new observation $\tilde{x}$, CBMLC predicts $\hat{Y} = (h_1(\tilde{x}), \cdots, h_3(\tilde{x}))$, with h_j the ML classifier h_j^i for y_j that corresponds with the nearest cluster i, identified through a clustering algorithm *C* using $\tilde{x}$. Through splitting the training set into smaller parts of similar observations, CBMLC expects similar observations to have similar labels. CBMLC benefits from this local data strategy through problem decomposition through simplicity and training/testing efficiency (Lu, Mineichi, & Keigo, 2016).

Random k-labEL sets. RAkEL breaks the labels randomly (without replacement) into *m* smaller subsets R_i of size *k*, trains a ML classifier on each sub problem and uses a voting scheme to aggregate sub solutions and determine the total label set (Tsoumakas, Katakis, & Vlahavas, 2011). For a new observation $\tilde{x}$, predict $\hat{Y} = (h_1(\tilde{x}), \cdots, h_3(\tilde{x}))$, with $h_j(\tilde{x}) = 1$ if $(\sum_{i=1}^{votes_j} h_j^i(\tilde{x}))/votes_j > \theta$ (*0* otherwise), with h_j^i the ML classifier for label *j* corresponding with subset label set R_i and $votes_j$ the number of label subsets label *j* belongs to. RAkEL's complexity is limited by *k*, has more balanced training sets and can predict unseen label sets (Tsoumakas et al., 2011).

Ensemble of Classifier Chains. ECC trains m CC classifiers with a random chain ordering/subset of training data and uses a voting scheme to assign the label set (Read et al., 2011). For a new observation $\tilde{x}$, predict $\hat{Y} = (h_1(\tilde{x}), .., h_3(\tilde{x}))$, with $h_j(\tilde{x}) = 1$ if $(\sum_{i=1}^{m} h_j^i(\tilde{x}))/m > \theta$ (*0* otherwise), with h_j^i the CC classifier for label j and chain ordering *i*. ECC eliminates the dependency on label ordering and improves CC's accuracy through using multiple models in an ensemble approach (Read et al., 2011).

3.3. Evaluation metrics

Evaluating ML classifiers requires considering all class labels for a given observation, and can thus result in predictions to be fully correct, partially correct or fully wrong. Some ML evaluation measures evaluate class labels separately and average the results across all class labels, i.e. label-based metrics. Other measures evaluate the prediction for each observation separately and average the results across all observations, i.e. example-based metrics. As label-based measures ignore label dependencies (Gibaja & Ventura, 2015), ML studies often opt for example-based metrics. In particular, in this study, we chose example-based specificity (ES) and subset accuracy (SA). ES measures the overall true negative rate. It is calculated by taking the average of the true negative rates calculated for each observation individually. The true negative rate for an observation is defined as the division of the true negatives by the total real negative conditions. On the other hand, SA measures the percentage of correctly predicted labels (true positives and true negatives). It is calculated by the sum of all observations that have correct predictions divided by the total number of observations. SA is a strict measure of prediction success, as it requires the predicted set of class labels to be an exact match of the true set of labels, and thus it does not discriminate between partially correct and fully wrong classification of the inferior member participation labels. In sum, SA punishes a misclassification on one label as hard as a misclassification on all labels. ES is less stringent than SA as a partial match between the predicted and true negative labels is sufficient. More information on multi-label evaluation metrics is available in (Madjarov et al., 2012).

In literature many example-based measures exist, but Dembczynski, Waegeman, Cheng, & Hüllermeier (2012) argue that evaluation measures must be chosen in function of the problem that one is trying to solve. In our case, two important criteria are important, which can be evaluated by SA and ES. First, the ML models need to make correct predictions for both inferior and non-inferior member participation (true positives and true negatives), so the members with actual future inferior participation behavior can be targeted and members with actual non-inferior participation behavior can be safely ignored. Second, whenever a member is predicted to demonstrate non-inferior member participation, the moderator must feel safe to ignore this member in the prevention campaign as it is less likely that the member will show non-inferior member participation in reality. These two criteria can be obtained by models that have a high SA and ES, respectively.

4. EXPERIMENTAL DESIGN

4.1. Dataset description

The sample is obtained from a European market research consultancy firm and consists of the posting behavior of 1,407 members in 7 online innovation communities. The companies requested the marketing research agency to organize these communities to hear the voice of the consumers on innovation challenges that could result in consumer insights useful for their innovation processes. Community moderators of the marketing research agency organized innovation challenges and were responsible to oversee and sustain community dynamics. Community members were recruited based on their knowledge or interest in the topic and received a small financial incentive to participate. Their contribution is limited to one community only.

4.2. Operationalization and benchmark set-up

To investigate inferior member participation throughout the lifetime of the community, we use a time-sliding window approach with shifts of one month. The timeline includes two months to calculate the independent variables and a consequent two months to observe the dependent variables. Previous research shows the impact of past behavioral information and language use on community participation (Kristof Coussement et al., 2017; Ludwig et al., 2014). As a consequence, this study extracts behavioral information from the transactional post database, and writing style information from the posts using the text-mining software LIWC (Pennebaker, 2007). The latter program analyzes post content by using dictionaries of words that do belong to specific language dimensions. It calculates for each post the percentage of words that belongs to that specific dimension. Furthermore, previous research on inferior member participation identifies that, in addition to the member's behavior and writing style, external influences of the moderator and the community have an impact on community participation (Bagozzi & Dholakia, 2002; Kristof Coussement et al., 2017; Sibai, Valck, Farrell, & Rudd, 2015). As a result, this study operationalizes a total of 60 independent variables that reveal past behavior and language subtleties in posts on the member, moderator and community level:

- Behavioral variables: participated innovation topics, posts, replies, elapsed time since last post, elapsed time between participation to two innovation topics

- Average contribution length expressed in words
- Function words: first-person singular pronouns, first-person plural pronouns, second-person pronouns, third-person pronouns, words captured by dictionary, self-referencing words, references to other people, pronouns
- Punctuation marks: exclamation marks, question marks, colons, semicolons, commas, periods

To construct the dependent variables, we rely on the definitions of member participation by Ludwig et al. (2014) and consumer engagement by Hollebeek, Glynn and Brodie (2014). Participation quantity is measured by the percentage of active community topics the member interacts in. As cognitive words like `cause', `know' and `ought' reflect how well elaborated contributions are, we calculate participation quality by measuring for each member the average used amount of cognitive words per post. Participation emotionality is determined by a member's average percentage of positive words per post. To measure participation quality and participation emotionality, we used the LIWC categories of positive emotions ('posemo') and cognitive words ('cogmech').

To evaluate and benchmark the ML models, for each community, we performed a 5x2-fold cross validation. In each fold, 50% of the community members were randomly and without replacement assigned to the training set, while the other 50% were allocated to the validation set. Different versions of each ML classifier using various experimental parameters were evaluated on a random split of the original training set into 2/3 for learning the ML classifier and 1/3 for testing the ML classifier, i.e. the test set. For both evaluation metrics, the best performing ML model with the corresponding parameter (combination) on the test set was chosen, trained on the entire original training set, and validated on the validation set. The ML models are benchmarked by averaging the 5x2-fold cross-validation performances on the validation test. We follow existing benchmarking studies in the ML literature (Dembczynski et al., 2012; Madjarov et al., 2012), and use all independent variables as input for the ML classifiers.

Because no binary dependent variable labels operationalized in line with the definitions of member participation were readily available in the database, in each iteration, the median split technique was used to dichotomize the continuous participation variables. In concrete, the median value of each dependent variable is calculated on the training set, and used as cut-off value to distinguish between inferior- and non-inferior member participation levels. Values lower than the median were labeled 1, signaling inferior member participation; values higher than the median were assigned a 0, defining non-inferior member participation. Dichotomizing is inevitable for a community management setting for three main reasons. First, community managers need an action-oriented signal about whether to intervene for a member in the community, which entails a binary decision problem. Second, by ensuring that the outcome of the prediction models lies between 0 and 1, we facilitate the interpretation for community managers: The higher the posterior probability of inferior member participation, the worse the impact on the viability of the community. Third, the outputs of prediction models are comparable, so community managers gain a better sense of the dimension(s) (participation quantity, quality and/or emotionality) that require interventions to guarantee healthy communities.

Table 4 presents for each community the 5x2 cross validated average of the median values for each dependent dimension and the number of observations. Table 5 gives insights into the label cardinality, label density and unconditional label dependency values per community. The cardinality and density reflect how much multi-label a community dataset is, while the label dependency reflects the correlation between the inferior member participation labels. The cardinality is defined as the average number of inferior participation labels of the members in a community, while the density is defined as the average number of inferior participation labels of the members in a community divided by the total number of different inferior participation labels, i.e. three in this ML classification context (Tsoumakas & Katakis, 2007). The label dependency is defined as the 5x2 cross validated average of the phi coefficient, which measures the degree of association between two dichotomous variables. The values range from -1 to 1, with a positive (negative) number indicating a positive (negative) correlation. The further the phi coefficient is removed from 0, the stronger the dependency between the labels. Table 5 reveals that our sample of communities is an ideal test bed for this ML study given that the label characteristics are similar across innovation communities. First, the quite dense ML communities (with density of about 0.5) with 1.5 inferior participation labels per member on average hint towards a good performance of the ML approaches. Second, the label dependency values deviate from 0 concluding that label correlations exist, so that the ML methods have the possibility to exploit it and perform well. Third, the label dependencies are interpretable in a consistent way across communities, i.e. {*quality*, emotionality} has lower dependency values than {quantity, quality} and {quantity, emotionality} which both hold equal height.

We used SAS 9.4 to process the data, Mulan 1.5, the ML version of Weka 3.7.10 to build, evaluate and compare the models and R 3.3.1 with the packages `stats 3.5.0', `scmamp 0.2.55', `xtable 1.8-2' for the statistical evaluation and the export of tables and figures.

Community	**Number of observations**	**Median quantity**	**Median quality**	**Median emotionality**
1	1020	0.27	5.66	1.34
2	1208	0.32	5.76	1.1
3	1362	0.41	8.25	1.55
4	2447	0.37	5.56	2.66
5	1520	0.44	7.43	1.74
6	421	0.7	10.24	1.79
7	665	0.54	6.95	2.12

Table 4 Sample characteristics

Community	**Cardinality**	**Density**	**{quantity, quality}**	**{quantity, emotionality}**	**{quality, emotionality}**
1	1.500	0.500	0.584	0.613	0.582
2	1.502	0.501	0.595	0.554	0.514
3	1.443	0.481	0.345	0.381	0.254
4	1.477	0.492	0.177	0.141	0.023
5	1.495	0.498	0.292	0.334	0.211
6	1.423	0.474	0.335	0.395	0.254
7	1.535	0.512	0.457	0.347	0.204

Table 5 Member participation label cardinality; density, and dependency values

4.3. Experimental parameters

The parameter optimization procedure for the base classifiers is the following. The kNN is optimized by ranging the number of neighbors equal to 2, 4, 8, 16, 32, 64 and 128. The Euclidean distance function was used to identify the nearest neighbors for a specific observation. For AdaBoost, the amount of iterations to update weights for incorrect classifications ranged from 20 to 100 in steps of 20. We relied on the AdaBoost.M1 approach (Freund & Schapire, 1996) and employed a decision stump, the one-level decision tree, as the weak classifier. For the PT methods, for Stacking, the percentage values 0.3, 0.5, 0.8 and 1 were used to include 1, 2 or 3 labels in the meta-learning stage (Tsoumakas et al., 2009). In addition to integrating label dependency information in the meta-level, the original independent variables of the first level were also included. For the AA methods, for ML-kNN and IBLR, the same parameters for the nearest neighbors and distance function were explored as the base classifier kNN. We opted for the IBLRplus version of IBLR that takes into account, in addition to labels of neighboring instances, the original features as independent variables (Cheng & Hüllermeier, 2009). For AdaBoost.MH, the same parameters as AdaBoost.M1 were used. For the Ensemble methods, for ECC, we explored different amounts of chain orderings through 2 to 8 models with a 2 step iteration. For RAkEL, we explored 1 to 3 models to aggregate individual label predictions of label subsets of size 2 that can be overlapping. HOMER broke nodes of labels into 2 partitions through both the clustering (distribution based on label similarity) and balanced clustering approach (balanced distribution of positive examples for each meta-label based on label similarity) (Tsoumakas, Katakis, & Vlahavas, 2008). For CBMLC, we explored different amounts of clusters in the training set ranging from 2, 4 to 8 clusters by testing both the simple k-means (Arthur & Vassilvitskii, 2007) and expectation maximization clustering method with a maximum of 500 iterations to fine tune cluster centroids.

4.4. Statistical evaluation

To make statistically supported conclusions, we follow a two-stage approach that involves a test to check whether differences in performance exist between multiple classifiers and if this is the case, a post-hoc test to identify performance differences. Recommended by Demšar (2006) and consistent with the extensive ML classifier comparison of Madjarov et al. (2012), we employ the Friedman test with Iman-Davenport correction (Iman & Davenport, 1980). The Friedman test ranks the classifiers for each data separately with the best performing classifier getting the rank 1, the second best the rank 2, etc. In case of ties, average ranks are assigned. Next, the Friedman test compares the average classifier ranks and calculates the Friedman statistic χ_F^2, distributed according to the χ_F^2 distribution with $k-1$ degrees of freedom (k the number of classifiers). As Iman & Davenport (1980) identified the Friedman statistic χ_F^2 to be undesirably conservative, they proposed the better statistic F_F, distributed according to the F distribution with $k-1$ and $(k-1)(N-1)$ degrees of freedom (k the number of classifiers and N the number of datasets).

As the post-hoc test involves multiple pairwise comparisons of classifiers to reveal the performance differences, we need to control for the accumulated error coming from combining these multiple pairwise comparisons, i.e. the Family Wise Error Rate (FWER). The FWER is defined as the probability of making one or more false discoveries among the hypotheses when performing multiple pairwise tests. As the p-value in a multiple comparison reflects the probability error of a certain comparison, García, Fernández, Luengo, & Herrera (2010) suggest to report an adjusted p-value that takes into account the remaining comparisons belonging to that family and can be directly compared to a significance level α. In literature, many post-hoc tests exist but differ in the way they adjust the value of α to compensate for multiple comparisons. We consider the significance level for the post-hoc test at $\alpha = 0.05$.

As for R1 to R4, ML classifiers need to be compared with a control method, we use the Finner test recommended by García, Fernández, Luengo, & Herrera (2010) as it's easy to understand and offers good performance. The Finner post-hoc test is applied to results of the Friedman test. The Finner test sequentially test the hypotheses (H_1, H_2, etc.) ascendingly ordered by their significance (p_1, p_2, etc.) and adjusts the value of α in a step-down manner. It rejects H_1 to H_{i-1} if i is the smallest integer so that $p_i > 1 - (1 - \alpha)^{(k-1)/i}$ (with i corresponding to the hypothesis which adjusted p-value is being computed and k the number of classifiers). As for R2 for Adaboost, only two methods need to be compared, on recommendation of, we use the paired Wilcoxon Signed-Rank Test. The Wilcoxon Signed-Rank test assigns ranks to the absolute value of the differences between pairs of data (with the smallest value getting the rank 1) and adds up the ranks of all positive and negative differences (W^+ and W^-). It computes the statistic W based on the minimum W^+ and W^- and assumes similar numbers for both as the null hypothesis.

As for R5, all ML classifiers need to be compared to each other, we use the Shaffer test recommended by Garcia & Herrera (2008). The Shaffer test sequentially test the hypotheses (H_1, H_2, etc.) ascendingly ordered by their significance (p_1, p_2, etc.) and adjusts the value of α in a step-down manner. The Shaffer test at stage j rejects H_i if $p_i \leq \alpha/t_i$, where t_i is the maximum number of hypotheses which can be true given that any $(i - 1)$ hypotheses are false and $m = k(k - 1)/2$ the number of comparisons.

5. RESULTS

This section displays the results of all five research questions. A summary of the results can be found in Table 6.

5.1. R1: PT methods > BR counterpart?

For BR.kNN, we reject the null-hypothesis of equal rank performance with PT methods for both ES ($F_F(2,12) = 8, p = 0.0062$) and SA ($F_F(2,12) = 23.4, p = 0.0001$). Friedman's average ranking in Table 7 and Finner's post hoc test in Table 8, indicate a superior performance of CC, significant for ES ($p_{Finner} = 0.0150$), but not for SA ($p_{Finner} = 0.4227$). Stacking performs significantly better for ES ($p_{Finner} = 0.0325$), but worse for SA ($p_{Finner} = 0.0321$). For BR.AdaBoost, we reject the null-hypothesis of equal rank performance with PT methods for both ES ($F_F(2,12) = 18, p = 0.0002$) and SA ($F_F(2,12) = 18, p = 0.0002$). Friedman's average ranking in Table 9 and Finner's post hoc test in Table 10, reveal a significant superior performance of CC for both ES ($p_{Finner} = 0.0100$) and SA ($p_{Finner} = 0.0100$). Stacking has equal performance to BR, but is not significant for both ES (p_{Finner} =1.0) and SA ($p_{Finner} = 1.0$).

5.2. R2: AA methods > BR counterpart?

For BR.kNN, we reject the null-hypothesis of equal rank performance with AA methods for both ES ($F_F(2,12) = 43, p$ =0.0000) and SA ($F_F(2,12) = 23.4, p$ =0.0001). Friedman's average ranking in Table 11 and Finner's post hoc test in Table 12, indicate the significant superior performance of IBLR for both for ES (p_{Finner} =0.0010) and SA (p_{Finner} =0.0321). MLkNN performs without significant impact better than BR for ES (p_{Finner} =0.1814), but worse for SA (p_{Finner} =0.4227). Table 13 presents the Wilcoxon Signed Rank test for R2b. For BR.AdaBoost, we find significant difference and better performance of AdaBoost.MH for example-based specificity (W =0, p =0.0078), but not for subset accuracy (W =6, p =0.1094).

5.3. R3: EPT methods > PT counterpart?

For Stacking.kNN, we reject the null-hypothesis of equal rank performance with EPT methods for ES ($F_F(3,18) = 10.07, p = 0.0004$), but not for SA ($F_F(3,18) = 1.72, p = 0.1994$). Table 14 displays the average ranking. The post-hoc test for ES, displayed in Table 15, reveals that RAkEL.Stacking performs better ($p_{Finner} = 0.8360$) than Stacking, as opposed to CBMLC.Stacking (p_{Finner} =0.7515) (and HOMER.Stacking (p_{Finner} =0.0080). However, only for HOMER.Stacking the effect is significant. For CC.kNN, we can reject the null-hypothesis of equal rank performance with EPT methods for both ES ($F_F(4,24) = 7.74, p = 0.0004$) and SA ($F_F(4,24) = 10.90, p = 0.0000$). Friedman's average ranking in Table 16 and Finner's post hoc test in Table 17, reveal for ECC.CC, equal performance for ES (p_{Finner} =1.0000) and superior performance for SA (p_{Finner} =0.1737), yet this effect is not significant. CBMLC.CC, for both ES (p_{Finner} =0.6021) and SA (p_{Finner} =0.4990), RAkEL.CC for both ES (p_{Finner} =0.0832) and SA (p_{Finner} =0.3024) and HOMER.CC for both ES ($p_{Finner} = 0.0053$) and SA (p_{Finner} =0.0699) perform worse, yet only the effect for HOMER.CC for ES is significant. For Stacking.AdaBoost, we reject the null-hypothesis of equal rank performance with EPT methods for ES ($F_F(3,18) = 9.23, p = 0.0006$), but not for SA ($F_F(3,18) = 2.72, p = 0.0747$). Friedman's average ranking in Table 18 and Finner's post hoc test in Table 19, reveal that RAkEL.Stacking has equal performance to Stacking (p_{Finner} =1.0000). CBMLC.Stacking (p_{Finner} =0.0443) and HOMER.Stacking (p_{Finner} =0.0155) perform significantly worse. For CC.AdaBoost, we reject the null-hypothesis of equal rank performance with EPT methods for both ES ($F_F(4,24) = 38.55, p = 0.0000$) and SA ($F_F(4,24) = 29, p = 0.0000$). Friedman's average ranking in Table 20 and Finner's post hoc test in Table 21, reveal that no method performs better than CC. ECC.CC for ES (p_{Finner} =0.8658) and SA (p_{Finner} =0.7353) and RAkEL.CC for ES ($p_{Finner} = 0.0563$) and SA (p_{Finner} =0.3024) perform unsignificantly worse. HOMER.CC for ES (p_{Finner} =0.0008) and SA (p_{Finner} =0.0047) and CBMLC.CC for ES (p_{Finner} =0.0014) and SA (p_{Finner} =0.004), perform significantly worse.

5.4. R4: EAA methods > AA counterpart?

For MLkNN.kNN, we reject the null-hypothesis of equal rank performance with EAA methods for ES ($F_F(3,18) = 6.89, p = 0.0027$), but not for SA ($F_F(3,18) = 1.21, p = 0.3360$). Friedman's average ranking in Table 22 and Finner's post hoc test in Table 23, reveal that the superior performance of CBMLC. MLkNN ($p_{Finner} = 0.1109$) and RAkEL.MLkNN ($p_{Finner} = 0.6788$) and the inferior performance of HOMER.MLkNN ($p_{Finner} = 0.3034$) is not significant. For IBLR.kNN, we reject the null-hypothesis of equal rank performance with EAA methods for both ES ($F_F(3,18) = 30.75, p = 0.0000$) and SA ($F_F(3,18) = 12.38, p = 0.0001$). Friedman's average ranking in Table 24 and Finner's post hoc test in Table 25, indicate the inferior performance of the RAkEL.IBLR, HOMER.IBLR and CBMLC.IBLR ensembles. The effect is significant for CBMLC.IBLR for both ES ($p_{Finner} = 0.0013$) and SA ($p_{Finner} = 0.0013$), and for HOMER.IBLR only ES ($p_{Finner} = 0.0056$). For RAkEL.IBLR for both ES ($p_{Finner} = 0.5346$) and SA ($p_{Finner} = 0.5346$), and for HOMER.IBLR for SA ($p_{Finner} = 0.3034$), the effect is insignificant. For AdaBoostMH.AdaBoost, we reject the null-hypothesis of equal rank performance with EAA methods for both ES ($F_F(3,18) = 27.41, p = 0.0000$) and SA ($F_F(3,18) = 13.34, p = 0.0001$). Friedman's average ranking in Table 26 and Finner's post hoc test in Table 27, indicate the inferior performance of all ensembles. The effect is significant for HOMER.AdaBoostMH for both ES ($p_{Finner} = 0.0001$) and SA ($p_{Finner} = 0.0013$), for CBMLC.AdaBoostMH for both ES ($p_{Finner} = 0.0340$) and SA ($p_{Finner} = 0.0194$). RAkEL.AdaBoostMH perform significantly worse for ES ($p_{Finner} = 0.0340$), but insignificantly for SA ($p_{Finner} = 0.3006$).

5.5. R5: overall comparison

For kNN, we reject the null-hypothesis of equal rank performance for all BR, PT, AA, EPT and EAA methods for ES ($F_F(17,102) = 9.09, p = 0.0000$) and SA ($F_F(17,102) = 14.88, p = 0.0000$). Figure 4 and Figure 5 display the average rankings in a critical difference diagram for ES and SA. The top performing classifiers overall are IBLR and CC. For AdaBoost, we reject the null-hypothesis of equal rank performance for all BR, PT, AA, EPT and EAA methods for ES ($F_F(13,78) =, p = 0.0000$) and SA ($F_F(13,78) =, p = 0.0000$). Figure 6 and Figure 7 display the average rankings in a critical difference diagram for ES and SA. The top performing classifiers overall are CC and AdaBoostMH.

5.6. Summary

Our experiments showcase several important and insightful findings that proof that ML methods have a beneficial effect in predicting ML inferior member participation. First, our results show that PT and AA methods improve the prediction performance over building independent classifiers for each of the labels. Our results suggest to use CC as best and most consistent performing PT method, while multi-label versions IBLR for kNN and AdaBoost.MH for Adaboost are preferred as AA methods. Second, our study demonstrates that PT and AA methods do not benefit from a ML ensemble approach that breaks down the original ML problem into smaller sub problems. Generally-speaking EPT and EAA methods show inconclusive and inconsistent results over their PT and AA counterpart methods, at times even resulting in a significant drop in prediction performance. Third, our results show that in the context of a three label inferior member participation prediction context, IBLR for kNN and AdaBoost.MH for AdaBoost are the best performing methods across the *10* state-of-the art ML classifiers included in this benchmark study.

Fourth, we do underline that evaluating ML methods in the context of inferior participation prediction using example-based specificity and subset accuracy is interesting, as these metrics allow community moderators to verify how safe it is to ignore predicted non-inferior participation behavior and assess the overall prediction performance.

6. CONCLUSION

Recent advances in innovation literature by Coussement et al. (2017) on innovation community management dictate that moderators must shift from reactive to proactive community management to build viable communities. By anticipating on inferior member participation predictions and targeting the most risky members, moderators can prevent future negative community impact by taking corrective actions in a proactive manner. The decision to target a certain member is directly made on the basis of the prediction model output that returns a probability of future destructive behavior. Hence, the prediction model performance directly determines the success of the targeting ability and the prevention campaign accordingly. As only those members with real intentions of future inferior participation behavior must be targeted while safely excluding actual non-risky members, one must strive for the greatest prediction performance possible. However, our setup describes the special classification problem where multiple labels may be associated with one single member because inferior member participation can occur through inferior participation quantity, quality and/or emotionality, which in ML literature is described as a multi-label problem. Recently, this problem has been tackled by constructing independent classification models for each label (Kristof Coussement et al., 2017), however, ML literature lists better alternatives to solve these types of problems and uses label dependencies and ML classification methodology to increase prediction performance.

Relying on a sample of 1,407 members in 7 innovation communities and an extensive experimental comparison of 10 state-of-the-art ML classifiers using the evaluation metrics example-based specificity and subset accuracy, the contributions of this study are four-fold. First, this paper introduces ML methodology to online innovation communities and explores the benefit for ML member participation classification. Second, our study proposes a framework for inferior member participation prediction that benchmarks ten state-of-the-art ML classifiers. Third, based on the experimental results, we demonstrate that the ML methodology is beneficial, even in the case of a three class problem. Fourth, we observe that PT and AA methods are superior over building independent classifiers for each class separately and that ensembles of PT and AA do not deliver superior performance in our prediction context. IBLR for kNN and AdaBoost.MH for AdaBoost are the best performing algorithms in this benchmarking exercise.

Despite the huge contributions of this study to literature, there are four shortcomings which highlight interesting paths for future research. First, we performed an extensive experimental comparison of ML classifiers, but focused on the most popular PT and AA methods. However, not all available ML classifiers have been explored. Therefore, further research can explore how other ML classifiers perform in the context of inferior member participation classification. Second, no feature selection schemes were used and benchmarked. Therefore, further research can investigate how the use of feature reduction mechanisms could relate to differences in performance between the ML classifiers. Third, although we performed our experiments on 7 real-life datasets in inferior member participation classification, further research can extend the current benchmarking framework to related online community contexts, e.g. online product feedback fora (Hoornaert, Ballings, Malthouse, & Van den Poel, 2017). Fourth, in the light of the growing popularity of combining human expert opinions with pure data-driven algorithmic approaches (K. Coussement, Benoit, & Antioco, 2015; Sinha & Zhao, 2008), a valuable path for further research is setting up a field test that compares and benchmarks the performance of the moderator's identification of inferior member participation with the ML approach.

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	Research question	Comparison case	ES	SA	ES	SA
RQ1	PT > BR?	CC > BR?	yes*	yes	yes*	yes*
		Stacking > BR?	yes*	no*	equal	equal
RQ2	AA > BR?	ML-kNN > BR?	yes	no	-	-
		IBLR > BR ?	yes*	yes*	-	-
		AdaBoost.MH > BR ?	-	-	yes*	yes
RQ3	EPT > CC?	HOMER.CC > CC?	no*	no	no*	no*
		CBMLC.CC > CC?	no	no	no*	no*
		RAkEL.CC > CC?	no	no	no	no
		ECC.CC > CC?	equal	yes	no	no
	EPT > Stacking?	HOMER.Stacking > Stacking?	no*	n.s.	no*	n.s.
		CBMLC.Stacking > Stacking?	no	n.s.	no*	n.s.
		RAkEL.Stacking > Stacking?	yes	n.s.	equal	n.s.
RQ4	EAA > ML-kNN?	HOMER.ML-kNN > ML-kNN?	no	n.s.	-	-
		CBMLC.ML-kNN > ML-kNN?	yes	n.s.	-	-
		RAkEL.ML-kNN > ML-kNN?	yes	n.s.	-	-
	EAA > IBLR?	HOMER.IBLR > IBLR?	no*	no	-	-
		CBMLC.IBLR > IBLR?	no*	no*	-	-
		RAkEL.IBLR > IBLR?	no	no	-	-
	EAA > AdaBoost.MH?	HOMER.AdaBoost.MH > AdaBoost.MH?	-	-	no*	no*
		CBMLC.AdaBoost.MH > AdaBoost.MH?	-	-	no*	no*
		RAkEL.AdaBoost.MH > AdaBoost.MH?	-	-	no*	no

Table 6 Summary of the research questions (yes/no: there is a significant rank performance difference and the expression is true/wrong; n.s.: there is not a significant rank performance difference; *: the comparison is statistically supported

Example-based specificity	Ranking	Subset accuracy	Ranking
CC.kNN	1.43	CC.kNN	1.29
Stacking.kNN	1.71	BR.kNN	1.71
BR.kNN	2.86	Stacking.kNN	3.00

Table 7 R1a: Friedman's average ranking

Example-based specificity	p-value	p_{Finner}	Finner score	Subset accuracy	p-value	p_{Finner}	Finner score
CC.kNN	0.0075	0.0150	0.0253	Stacking.kNN	0.0162	0.0321	0.0253
Stacking.kNN	0.0325	0.0325	0.05	CC.kNN	0.4227	0.4227	0.0500

Table 8 R1a: Adjusted p-values for Finner post hoc procedure with BR.kNN as the control method

Example-based specificity	Ranking	Subset accuracy	Ranking
CC.Adaboost	1.00	CC.Adaboost	1.00
BR.Adaboost	2.50	BR.Adaboost	2.50
Stacking.Adaboost	2.50	Stacking.Adaboost	2.50

Table 9 R1b: Friedman's average ranking

Example-based specificity	p-value	p_{Finner}	Finner score	Subset accuracy	p-value	p_{Finner}	Finner score
CC.Adaboost	0.0050	0.0100	0.0253	CC.Adaboost	0.005	0.0100	0.0253
Stacking.Adaboost	1.0000	1.0000	0.0500	Stacking.Adaboost	1.000	1.0000	0.0500

Table 10 R1b: Adjusted p-values for Finner post hoc procedure with BR.Adaboost as the control method

Example-based specificity	Ranking	Subset accuracy	Ranking
IBLR.kNN	1.00	IBLR.kNN	1.00
MLkNN.kNN	2.14	BR.kNN	2.29
BR.kNN	2.86	MLkNN.kNN	2.71

Table 11 R2a: Friedman's average ranking

Example-based specificity	p-value	p_{Finner}	Finner score	Subset accuracy	p-value	p_{Finner}	Finner score
IBLR.kNN	0.0005	0.0010	0.0253	IBLR.kNN	0.0162	0.0321	0.0253
MLkNN.kNN	0.1814	0.1814	0.0500	MLkNN.kNN	0.4227	0.4227	0.0500

Table 12 R2a: Adjusted p-values for Finner post hoc procedure with BR.kNN as the control method

Example-based specificity	W+	W-	p-value	Subset accuracy	W+	W-	p-value
BR.Adaboost-AdaboostMH.Adaboost	0	28	0.0253	BR.Adaboost-AdaboostMH.Adaboost	6	22	0.1094

Table 13 Wilcoxon signed-rank test for R2 (Adaboost)

Example-based specificity	Ranking	Subset accuracy	Ranking
RAkEL.Stacking.kNN	1.79	RAkEL.Stacking.kNN	1.64
Stacking.kNN	1.93	Stacking.kNN	2.50
CBMLC.Stacking.kNN	2.29	HOMER.Stacking.kNN	2.86
HOMER.Stacking.kNN	4.00	CBMLC.Stacking.kNN	3.00

Table 14 R3a (Stacking): Friedman’s average ranking

Example-based specificity	p-value	p_{Finner}	Finner score
HOMER.Stacking.kNN	0.0027	0.0080	0.0170
CBMLC.Stacking.kNN	0.6048	0.7515	0.0336
RAkEL.Stacking.kNN	0.8360	0.8360	0.0500

Table 15 R3a (Stacking): Adjusted p-values for Finner post hoc procedure with Stacking.kNN as the control method

Example-based specificity	Ranking	Subset accuracy	Ranking
CC.kNN	2.00	ECC.kNN	1.14
ECC.kNN	2.00	CC.kNN	2.57
CBMLC.CC.kNN	2.57	CBMLC.CC.kNN	3.14
RAkEL.CC.kNN	3.71	RAkEL.CC.kNN	3.57
HOMER.CC.kNN	4.71	HOMER.CC.kNN	4.57

Table 16 R3a (CC): Friedman’s average ranking

Example-based specificity	p-value	p_{Finner}	Finner score	Subset accuracy	p-value	p_{Finner}	Finner score
HOMER.CC.kNN	0.0013	0.0053	0.0127	HOMER.CC.kNN	0.018	0.0699	0.0127
RAkEL.CC.kNN	0.0425	0.0832	0.0253	ECC.kNN	0.091	0.1737	0.0253
CBMLC.CC.kNN	0.4990	0.6021	0.0377	RAkEL.CC.kNN	0.2367	0.3024	0.0377
ECC.kNN	1.0000	1.0000	0.0500	CBMLC.CC.kNN	0.4990	0.4990	0.0500

Table 17 R3a (CC): Adjusted p-values for Finner post hoc procedure with CC.kNN as the control method

Example-based specificity	Ranking	Subset accuracy	Ranking
Stacking.Adaboost	1.64	Stacking.Adaboost	2.07
RAkEL.Stacking.Adaboost	1.64	RAkEL.Stacking.Adaboost	2.07
CBMLC.Stacking.Adaboost	3.14	HOMER.Stacking.Adaboost	2.29
HOMER.Stacking.Adaboost	3.57	CBMLC.Stacking.Adaboost	3.57

Table 18 R3b (Stacking): Friedman's average ranking

Example-based specificity	p-value	p_{Finner}	Finner score
HOMER.Stacking.Adaboost	0.0052	0.0155	0.0170
CBMLC.Stacking.Adaboost	0.0297	0.0443	0.0336
RAkEL.Stacking.Adaboost	1.0000	1.0000	0.0500

Table 19 R3b (Stacking): Adjusted p-values for Finner post hoc procedure with Stacking.Adaboost as the control method

Example-based specificity	Ranking	Subset accuracy	Ranking
CC.Adaboost	1.43	CC.Adaboost	1.57
ECC.Adaboost	1.57	ECC.Adaboost	1.86
RAkEL.CC.Adaboost	3.14	RAkEL.CC.Adaboost	2.57
CBMLC.CC.Adaboost	4.29	HOMER.CC.Adaboost	4.14
HOMER.CC.Adaboost	4.57	CBMLC.CC.Adaboost	4.86

Table 20 R3b (CC): Friedman's average ranking

Example-based specificity	p-value	p_{Finner}	Finner score	Subset accuracy	p-value	p_{Finner}	Finner score
HOMER.CC.Adaboost	0.0002	0.0008	0.0127	CBMLC.CC.Adaboost	0.0001	0.0004	0.0127
CBMLC.CC.Adaboost	0.0007	0.0014	0.0253	HOMER.CC.Adaboost	0.0023	0.0047	0.0253
RAkEL.CC.Adaboost	0.0425	0.0563	0.0377	RAkEL.CC.Adaboost	0.2367	0.3024	0.0377
ECC.Adaboost	0.8658	0.8658	0.0500	ECC.Adaboost	0.7353	0.7353	0.0500

Table 21 R3b (CC): Adjusted p-values for Finner post hoc procedure with CC.Adaboost as the control method

Example-based specificity	Ranking	Subset accuracy	Ranking
CBMLC.MLkNN.kNN	1.29	CBMLC.MLkNN.kNN	1.71
RAkEL.MLkNN.kNN	2.43	MLkNN.kNN	2.71
MLkNN.kNN	2.71	RAkEL.MLkNN.kNN	2.71
HOMER.MLkNN.kNN	3.57	HOMER.MLkNN.kNN	2.86

Table 22 R4a (MLkNN): Friedman’s average ranking

Example-based specificity	p-value	p_{Finner}	Finner score
CBMLC.MLkNN.kNN	0.0384	0.1109	0.0170
HOMER.MLkNN.kNN	0.2142	0.3034	0.0336
RAkEL.MLkNN.kNN	0.6788	0.6788	0.0500

Table 23 R4a (MLkNN): Adjusted p-values for Finner post hoc procedure with MLkNN.kNN as the control method

Example-based specificity	Ranking	Subset accuracy	Ranking
IBLR.kNN	1.29	IBLR.kNN	1.57
RAkEL.IBLR.kNN	1.71	RAkEL.IBLR.kNN	2.00
HOMER.IBLR.kNN	3.29	HOMER.IBLR.kNN	2.43
CBMLC.IBLR.kNN	3.71	CBMLC.IBLR.kNN	4.00

Table 24 R4a (IBLR): Friedman’s average ranking

Example-based specificity	***p*-value**	p_{Finner}	**Finner score**	**Subset accuracy**	***p*-value**	p_{Finner}	**Finner score**
CBMLC.IBLR.kNN	0.0004	0.0013	0.0170	CBMLC.IBLR.kNN	0.0004	0.0013	0.0170
HOMER.IBLR.kNN	0.0038	0.0056	0.0336	HOMER.IBLR.kNN	0.2142	0.3034	0.0336
RAkEL.IBLR.kNN	0.5346	0.5346	0.0500	RAkEL.IBLR.kNN	0.5346	0.5346	0.0500

Table 25 R4a (IBLR): Adjusted p-values for Finner post hoc procedure with IBLR.kNN as the control method

Example-based specificity	**Ranking**	**Subset accuracy**	**Ranking**
AdaboostMH.Adaboost	1.00	AdaboostMH.Adaboost	1.29
CBMLC.AdaboostMH.Adaboost	2.57	RAkEL.AdaboostMH.Adaboost	2.00
RAkEL.AdaboostMH.Adaboost	2.57	CBMLC.AdaboostMH.Adaboost	3.00
HOMER.AdaboostMH.Adaboost	3.86	HOMER.AdaboostMH.Adaboost	3.71

Table 26 R4b (AdaboostMH): Friedman's average ranking

Example-based specificity	***p*-value**	p_{Finner}	**Finner score**	**Subset accuracy**	***p*-value**	p_{Finner}	**Finner score**
HOMER.AdaboostMH.Adaboost	0.0000	0.0001	0.0170	HOMER.AdaboostMH.Adaboost	0.0004	0.0013	0.0170
CBMLC.AdaboostMH.Adaboost	0.0228	0.0340	0.0336	CBMLC.AdaboostMH.Adaboost	0.0130	0.0194	0.0336
RAkEL.AdaboostMH.Adaboost	0.0228	0.0340	0.0500	RAkEL.AdaboostMH.Adaboost	0.3006	0.3006	0.0500

Table 27 R4b (AdaboostMH): Adjusted p-values for Finner post hoc procedure with AdaboostMH.Adaboost as the control method

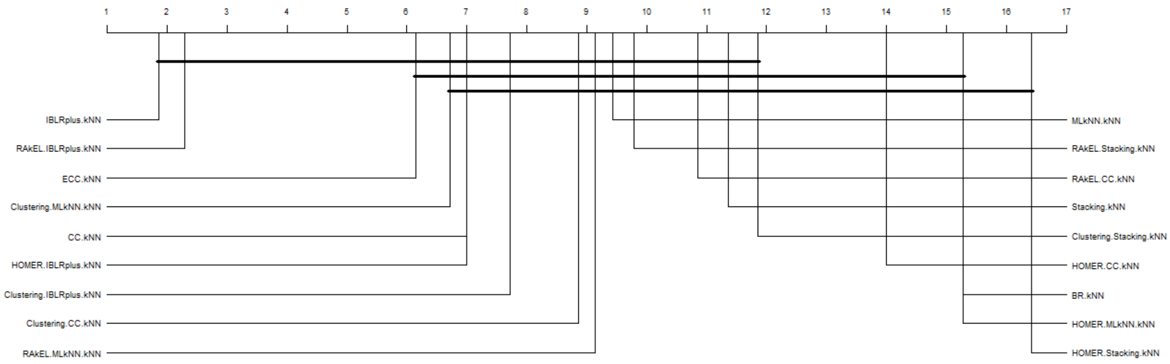

Figure 4 Shaffer procedure for R5 (kNN - ES)

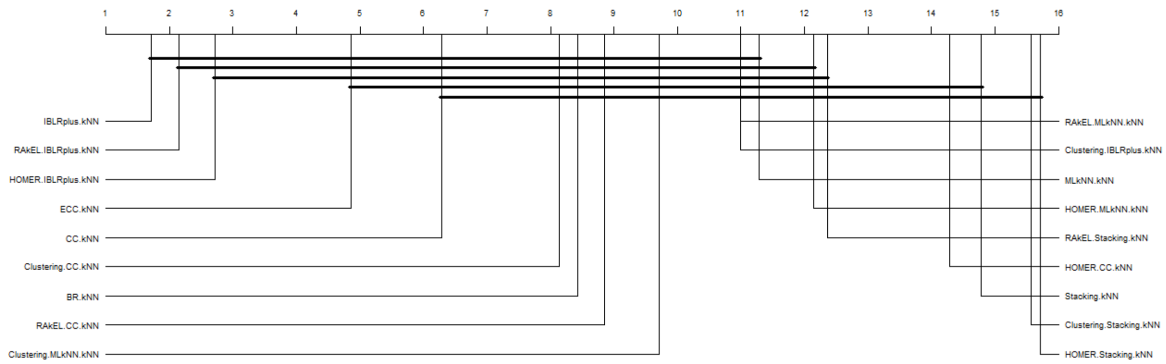

Figure 5 Shaffer procedure for R5 (kNN - SA)

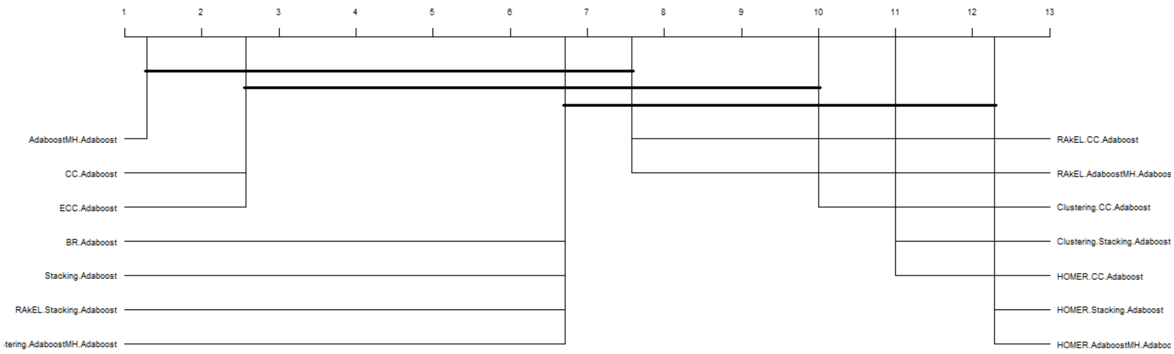

Figure 6 Shaffer procedure for R5 (Adaboost - ES)

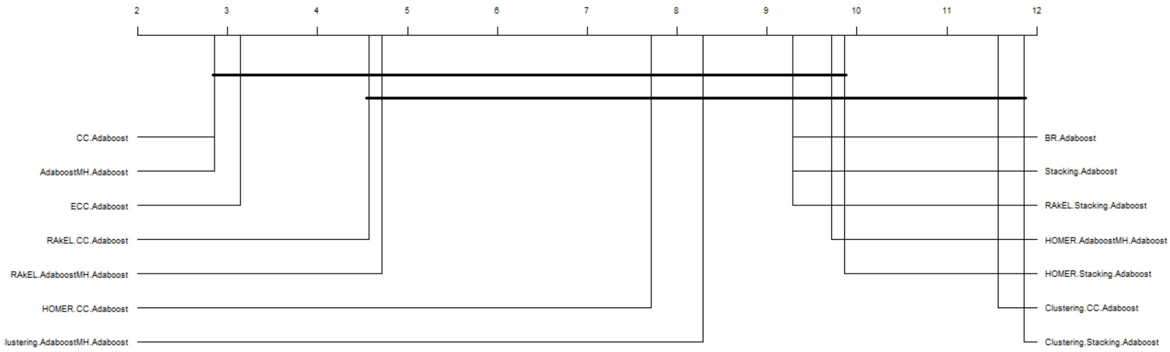

Figure 7 Shaffer procedure for R5 (Adaboost - SA)

	1	2	3	4	5	6	7
BR.kNN	0.80	0.52	0.49	0.49	0.46	0.49	0.52
CC.kNN	0.81	0.60	0.59	0.53	0.53	0.64	0.53
Clustering.CC.kNN	0.81	0.60	0.59	0.52	0.52	0.59	0.53
Clustering.IBLR.kNN	0.78	0.56	0.62	0.61	0.54	0.59	0.56
Clustering.MLkNN.kNN	0.75	0.57	0.63	0.58	0.54	0.61	0.6
Clustering.Stacking.kNN	0.74	0.58	0.58	0.53	0.53	0.56	0.52
ECC.kNN	0.78	0.6	0.59	0.6	0.56	0.59	0.61
HOMER.CC.kNN	0.80	0.55	0.57	0.51	0.48	0.54	0.50
HOMER.IBLR.kNN	0.78	0.57	0.58	0.62	0.54	0.59	0.61
HOMER.MLkNN.kNN	0.76	0.49	0.47	0.49	0.4	0.53	0.57
HOMER.Stacking.kNN	0.69	0.51	0.53	0.50	0.49	0.54	0.49
IBLR.kNN	0.81	0.61	0.64	0.64	0.6	0.61	0.64
MLkNN.kNN	0.74	0.55	0.62	0.57	0.52	0.6	0.6
RAkEL.CC.kNN	0.79	0.59	0.58	0.53	0.51	0.59	0.52
RAkEL.IBLR.kNN	0.81	0.61	0.64	0.64	0.59	0.61	0.64
RAkEL.MLkNN.kNN	0.74	0.55	0.62	0.57	0.52	0.6	0.61
RAkEL.Stacking.kNN	0.73	0.57	0.59	0.53	0.53	0.62	0.52
Stacking.kNN	0.74	0.57	0.59	0.53	0.53	0.58	0.52

Table 28 5x2 cross-validated average of example-based specificity for kNN

	1	2	3	4	5	6	7
BR.kNN	0.5	0.36	0.3	0.27	0.26	0.27	0.32
CC.kNN	0.51	0.36	0.31	0.28	0.25	0.31	0.31
Clustering.CC.kNN	0.51	0.36	0.31	0.27	0.24	0.26	0.32
Clustering.IBLR.kNN	0.42	0.34	0.28	0.30	0.26	0.28	0.30
Clustering.MLkNN.kNN	0.50	0.33	0.31	0.26	0.24	0.30	0.32
Clustering.Stacking.kNN	0.49	0.33	0.29	0.26	0.23	0.24	0.29
ECC.kNN	0.54	0.37	0.32	0.30	0.28	0.27	0.34
HOMER.CC.kNN	0.48	0.32	0.32	0.26	0.22	0.25	0.29
HOMER.IBLR.kNN	0.57	0.39	0.32	0.34	0.32	0.30	0.37
HOMER.MLkNN.kNN	0.50	0.34	0.27	0.26	0.25	0.29	0.30
HOMER.Stacking.kNN	0.47	0.29	0.27	0.26	0.23	0.26	0.28
IBLR.kNN	0.59	0.39	0.34	0.35	0.32	0.31	0.37
MLkNN.kNN	0.50	0.30	0.30	0.27	0.24	0.28	0.31
RAkEL.CC.kNN	0.50	0.35	0.30	0.27	0.25	0.26	0.32
RAkEL.IBLR.kNN	0.59	0.40	0.34	0.33	0.32	0.30	0.37
RAkEL.MLkNN.kNN	0.50	0.30	0.30	0.27	0.24	0.28	0.33
RAkEL.Stacking.kNN	0.50	0.34	0.29	0.26	0.23	0.30	0.29
Stacking.kNN	0.50	0.32	0.29	0.26	0.23	0.26	0.28

Table 29 5x2 cross-validated average of subset accuracy for kNN

	1	2	3	4	5	6	7
AdaboostMH.Adaboost	0.84	0.70	0.63	0.66	0.64	0.66	0.68
BR.Adaboost	0.81	0.63	0.61	0.65	0.59	0.62	0.62
CC.Adaboost	0.82	0.68	0.64	0.65	0.62	0.65	0.66
Clustering.AdaboostMH.Adaboost	0.79	0.65	0.61	0.64	0.61	0.61	0.65
Clustering.CC.Adaboost	0.75	0.61	0.59	0.62	0.56	0.63	0.60
Clustering.Stacking.Adaboost	0.75	0.59	0.59	0.61	0.55	0.65	0.58
ECC.Adaboost	0.83	0.67	0.63	0.66	0.61	0.65	0.65
HOMER.AdaboostMH.Adaboost	0.82	0.60	0.46	0.41	0.45	0.55	0.54
HOMER.CC.Adaboost	0.80	0.63	0.56	0.61	0.54	0.60	0.61
HOMER.Stacking.Adaboost	0.79	0.60	0.54	0.59	0.51	0.59	0.60
RAkEL.AdaboostMH.Adaboost	0.83	0.65	0.60	0.58	0.57	0.62	0.62
RAkEL.CC.Adaboost	0.80	0.64	0.60	0.64	0.58	0.62	0.62
RAkEL.Stacking.Adaboost	0.81	0.63	0.61	0.65	0.59	0.62	0.62
Stacking.Adaboost	0.81	0.63	0.61	0.65	0.59	0.62	0.62

Table 30 5x2 cross-validated average of example-based specificity for AdaBoost

	1	2	3	4	5	6	7
AdaboostMH.Adaboost	0.62	0.50	0.37	0.27	0.34	0.35	0.40
BR.Adaboost	0.58	0.41	0.33	0.33	0.30	0.33	0.34
CC.Adaboost	0.60	0.48	0.36	0.33	0.33	0.35	0.37
Clustering.AdaboostMH.Adaboost	0.57	0.46	0.33	0.29	0.32	0.31	0.36
Clustering.CC.Adaboost	0.52	0.41	0.31	0.31	0.28	0.34	0.31
Clustering.Stacking.Adaboost	0.52	0.37	0.31	0.30	0.27	0.35	0.29
ECC.Adaboost	0.61	0.46	0.36	0.34	0.32	0.36	0.37
HOMER.AdaboostMH.Adaboost	0.60	0.45	0.31	0.23	0.28	0.34	0.35
HOMER.CC.Adaboost	0.58	0.45	0.33	0.32	0.31	0.33	0.36
HOMER.Stacking.Adaboost	0.57	0.41	0.32	0.32	0.30	0.33	0.35
RAkEL.AdaboostMH.Adaboost	0.61	0.48	0.36	0.28	0.33	0.34	0.38
RAkEL.CC.Adaboost	0.59	0.45	0.35	0.33	0.33	0.34	0.37
RAkEL.Stacking.Adaboost	0.58	0.41	0.33	0.33	0.30	0.33	0.34
Stacking.Adaboost	0.58	0.41	0.33	0.33	0.30	0.33	0.34

Table 31 5x2 cross-validated average of subset accuracy for AdaBoost

CHAPTER IV:
REDUCING INFERIOR MEMBER COMMUNITY PARTICIPATION USING A PROACTIVE MOTIVATIONAL E-MAIL CAMPAIGN: EVIDENCE FROM A FIELD EXPERIMENT

REDUCING INFERIOR MEMBER COMMUNITY PARTICIPATION USING A PROACTIVE MOTIVATIONAL E-MAIL CAMPAIGN: EVIDENCE FROM A FIELD EXPERIMENT

Abstract

Nowadays, many companies recognize the benefits of innovation communities to integrate external consumer knowledge into innovation processes. However, the viability of these ICs is threatened by the big data environment and inferior member participation. Therefore, community managers must reduce inferior member participation, while effectively dealing with the data-rich environment. This study examines the viability of a proactive motivational e-mail campaign to effectively reduce inferior member participation and explores the optimal treatment characteristics. In particular, it investigates the treatment scope (untargeted versus targeted), the message to be included (hedonic, cognitive and social message) and which member profile that can be positively influenced (self-interest oriented and positive emotional writing style). The findings indicate the viability of the proactive targeted e-mail with a cognitive motivational element to reduce inferior member participation. This study has important implications for innovation scholars and community managers.

Keywords: proactive e-mail campaign; inferior member participation reduction; uplift modeling

1. INTRODUCTION

In the new product development (NPD) process, companies have been breaking interaction boundaries and looking externally at consumers to identify information that increases success chances (Dahlander & Frederiksen, 2011). Companies have been recognizing innovation communities (IC) as a valuable tool to positively affect innovation outcomes (Bertels, Kleinschmidt, & Koen, 2011). ICs are defined as private online environments in which companies interact with consumers to help them integrate external knowledge into innovation processes (Kristof Coussement, Debaere, & De Ruyck, 2017). For example, to co-create the club of the future and improve the relevance of the nightlife journey for its clients, Heineken, a Dutch brewing company, obtained in a three-week IC collaboration 28 qualitative insights such as ordering a beer through an interactive bar surface. However, in the pursuit to reap benefits from ICs on the long-term, the community's viability is put under pressure due to two important challenges (Kristof Coussement et al., 2017). First, the big data-rich IC environments increases moderation difficulty of community managers. Many members (volume) participate frequently (velocity) producing a big data set that must be processed and analyzed. Participation behavior is often text-based, but could contain other media sources such as videos or pictures (variety), making analyses more difficult. Second, as online communities are dynamic environments (Faraj, Jarvenpaa, & Majchrzak, 2011), members' motivations change and inferior member participation (IMP) could occur for any member at any time. When members do not participate enough, there is not enough input to derive insights from. Furthermore, community activity will be lower, making the community less attractive to participate. To enjoy the benefits of innovation communities and guarantee community viability, there is a need for IC management to reduce IMP effectively.

Literature widely explored the concept of contact strategies and identified several dimensions that need to be explored: the amount of involved individuals (*scope*) (Blattberg, Kim, & Neslin, 2010), when they are treated (*moment*) (Blattberg et al., 2010), how behavior is influenced (*message*) (Kumar, 2010), who requires treatment (*profile*) (Guelman, Guillén, & Pérez-Marín, 2015) and how they are reached (*channel*) (Kumar, 2010). To obtain an effective treatment campaign for IMP reduction, these dimensions need to be carefully explored.

The *scope* of a treatment campaign can be untargeted or targeted (Blattberg et al., 2010). An untargeted strategy aims to treat every IC member, including constructive members, while targeting aims to identify and treat only specific members based on the condition of inferior IC participation. When choosing the *moment* of treatment, one can be reactive or proactive (Blattberg et al., 2010). Moderators can be reactive and wait for IMP to occur and treat it, or be proactive and identify it in advance and prevent it from impacting the IC. Previous research identified reactive approaches, both targeted approaches such as participation feedback (Liao, Huang, & Xiao, 2017) or acknowledgement (Stephan Ludwig et al., 2014) and untargeted such as governance policy (Preece, 2000). However, they are mainly executed when unconstructive behavior is observed and the community has already been impacted, suggesting the need for proactive approaches. Untargeted proactive approaches exist such as offline community events like brandfests (McAlexander, Schouten, & Koenig, 2002) or reward-based systems (Antikainen, Mäkipää, & Ahonen, 2010). However, in this approach every member is treated equally, which could potentially have a negative consequence as a treatment theoretically could trigger a negative reaction. Literature has been recently exploring proactive targeted approaches that identify members most likely to demonstrate future IMP through prediction models (Kristof Coussement et al., 2017; Debaere, Coussement, & De Ruyck, 2017). Yet, treating “high risk” members may not directly deliver a lower IMP rate as the treatment action could trigger a negative reaction or members would have participated favorably on their own accord resulting in useless action (Kane, Lo, & Zheng, 2014). To address these shortcomings, literature has identified a better approach that exactly identifies the right individuals that can be influenced through treatment, i.e. uplift modeling (N. . Radcliffe & Surry, 1999; Rzepakowski & Jaroszewicz, 2012). Uplift modeling is a machine learning method which aims to predict the causal effect of a treatment action and allows to identify individuals for whom a treatment is most effective. It is receiving increasingly more attention in literature and has already many successful applications in direct marketing (Rzepakowski & Jaroszewicz, 2012). Despite the benefits of proactive strategies, innovation literature lacks understanding on effective proactive strategies, both targeted and untargeted.

The campaign must deliver a *message* that is relevant to an individual’s behavior one aims to influence (Kumar, 2010). Thus, aiming to reduce IMP using a treatment campaign involves sending a message that is relevant to a member’s community participation. This is directly related to the members’ motivations of participation. Previous research has widely explored participation drivers, including reputation, experience, and integration (Wasko and Faraj, 2005); network position (Dahlander and Frederiksen, 2011); relational social capital (Wiertz and de Ruyter, 2007); hobbyism and firm recognition (Jeppesen and Frederiksen, 2006). In general, members only participate if they expect to receive benefits from future interaction (Nambisan, 2002). Hedonic, cognitive and social motives have been identified to explain member participation (Bagozzi & Dholakia, 2002; Baldus, Voorhees, & Calantone, 2015; Nambisan & Baron, 2009; Schau, Muñiz, & Arnould, 2009; M. Wasko & Faraj, 2000). Members anticipate to receive benefits from the pleasurable experience, product-related learning, and relational ties over time, respectively. However, despite that literature has widely recognized these drivers, to the best of our knowledge, it has not been explored whether these elements can be used as a strategic tool in campaign management by the community manager.

Understanding the *profile* of community members that can be properly treated, helps us to increase understanding of which members must be treated because of what reason. Members can be segmented based on traditional characteristics such as demographics, however, as communities are dynamics environments and members change over time (Faraj et al., 2011), dynamic variables such as activity and writing style are more useful (Kristof Coussement et al., 2017; Stephan Ludwig et al., 2014). Recent advances in literature has recognized that community writing style is an important signaling factor for member participation (Stephan Ludwig et al., 2014). In particular, a self-interest oriented and positive emotional style (Kristof Coussement et al., 2017). However, it has not been explored whether these linguistic traits can serve as indicators for which members that must be motivated using a treatment campaign.

Community members can be reached through many contact *channels*, ranging from physical channels such as meetups (McAlexander et al., 2002) to virtual such as discussion forums or e-mail. However, email campaigns are widely used to encourage IC participation (Troch & De Ruyck, 2014). From an IMP management perspective, an email strategy is favorable, as opposed to strategies that only can be used within community platform boundaries, as it allows to contact members outside the community platform, where members could be found that show IMP and are not motivated enough to go onto the platform itself. However, emails have important negative side effects due to low distribution costs (Pavlov, Melville, & Plice, 2008). They are omnipresent, increasing individuals' information processing costs. They sometimes lack usefulness, weighing on individuals' goodwill to open the email and satisfy anticipated usefulness. As a result, individuals are becoming increasingly prudent towards emails, reducing the potential positive impact of such communication strategies. Therefore, aiming to realize the full potential benefit of email campaigns suggests the need for moderators to identify the recommended treatment characteristics.

This study investigates the viability of a proactive motivational e-mail campaign to reduce IMP in online innovation communities. To identify the optimal treatment characteristics, it explores the usage of a targeted and untargeted scope, the motivational power of a hedonic, cognitive and social message and characteristics of persuadable member characteristics through analyzing a self-interest oriented and positive emotional writing style. Therefore, this study considers the following research questions:

RQ1a. *Does a proactive untargeted motivational email campaign reduce IMP?*
RQ1b. *Which motivational message in an untargeted proactive email works best?*
RQ2a. *Does a proactive targeted motivational email campaign reduce IMP?*
RQ2a. *Which motivational message in a targeted proactive email works best?*
RQ3. *Which member profile can be motivated?*

This paper contributes to IC literature in the following three ways. First, while research has mainly focused on reactive IMP reduction strategies (e.g., Preece 2000; Ludwig et al. 2014; Liao, Huang, and Xiao 2017), literature still lacks understanding on effective proactive strategies, both untargeted and targeted contact. Using a field experiment of 4 ICs and by comparing both a proactive untargeted and targeted strategy, this study reveals the viability of a targeted approach to proactively reduce IMP. Second, while literature has identified member participation motivational drivers and used these as suggestions for proper community management (Bagozzi & Dholakia, 2002; Baldus et al., 2015; Nambisan & Baron, 2009; Schau et al., 2009; M. Wasko & Faraj, 2000), it has not been explored whether these can be effective in treatment campaigns for IMP reduction. By comparing cognitive, hedonic and social motivational emails, this study compares the impact of difference and viability of the different motivational elements. The results confirm the impact difference between the different motivations and reveal that only cognitive motivation can be exploited to proactively reduce IMP. Third, while research has been recognizing the important signaling role of writing style for member participation (Kristof Coussement et al., 2017; Stephan Ludwig et al., 2014), it has not explored whether these traits can be used as indicators for persuasiveness of treatment. This study relies on automated text analysis and shows that members with a positive emotional writing style are more likely to be positively influenced by a motivational email and show constructive community behavior in the future.

This study is structured as follows: Section 2 clarifies the background by explaining untargeted, targeted communication, member motivation and member profile. Section 3 explains the experimental design through the dataset description, field test explanation, operationalization, experimental parameters and statistical evaluation, Section 4 describes the results and Section 5 the conclusion and directions for further research.be pursued to achieve positive community impact.

2. BACKGROUND

2.1. A proactive e-mail campaign

In innovation literature, the concept of proactivity is explored in the context of proactive member contributions containing more novel insights than reactive contributions (Mahr & Lievens, 2012) and suggested as an approach to manage the IC (Kristof Coussement et al., 2017; Nambisan & Baron, 2009). Proactive approaches anticipate on future expected events

(Blattberg et al., 2010) and are favored over reactive approaches (Coltman, 2007). Proactive treatment campaigns are already successfully applied to other domains such as for customer churn reduction (Verbeke, Dejaeger, Martens, Hur, & Baesens, 2012), suggesting the potential benefit for IMP reduction. Despite the proactivity term has been used (more or less as a loose term) in community literature, it's important to explicitly define it to indicate the benefit over reactive IC management.

Therefore, using Figure 8, formally, by relying on Blattberg, Kim, and Neslin (2010), to define the task of a proactive motivational e-mail campaign for IMP reduction in ICs, the following elements are considered:

- Three points in the community timeline, i.e. the present moment t_0, a point in time in the past $t_0 - t$ and future $t_0 + t$.
- Member participation behavior B is evaluated at the present moment t_0 (B_0) and at some point time t in the future (B_t). From a community perspective, member participation behavior B can be constructive and useful ($B = 0$) or useless and be inferior ($B = 1$).
- Member participation behavior X is evaluated between a point in time in the past $t_0 - t$ and the present moment t_0.
- The e-mail channel is used to reach community members and the e-mail E includes a motivational message to influence member participation behavior.
- Moderators can decide to treat a member ($E = 1$) or leave them at rest ($E = 0$).

Now, as opposed to a reactive approach, where the moderator sends the e-mail E at the present moment t_0, using information of observed participation behavior B_0, in a *proactive e-mail campaign*, the moderator sends an e-mail E at the present moment t_0, based on anticipated future participation behavior B_t.

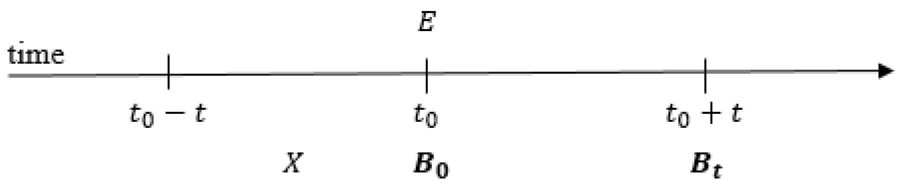

Figure 8 Proactive inferior member participation reduction

Proactive approaches have important benefits over reactive approaches due to preventive ability and cost effectiveness (Blattberg et al., 2010). Moderators will not have to pursue damage control and aim to minimize the impact for the community of observed IMP ($B_0 = 1$), but can anticipate on "latent" IMP ($B_t = 1$) and send a motivational e-mail to prevent it. Moderators will not have to go for other more expensive treatment actions, because things have not gotten so bad yet that IMP can be easily and cost effectively treated. However, as they anticipate on future IMP, they are subject to imperfect predictive accuracy (Blattberg et al., 2010). Both cases can occur of false negatives such as when IMP is expected, but future participation will be constructive ($B_t = 0$), and false positives such as when constructive participation is expected, but IMP will be observed ($B_t = 1$). This implies that some individuals may receive an unintended motivational email, increasing their e-mail processing costs, while others who had to be treated, are not, resulting in a loss for the community.

The purpose of a proactive motivational e-mail is to minimize the rate of future IMP ($B_t = 1$). To evaluate the impact of the campaign, one needs to distinguish between four theoretical outcomes of a treatment action (Nicholas Radcliffe, 2007; Spiegel, 2013), such as visualized in Figure 9. There are members who will have a higher participation rate ("sure things") or lower ("lost causes") regardless of the motivational e-mail. There are members who would demonstrate future IMP and participate less, but will participate more because of the e-mail ("persuadables"). There are members who would participate in more community topics, but changed their mind because of the action and will participate less ("do-not-disturbs"). For the latter case, this may be the e-mail too much as it has an averse negative participation reaction consequently. Evaluating the parameters of a proactive e-mail treatment campaign, in addition to the cost for community management, boils down to assessing the approaches with respect to obtaining the different member profiles.

Response when **treated** ($E = 1$)	Inferior participation ($B_t = 1$)	*Do-not-disturbs*	*Lost causes*
	Superior participation ($B_t = 0$)	*Sure things*	*Persuadables*
		Superior participation ($B_t = 0$)	Inferior participation ($B_t = 1$)
	Response when **not treated** ($E = 0$)		

Figure 9 Member response types to (none) treatment

2.2. *A proactive untargeted e-mail*

A *proactive untargeted e-mail* strategy for IMP reduction is a proactive method that follows the "one-size-fits-all" paradigm where the moderator treats all individuals equally using the same e-mail campaign. The untargeted approach is a straightforward option and must be viewed as the default way to determine the scope of the campaign. It is a simplistic approach as moderators treat all members using the same single e-mail, and is cost effective as no decision must be made on who to treat. Moderators can spend their time on the innovation task and when they receive signals of potential future reduced activity and thus expect IMP, they can use this approach to motivate the community as a whole. Through experience or automated approaches like language monitoring, moderators can become aware of these signals of reduced activity such as low positive emotional community vibes (Kristof Coussement et al., 2017) or divergent language style (Stephan Ludwig et al., 2014). However, the assumption of homogeneity may be difficult to support in an IC. All members are treated equally, yet, communities are fluid environments and members change over time (Faraj et al., 2011), suggesting a heterogeneous member base and the need for adapted treatment. A single general positive community impact is expected from the action, yet, negative reactions to the treatment could occur, such as visualized in Figure 9. Therefore, from an execution point of view, a proactive untargeted e-mail campaign is highly beneficial, but from an impact point of view, it should be used with extra caution.

2.3. A proactive targeted e-mail

Community literature expressed the need to avoid allocating untargeted resources to all types of members and need for heterogeneous treatment approaches (Liao et al., 2017). Previous research proved the benefit of proactive targeted efforts over untargeted (Langerak & Verhoef, 2003; Wei & Chiu, 2002) and usefulness for direct e-mailing (Reutterer, Mild, Natter, & Taudes, 2006). This shift towards customer-centric and segmented communication can be explained to technology (Kumar, 2010) such as big data analytics, which can be perfectly adopted in the data-rich environments of ICs (Kristof Coussement et al., 2017). Targeted approaches assume a heterogeneous member base as not everyone is treated equally. Moderators can use experience to make targeting decisions or can rely on analytical models to make more objective and cost effective decisions (Kristof Coussement et al., 2017). Using historical data and classification techniques, one can construct propensity models to predict future IMP behavior (Debaere et al., 2017) ($P(B_t = 1|X)$) or response models to predict favorable treatment response ($P(B_t = 0|E = 1, X)$). Then, moderators can focus their treatment efforts by only targeting those members with highest IMP risk or positive treatment response likelihood, respectively. However, despite the first modeling approach anticipates on future expected events, treating high risk individual can still result in unfavorable outcomes (Manahan, 2005) and while the latter already considers treatment, it considers only the response after treatment. Hence, these modeling approaches are not able to distinguish the different treatment outcomes such as visualized in Figure 9 (Rzepakowski & Jaroszewicz, 2012). Recognizing these flaws of traditional prediction methodology, literature explored a new approach to target the right individuals in a treatment campaign, i.e. uplift modeling.

Despite huge potential benefits, since one of the first papers on the topic by Radcliffe and Surry (1999), uplift modeling has receive little attention in literature. Uplift modeling is also known under many synonyms such as net lift modeling, differential response analysis or persuasion modeling. Uplift modeling has already many successful applications by increasing the effectiveness of marketing (Lo, 2002) and retention campaigns (Guelman, Guillén, & Pérez-Marín, 2012), while showing the huge benefits for direct e-mailing (Rzepakowski & Jaroszewicz, 2012). A *proactive targeted e-mail* strategy for IMP reduction is a proactive method where the moderator treats members differently and only targets those individuals that can be positively influenced with an e-mail campaign. Uplift modeling can evaluate the causal impact of a treatment action and is able to distinguish the four different member profiles of Figure 9 (Nicholas Radcliffe, 2007; Spiegel, 2013). It helps moderators to identify the members that will be positively influenced using an e-mail campaign, while making sure to avoid annoying the “do-not-disturbs”. It helps to leave the “sure things” at rest and avoid efforts on the “lost causes”. For those “lost causes” other treatments could be explored. To construct uplift models, a field experiment need to be set up, in which members are randomly allocated to either a treatment ($E = 0$) and non-treatment group ($E = 0$). Uplift modeling predicts $P(B_t = 1|E = 1, X) - P(B_t = 1|E = 0, X)$, which estimates the increase in response probability if members are treated over the probability if they are not treated. The output of the model, the uplift score, reflects the likelihood that a member can be motivated using the motivational e-mail. Important to mention is the framework of Figure 9 with the different member profiles is purely theoretical as a member can never be treated and not treated at the same time. In the modeling process, only a prediction model is constructed that aims to predict the incremental response, not whether a member belongs to one of the four different member profiles.

2.4. Motivational message

Members continue participation because they anticipate to receive benefits from future interaction (Nambisan & Baron, 2009). Literature has identified three important types of motivation for community participation: hedonic, social and cognitive. Members receive hedonic benefits from community participation as it is fun (Baldus et al., 2015; M. Wasko & Faraj, 2000), interesting, pleasurable as mentally stimulating through member interaction (Nambisan & Baron, 2009) and hedonic engagement evolves over time (Schau et al., 2009). Cognitive benefits reflect tapping into the knowledge exchange of the community (M. Wasko & Faraj, 2000), better understanding knowledge about the products, the underlying technology and their usage (Nambisan & Baron, 2007, 2009). Social benefits reflect the benefits that come from developing the social and relational ties over time (Nambisan, 2002; Nambisan & Baron, 2009) and the "we-intentions" that express to be part of the group (Bagozzi & Dholakia, 2002). As members interact because of the beliefs concerning benefits from future interaction, Nambisan and Baron (2009) argue that firms must take proactive measures to create ICs that would contribute to such benefits. This arguments in favor to pursue proactive stimulation of community members using a motivational message. Reminding members about their anticipated benefits through integrating them in a motivational message E would directly exploit their reasons of participation. In contrast to prior research (Nambisan & Baron, 2009), that explored the motivations at point t_0 and measured participation behavior (B_t) at a future point $t_0 + t$, in this study, we exploit their point of motivation at point t_0 to influence their behavior at a future point $t_0 + t$ through a motivational e-mail message.

2.5. Member profile

Literature identified self-interest orientation and positive emotionality to be important concepts in innovation and collaboration (Bagozzi & Dholakia, 2006; Kristof Coussement et al., 2017; Hu & Liden, 2015; Madrid, Patterson, Birdi, Leiva, & Kausel, 2014; Tsai & Bagozzi, 2014). First, self-interested individuals are more focused on pursuing personal goals and fulfilling their own needs than needs of the others (Meglino & Korsgaard, 2004, 2006). Self-interest is aligned with individuals' future actions (Miller, 1999). When members express self-interested behavior, this could indicate that they are concerned with their future actions, which could suggest that it is the right moment to influence and treat them. Second, individuals who exhibit positive emotionality tend to be positive into their affect, which translates into greater cognitive effort (Sullivan & Conway, 1989). The broaden-and-build process theory (Fredrickson, 2011) explains how experiencing positive emotions broadens people attention, cognition and action, which develops their physical, social and intellectual resources. When members express positivity in the IC, this could be an indicator of being in the broaden-and-build process and the right mindset to be influenced. Therefore, this could be the right moment to treat these individuals.

In ICs, in addition to analyzing members' language content ("what they say") to get insights for innovation challenges, moderators can analyze their language style ("how they say it") to get insights into future member participation (Kristof Coussement et al., 2017; Stephan Ludwig et al., 2014). The words people use reveal a lot about their psychological selves (Pennebaker, Mehl, & Niederhoffer, 2003). Self-interest oriented behavior and positive emotional writing style can be explored by analyzing members' writing style and is explicitly linked with IMP (Kristof Coussement et al., 2017). As online communities are dynamic environments (Faraj et al., 2011) and self-interest and positive emotionality change over time (Kuppens, Oravecz, & Tuerlinckx, 2010; Meglino & Korsgaard, 2006), the self-interest oriented and positive emotional writing styles in the ICs reflect the current behavior. Using indications through their writing style X that members are concerned with their future actions, could give moderators the opportunity to identify whether members could be motivated and persuaded through the motivational e-mail.

3. EXPERIMENTAL SETUP

3.1. Research setting

The sample is obtained from a European market research consultancy and contains 5,828 posts written by 355 members from 4 firm-hosted Dutch ICs. The market research consultancy firm organized these ICs commissioned by the companies and organized different community topics corresponding with different innovation challenges. The consultancy firm recruited members based on high interest in the focal community topic or extensive usage experience. Members did receive a small financial incentive to participate, but ongoing participation was mainly due to intrinsic motivation. The communities were managed by a moderator, who had to encourage participation and guide the innovation challenge process through introducing questions. In a collaborative way, members could participate and share their opinion by answering on the moderator's question or responding other members' posts.

3.2. Experimental setup

The time scope of the field experiment over all ICs ranged from February to June 2016. Using Figure 8, the field experiment can be explained as follows: the moderator send an e-mail E at moment t_0 .The independent period, ranging from a point in time in the past $t_0 - t$ to the moment a community member observed the e-mail, was two months, while the dependent period, ranging from the moment the e-mail was seen up to a point in the future $t_0 + t$, consisted of one month. Hence, the total time scope of the experiment was three months. In this period, community activity was high as many new topics were created. To make sure that there was sufficient participation throughout this whole period, an e-mail campaign in a two-step e-mail procedure was implemented at the end of the independent period to encourage participation and reduce IMP in the dependent period. At the end of the independent period, for a new topic, the moderator sent a motivational e-mail, while a reminder e-mail consisting of a copy of the first e-mail and a call to action for participation in the active topics was sent after the next new topic. To increase chances of opening the e-mail, this two-step email procedure was used. The members that are included in the sample are only those members that opened at least one of the two e-mails. Table 1 shows the opening rate of the e-mails for the different ICs.

For each community, members were randomly allocated without replacement to one of four groups. Members in three out of the four groups have been treated and received an e-mail ($E = 1$). The difference between these groups consists of a different motivational element that is included, i.e. a hedonic, social or cognitive element. The fourth group represents the control group as those members did not receive any email ($E = 1$). Table 32 shows the characteristics of the community and the experiment.

Id	**Sector**	**Purpose**	**Members ($E = 1$)**	**Members ($E = 0$)**	**Open rate**	**Posts**	**First e-mail (t_0)**	**Second e-mail**
1	FMCG	New marketing strategy	61	18	67,77%	951	09/03/2016	23/03/2016
2	Technology	Improvements for online consumer platform	45	20	58.44%	1266	11/04/2016	13/04/2016
3	FMCG	New shop design and footwear	42	16	71,18%	449	29/03/2016	12/04/2016
4	FMCG	New food products	115	38	79,31%	3162	21/03/2016	23/03/2016

Table 32 Descriptive and experimental characteristics of each community

3.3. Motivational e-mail

To motivate members to participate constructively, a motivational email campaign was created and three types of motivational messages were included. The general motivational format of the message is the same for all three types of emails and expressed the moderator's personal wish for the member to participate constructively in the upcoming period. The subject of the email was "two wishes which you have not received". For each of the three e-mails, the two wishes corresponded with social, cognitive and hedonic anticipated benefits of Nambissan and Baron (2009) for community participation. The whishes were expressed as wishes from the moderator and the content directly related to items of the scale of Nambissan and Baron (2009). As the language of interaction in the ICs was Dutch, the motivational email was written in Dutch. Table 33 lists the wishes that are used for the different motivations and indicates the direct link to the items used by Nambissan and Baron (2009). A direct translation of these items from literature was used and a pretest among academics made sure the motivational e-mails are valid and meet the intended anticipated benefit. The e-mail was finalized with a rhetoric question and related directly to the type of anticipated benefit: i.e. "Do you think this year will become a <type> year?", for which the type relates to "pleasurable", "educational"," social" for the hedonic, cognitive and social motivational type, respectively. Appendix 1 shows an example of the motivational e-mail and represents the hedonic e-mail and the reminder that was sent.

Benefit	**Moderator whishes**	**Items**
Hedonic	"I hope you will get a lot of **enjoyment** from **co-developing** and **influencing new concepts and ideas** in the world of <domain>"	Derive enjoyment from problem solving, idea generation, etc.
	"I hope you will experience **fun** and **receive pleasure** from your **participation** in the community and you will be **entertained** through all the **brainstorms and challenges** that we have created for you"	Derive fun and pleasure. Entertain and stimulate my mind
Social	"I hope that because of your participation in this community you **will meet plenty of new people** or even make **extra friends** for life"	Expand my personal/social network.
	"I hope that we can make you **feel at home**, so you will become **more involved** and **experience yourself as one of us**"	Enhance my sense of belongingness with this community. Enhance the strength of my affiliation with the customer community.
Cognitive	"I hope that through all the brainstorms and challenges we have created for you, you will become better **informed** about the existing <domain> **concepts, ideas** and **daily usage**"	Enhance my knowledge about the product and its usage.

“I hope you will gain more **information** about the **newest trends** and **developments** in the world of <domain>”	Enhance my knowledge about advances in product, related products, and technology.

Table 33 Used items of Nambisan and Baron (2009) for the motivational e-mails

3.4. Variable operationalization

Dependent variables

To operationalize the dependent variable, this study builds on the definition of member participation quantity of Coussement et al (2017), which reflects the degree of active community topics, a members posts in. Using Figure 8, for the dependent variable, member participation quantity at the end of the independent period t_0 (B_0) is compared to the end of the dependent period $t_0 + t$ (B_t). As the purpose of the treatment campaign is to target those individuals that will demonstrate future IMP, if there is a decrease in participation quantity from t_0 to $t_0 + t$, the dependent variable is labeled as ‘1’, while for an increase, the variable is labeled as ‘0’.

Model variables

To make targeting decisions, the uplift models need to have information at their disposal, which in this study are represented by different types of member variables: activity behavior, language style, language content, interaction variables and the treatment variable. As an input for direct marketing models, behavioral data is easy accessible and of high significance as it is able to influence the choice of customers (Bose & Chen, 2009). The activity variables are defined in function of members’ posting behavior and relate to recency, frequency and monetary (RFM) variables, which are widely used in marketing models (Olson & Chae, 2012; Tamaddoni Jahromi, Stakhovych, & Ewing, 2013). The language style variables are constructed using LIWC (Pennebaker, 2007), which allows to analyze how members’ posts are written. LIWC is a dictionary based approach that measures for each post the percentage of words that belong to respective word categories and widely used in academic literature (Barasch & Berger, 2014; S Ludwig, Ruyter, & Friedman, 2013; Stephan Ludwig et al., 2014). Consistent with prior research, several word categories as an input for member participation models are used such as emotions (Kristof Coussement et al., 2017), cognitive words and pronouns (Stephan Ludwig et al., 2014). Content variables are constructed to identify shared content characteristics between members’ posts. Following literature (K. Coussement, Benoit, & Antioco, 2015), the language content variables are constructed using the guidelines of Feldman and Sanger (2007).

The bag-of-words approach is used to convert textual information into numerical information, while latent semantic analysis was used to construct a low-dimensional matrix. Appendix 2 visualizes this whole process. The treatment variable is binary and indicates whether a member is treated (1) or not (0).

Member profile

To operationalize the self-interest oriented and positive emotional writing style, this study builds on the operationalization of Coussement et al. (2017). The variables are constructed using LIWC (Pennebaker, 2007). For self-interest orientation, we rely on literature that defines self-interest as a bipolar continuum in which high self-focus and other-focus is positioned at both ends of a bipolar continuum (Haynes, Josefy, & Hitt, 2015; Meglino & Korsgaard, 2004, 2006). The self-interest-oriented writing style is operationalized by considering the percentage of the self-referential word category (*self*) and other-referential (*other*) words. Both categories contains 12 words such as "I", "me" and "mine" versus "her," "they," and "one." Members' self-interest oriented writing style is calculated by subtracting the average of used self-referential words and other referential words per post in the independent period. For positive emotionality, we rely on both positive and negative affect (Kowalski, 2000). The operationalization of positive emotional writing style is similar to self-interest oriented writing style. Here, the positive (*posemo*) and negative word (*negemo*) categories of LIWC are used. The LIWC dictionary contains 685 and 1332 negative emotion words respectively.

The control variables are consistent with Coussement et al. (2017) and are membership length, member participation quantity, community size and community participation quantity. Membership length is calculated by the number of days the member is active in the community. Member participation quantity is measured by the total number of posts. Community size is measured by the number of active members in the community. The community participation quantity reflects the number of posts in the community.

3.5. Uplift model

In literature on uplift modeling, regression-based and tree-based approaches have been mainly explored. This study considers the tree-based approach as these are often adaptions from well-known classification algorithms, while accommodating for the treatment and control group explicitly. To cope with the problems of single-based decision trees such as high variance because of the hierarchical nature of the splitting process, the use of multiple decision trees have been proposed (e.g. Guelman et al., 2012; Soltys, Jaroszewicz, & Rzepakowski, 2015). This study considers the causal conditional inference forest (ccif) (Guelman et al., 2015), as it is constructed for decision support in marketing interventions explicitly and shows the best performance among alternative methods (Guelman et al., 2015). Furthermore, random forest models are reliable in churn prediction settings (Kristof Coussement & De Bock, 2013). The ccif classifier proposes an improved tree-based method that estimates personalized treatment effects. It solves the problem of the uplift random forest (Guelman et al., 2012) such as over fitting and the selection bias towards covariates with many possible splits. This method implements recursive partitioning in a causal conditional inference framework. The method recursively partitions the input space into subgroups with heterogeneous treatment effects. Appendix 3 shows the pseudo-code for the ccif approach. The different split criteria that are explored are Euclidean Distance, Kullback-Leibler divergence, Chi-squared divergence and the Interaction method.

Consistent with prior research (Buckinx, Verstraeten, & Van den Poel, 2007), we use leave-one-out-cross validation to generalize the model over the dataset. We opt for this method as it is superior for smaller datasets (Goutte, 1997). This cross validation scheme iteratively loops through all observations for which at each iteration it takes one observation as a test set and the other observations as the training set. This approach has the advantage of giving a maximal amount of observations to train the model and being a deterministic procedure as there is no random sampling is used (Witten & Frank, 2005). However, the approach is computationally intensive, but feasible in this study context.

To select the final model, through exploring the different experimental model parameters in the leave-one-out cross validation setting, the model is selected with the highest qini performance on the training sample. This metric is explained in the following paragraph.

3.6. Evaluation

To evaluate the impact of the email for different groups, we use the chi-squared test. It is a non-parametric test to analyze group differences when the dependent variables is categorical. To evaluate the quality of the uplift models, consistent with previous research (Nj Radcliffe & Surry, 2011; Rzepakowski & Jaroszewicz, 2012), we use the qini coefficient and the qini curve. The qini coefficient is a generalization of the Gini coefficient, which allows to analyze the goodness-of-fit of response models. The qini measure is based on the area under the incremental gains curve or qini curve (Nj Radcliffe & Surry, 2011). The qini curve plots the cumulative difference of the IMP rate between the treatment group and control group as a function of the selected proportion of the member base. As it cannot be determined whether an individual is a persuadable or a sure thing of the framework in Figure 9 as a member cannot be treated and not treated at the same time, the evaluation must be done for each specific proportion of the member base. As data of the experiment is sparse, this proportion is determined by quintiles. The qini value is the ratio of two area, i.e. the area between the actual gains curve and the diagonal corresponding to random targeting and the same area but now for the optimal gains curve.

4. RESULTS

	General	Hedonic	Cognitive	Social
Treatment	36.50%**	37.50%*	33.33%	38.82%**
Control	25.00	25.00		

** *p<.05;* *p<.10*

Notes: Results from the chi-squared test are reported with asterisks indicating significance levels.

Table 34 Inferior member participation rate of the untargeted proactive motivational e-mail

Table 34 demonstrates the effect of a proactive untargeted motivational e-mail campaign and the impact of the "no e-mail" strategy. It shows both the results for the general motivational e-mail campaign (RQ1a) and the e-mail campaign with different motivational elements (RQ1b).

4.1. RQ1a

The IMP rate for the treatment group is 36.50%, while the control group has an IMP rate of 25.00% ($\chi^2 = 4.05, p < .05$). Thus, the average treatment effect of a proactive untargeted motivational email is 11.5% increase in IMP.

4.2. RQ1b

The motivational e-mail with a hedonic element returns an IMP rate of 37.50% ($\chi^2 = 3.28, p < .10$), for the cognitive element 33.33% ($\chi^2 = 1.53, p > .10$), while a social message has an IMP rate of 38.82% ($\chi^2 = 3.90, p < .05$). Given the control group has an IMP rate of 25%, this implies that the treatment effect of a proactive untargeted e-mail with hedonic motivational message obtains a 12.50% increase in IMP, a cognitive motivational message increases the IMP rate by 8.33%, while an e-mail with social message obtains a 13.82% increase in IMP.

	% of members	General	Hedonic	Cognitive	Social
Random model	**20%**	-.0230	-.0250	-.0166	.0276

	40%	-.0460	-.0500	-.0333	-.0552
Uplift model	**20%**	-.0027	-.0817	.0129	-.0371
	40%	-.0411	-.0129	.0297	.0485

Table 35 Cumulative incremental gain of the proactive targeted motivational e-mail on the inferior member participation rate

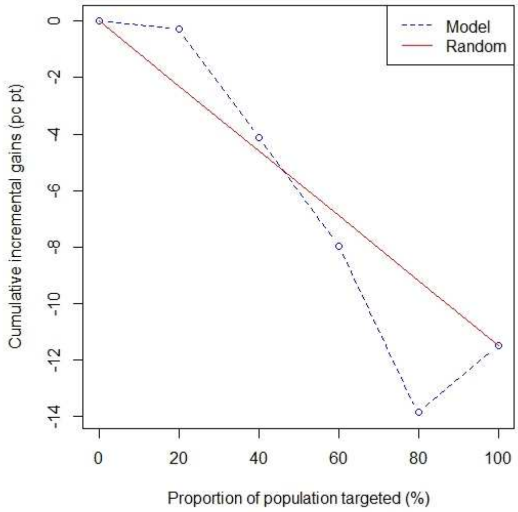

Figure 10 Qini curve of a motivational e-mail campaign (RQ2a)

Table 35 shows the effect of the proactive targeted motivational e-mail in general (RQ2a) and using the different motivational elements (RQ2b). A positive gain indicates a positive impact of the motivational e-mail and a lower IMP rate consequently. A negative gain indicates a negative impact of the motivational e-mail and a corresponding higher IMP rate. Figure 10 demonstrates the qini curve and visualizes the incremental impact for all the five groups of members of a general proactive targeted motivational e-mail (RQ2a). Figure 11, Figure 12, Figure 13 show the qini curves for the proactive targeted motivation e-mail with a hedonic, cognitive and social element, respectively.

4.3. RQ2a

Treating members with a proactive targeted motivational e-mail and selecting them at random increases the IMP rate as the cumulative incremental gain for 20% of members is -.0230, while for 40% of members this is -.0460. When targeting members using the uplift model, treating 20% most persuadable members gives a cumulative incremental gain of -.0027, while for 40% of most persuadable members this is -.0411. Thus, a proactive targeted e-mail using the uplift model obtains higher incremental gains than the random model, but does not achieve positive incremental gains.

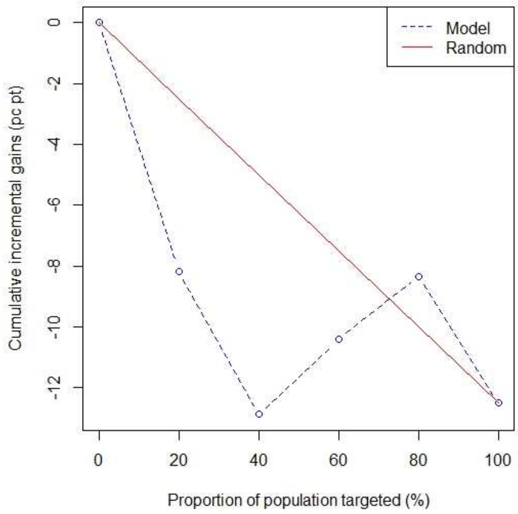

Figure 11 Qini curve of a motivational e-mail campaign (RQ2b) - hedonic motivational message

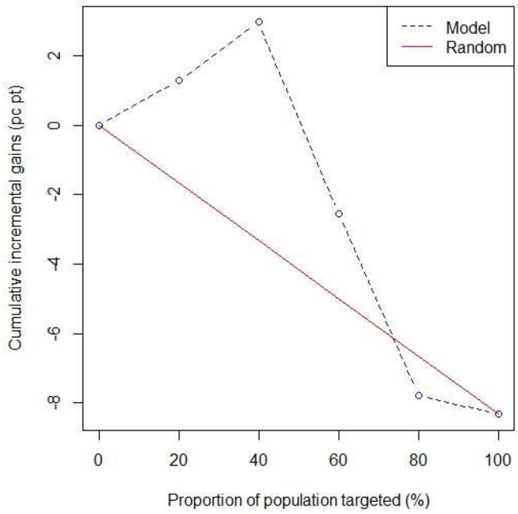

Figure 12 Qini curve of a motivational e-mail campaign (RQ2b) - cognitive motivational message

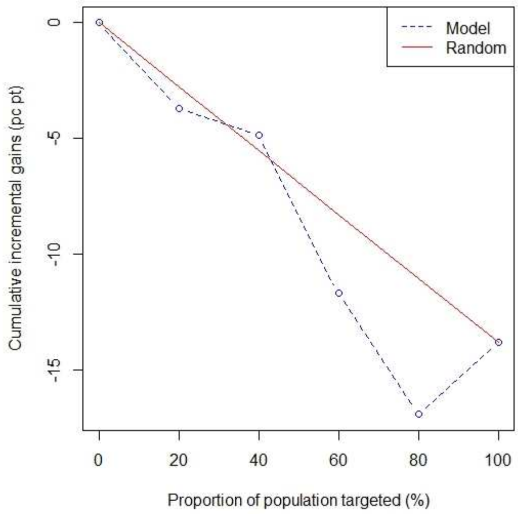

Figure 13 Qini curve of a motivational e-mail campaign (RQ2b) - social motivational message

4.4. RQ2b

Treating members with a proactive targeted e-mail with a hedonic motivational message and selecting members at random increases the IMP rate as for 20% the cumulative incremental gain is -.0250, while for 40% of members this is -.0500. Treating members with a proactive targeted hedonic motivational e-mail using the uplift model has a similar negative IMP effect as the incremental gain for 20% of the most persuadable members is -.0817, while for 40% of members this is -.0129. Thus, the proactive targeted e-mail using the uplift model performs worse than the random model and does not achieve positive incremental gains.

When targeting members at random using a proactive targeted e-mail with a cognitive motivational message increases the IMP rate as the cumulative incremental gain for 20% of members is -.0166, while for 40% of members this is -.0333. Selecting members using the uplift model and treating them using an e-mail with a cognitive motivational message decreases the IMP rate as the cumulative incremental gain for 20% of the most persuadable members is .0129, while for 40% of members this is .0297. Thus, using the proactive targeted e-mail and selecting members through the uplift model performs better than the random model and achieves positive incremental gains.

Treating members at random with a proactive targeted e-mail with a social motivational message increases the IMP rate as for 20% of members the cumulative incremental gain is -.0276, while for 40% of members this is -.0552. Selecting members using the uplift model and treating them with an e-mail with social motivational message increases the IMP rate as the cumulative incremental gain for 20% of members is -.0371, while for 40% of members this is

-.0485. Thus, the uplift model performs worse than the random model and achieves no positive incremental gains.

Variable	**Uplift score**
Self-interest oriented writing style	-1.32E-03
Positive emotional writing style	8.548E-03**
Membership length	1.186E-05
Member participation quantity	-8.517E-04
Community size	-1.462E-03**
Community participation quantity	4.376E-05**

*** p<.05; *p<.10*
Notes: Regression coefficients are reported with asterisks indicating significance levels.

Table 36 Regression results of the relationship between member's linguistic profile and the uplift score

Table 36 demonstrates the regression results of the relationship of member’s writing style and the control variables with their uplift score.

4.5. RQ3

As from all the approaches only the proactive targeted e-mail with cognitive motivational is able to positively influence the members, to analyze which members that can be motivated using a motivational e-mail, this analysis focuses only on the motivational e-mail with a cognitive motivational message.

A self-interest oriented writing style of the member is non-significantly negatively related to the uplift score ($\beta = -1.32E^{-3}, p > .10$), while a positive emotional writing style is positively significantly related to the uplift score ($\beta = 8.548E^{-3}, p < .01$). Membership length has no significant relationship with the uplift score ($\beta = 1.186E^{-5}, p > .10$). Membership participation quantity is not significantly positively related to the uplift score ($\beta = -8.517E^{-4}, p > .10$). Community size is significantly negatively related to the uplift score ($\beta = -1.462E^{-3}, p < .01$). Community participation quantity is significantly positively related to the uplift score ($\beta = 4.376E^{-5}, p < .01$).

5. DISCUSSION

Recent advances on innovation community management dictate that moderators must shift from reactive to proactive community management to effectively reduce IMP. When aiming to solve this problem using the business analytics paradigm, three stages need to be tackled (Delen & Demirkan, 2013). A descriptive stage that identifies IMP (“what has happened?”), a predictive stage that allows to proactively identify it ("what might happen?"), a prescriptive stage that tells the moderator how to prevent it ("what should we do"). Coussement et al. (2017) tackled the descriptive phase and showed that linguistic style indicates inferior member participation, while Debaere et al. (2018) proved that IMP can be predicted using multi-label classification methodology. Despite these valuable efforts, the last prescriptive phase has not been tackled. This study builds on previous research and tackles the last prescriptive step by exploring how the moderator should construct a proactive e-mail campaign to proactively reduce IMP.

5.1. Treatment scope

With regards to the treatment scope of the motivational e-mail, in general, the results indicate that both a proactive targeted and an untargeted motivational e-mail campaign are not able to reduce IMP in online innovation communities. When comparing to the strategy of sending no motivational e-mail at all, the untargeted e-mail increases the IMP rate by 11.5%. A similar negative community impact is also observed for the targeted e-mail that selects members based on their probability of being positively influenced by the e-mail. However, the results indicate that the discussion should be more nuanced as the viability of the treatment scope depends on the construction of the e-mail and the usage of the motivational element. For the proactive untargeted e-mail, all motivational elements still produce an e-mail that performs inferior to the strategy of no e-mail. The untargeted motivational e-mail with a hedonic, cognitive and social element increases the IMP rate with 12.50%, 8.33% and 13.82% respectively. The proactive targeted e-mail with a hedonic and social motivational element is still inferior to sending no e-mail at all as treating the 20% most persuadable members increases already the IMP rate with 8.17% and 3.71%, respectively. Yet, a proactive targeted e-mail with a cognitive motivational element allows to reduce IMP in online innovation communities. When 20% of the most persuadable members are treated, the IMP rate can be reduced with 1,29%, while targeting the top 40% results in a reduction of the IMP rate by 2,97%. As the IMP rate of the control group is relatively high, these results indicate the huge benefits of this approach. When observing that random selection of 20% of members increases the IMP rate by 1,66%, while at 40% it is increased by 3,33%, the results prove that the uplift model allows to target the right individuals. When leaving the other members at rest, IMP in online innovation communities is effectively reduced.

Consistent with previous research (Langerak & Verhoef, 2003; Wei & Chiu, 2002), the results indicate the superiority of the targeted strategy over the untargeted approach. Furthermore, they support prior research (Reutterer et al., 2006) that identify the negative effect of the untargeted email campaign as opposed to the positive effect of a targeted campaign. Despite the benefits of simplicity and ease of use of the untargeted approach, which are less prominent in the targeted approach, the adoption of the untargeted motivational e-mail over the targeted cannot be supported due to the difference in impact on the community. The increase effect in the IMP rate of the untargeted approach can be directly attributed to inability to make a distinction between the members that need treatment and those that do not. The IMP reduction effect of the targeted approach can be directly attributed to uplift modeling that allows to identify the members which future IMP behavior can be reduced by sending them a motivational email. The ability to only treat those members is especially useful in the context of e-mail campaigns. Moderators must send a motivational e-mail to the “the persuadables” as they are motivated by it and would otherwise negatively impact the community without treatment. They should not treat the “do-not-disturbs” as a motivational e-mail stimulates them into inferior participation, while they would have participated constructively otherwise due to “the e-mail too much”. The “lost causes” cannot be rescued by a motivational e-mail, but potentially other (more expensive) treatment actions could trigger them. The “sure things” are not directly bothered by the e-mail, but they should not be treated as it is not directly useful. The treatment could increase their annoyance towards e-mails and become a “do-not-disturb” or “lost cause” in the long term.

5.2. Motivational element

The results indicate that the choice of the motivational element influences the outcome of the e-mail campaign. In the untargeted approach, all motivational elements create e-mails that perform worse than sending no e-mail at all. The e-mail with a hedonic, cognitive and social motivational element increases the IMP rate by 12.50%, 8.33% and 13.82%, respectively. The e-mail with cognitive motivational element performs the best, yet, worse than sending no e-mail at all. In the targeted approach, both e-mails with hedonic and social elements are not able to positively influence individuals as treating the top 20% most persuadable members increases the IMP rate by 8.17% and 3.71%, respectively. However, this is not the case for the e-mail with cognitive element as up to 40% of the most persuadable members can be treated, decreasing the IMP rate by 2.97%. The stronger effect of the cognitive motivation compared to hedonic and social is consistent with prior research (Nambisan & Baron, 2009). This effect would support social exchange theory that states that community members are motivated to share knowledge in ICs as it helps them to move closer to their personal goal of enhancing their reputation (Blau, 1964; M. M. Wasko & Faraj, 2005). This study builds on it by revealing that moderators can anticipate on this need through a cognitive e-mail message to motivate community participation.

The ability to include a cognitive motivational element in an e-mail, but not a social and hedonic one could be explained by Nambisan and Baron (2009) that explored how product content, member identity and human interactivity shape these benefits. They find that learning benefits are shaped by product content, but not member identity and human interactivity, while hedonic and social benefits are in addition to product content also influenced by product content and human interactivity. As the moderator has direct influence on product content, through organizing and managing innovation challenges (Troch & De Ruyck, 2014), while the moderator has less direct influence on member identity and human interactivity as this is mainly created by the member and the others, sending a motivational e-mail from the position of the moderator may feel credible through cognitive motivation, but not hedonic and social.

5.3. Member profile

The results indicate that moderators cannot use member's self-interest oriented writing style to observe which members can be motivated, while a member's positive emotional writing style signals members' persuadability. Building on Coussement, Debaere and De Ruyck (2017) who revealed the inability of member's self-interest oriented writing style to signal future IMP, this study indicates that this type of linguistic style can also not be used to see whether they must be targeted. However, the effect for member's positive emotional writing style is significant. The more positive emotional words a member uses in his community language, the higher the likelihood that he can be motivated using a proactive targeted e-mail with a cognitive motivational message. Relying on the broaden-and-build process theory (Fredrickson, 2011), moderators could interpret a positive emotional writing style as a reflection of being in the broaden-and-build process, which indicates that they are broadening their attention, cognition and action. As members with a positive emotional writing style can be motivated using a cognitive motivational message shows that the right profile and moment is found to trigger future constructive participation.

6. CONCLUSION

Aiming to realize benefits of innovation communities on the long-term is threatened by the big data environment and inferior member participation (IMP). The continuously increasing volume of difficult analyzable data puts pressure on moderator resources to manage the community, while IMP does not allow to get enough input for input for innovation challenges. Motivational email campaigns are widely used to reduce IMP. However, as e-mails are widely used and often lack usefulness due low distribution costs, it is a difficult challenge to obtain positive community impact. Therefore, this study explores the characteristics of a motivational e-mail campaigns in innovation communities. By comparing the viability of a targeted and untargeted treatment scope, analyzing the usage of several motivational messages and exploring which member profile can be motivated, it can unravel the optimal characteristics of effective motivational email campaigns to reduce IMP in innovation communities and make important conclusions.

First, when pursuing a proactive motivational e-mail campaign, a targeted treatment scope should be favored over an untargeted approach. While an untargeted proactive e-mail increases the IMP rate, a targeted proactive e-mail using uplift models allows to identify those individuals that can be positively influenced. By selecting the top 40% of most persuadable members, the IMP rate can be reduced by 2.97%. Second, when choosing a motivational message to include in the e-mail, anticipating on the hedonic and social motivation do not allow to create positive community impact, while a cognitive motivational message allows to meet the intended campaign purpose. Third, when observing members' community behavior, a positive emotional writing style indicates the member profile that can be motivated using a motivational e-mail.

Despite the important contributions, this study has also some limitations. First, right now only hedonic, cognitive and social motivation is explored. However, Nambisan and Baron (2009) explore a fourth type of motivation, i.e. personal integrative. Therefore, further research can investigate whether anticipating on reputation can help to motivate member participation. Second, for the targeted approach, this study considers only one uplift model. In literature there are also other uplift models such as regression-based uplift models. Further research can investigate whether different models can reveal better results. Third, this study focused on a motivational e-mail, yet, several other IMP reduction techniques also exist such as financial incentives. As firms are always on the look for better approaches to manage ICs, in the light of uplift modeling, these approaches can be reconsidered to obtain potentially more cost effective treatment campaigns. Fourth, all untargeted campaigns, either using a hedonic, cognitive and social motivational element, increase the IMP rate. As the results show that these untargeted motivational campaigns are not viable for IC management, further research must explore i) how these campaigns can be improved and have positive outcomes through other email implementations or ii) if in today's environment the email channel is not viable anymore, how other contact channels can be used to motivate.

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APPENDIX 1

E-MAIL 1: EXAMPLE OF E-MAIL WITH HEDONIC MOTIVATIONAL MESSAGE

2 Wishes You Never Got...

Hello you there,

Now that we have been active with the <name of community> for some time, I would like to take a quick look at some of the community wishes I have made for a while.

1. I hope you will get a lot of **satisfaction** by working out and **influencing new concepts and ideas** in the wonderful world of <domain>.

2. I hope you will experience a lot of **fun** and **enjoyment** through your participation in this community and that you will be **fully integrated** with all the brainstorms and challenges we have for you.

Do you think that this year may also be a **PLEASURABLE** <name of community> Year?

I sincerely hope so!

Let's start working on it in the coming days and weeks. Let's do this! We will succeed.

Thank you very much.

Greetings,

<name of the moderator>

E-MAIL 2

Are The 2 Wishes Coming To It?

Hello you there,

Do you still remember my email that I sent you back a while? Do you think these two wishes are already coming for you?

With our last topic <URL to last topic> we can make this all the way.

I'm curious!!

Greetings.

<name of the moderator>

<Copy of e-mail 1>

APPENDIX 2

Following the guidelines of Feldman and Sanger (2007) and consistent with Coussement, Benoit, and Antioco (2015):

- Bag-of-words methodology: convert textual information into numeric representation
    - Remove special characters and punctuation from terms
    - Benchmark words to word database
    - Remove rare words
    - Eliminate stop words
    - Conflate term variations into single representative form (Snowball stemmer)
    - Construct weigh-term vectors (higher frequency of term results in lower weight)
- Latent semantic indexing: construct a low-dimensional concept-by-post matrix
    - Use SVD method (Deerwester, Dumais, & Harshman, 1990)
    - Determine ideal dimensions

APPENDIX 3

Causal Conditional Inference Forest (ccif) of Guelman, Guillén, and Pérez-Marín (2015)

for $b = 1$ to B **do**
  Draw a sample with replacement from the training observations L such that $P(A = 1) = P(A = 0) = 1/2$
  Grow a conditional causal inference tree $CCIT_b$ to the sampled data:
  for each terminal node **do**
    repeat
      Select n covariates at random from the p covariates
      Test the global null hypothesis of no interaction effect between the treatment A and any of the n covariates (i.e., $H_0 = \cap_{j=1}^{n} H_0^j$, where $H_0^j : E[W|X_j] = E[W]$) at a level of significance α based on a permutation test
      if the null hypothesis H_0 cannot be rejected **then**
        Stop
      else
        Select the j^*th covariate X_{j*} with the strongest interaction effect (i.e., the one with the smallest adjusted P value)
        Choose a partition Ω^* of the covariate X_{j*} into two disjoint sets $\mathcal{M} \subset X_{j*}$ and $X_{j*} \setminus \mathcal{M}$ based on the $G^2(\Omega)$ split criterion
      end if
    until a minimum node size $l_{\min}$ is reached
  end for
end for
Output the ensemble of causal conditional inference trees $CCIT_b$; $b = \{1, \ldots, B\}$
The predicted personalized treatment effect for a new data point $\mathbf{x}$, is obtained by averaging the predictions of the individual trees in the ensemble: $\hat{\tau}(\mathbf{x}) = \frac{1}{B} \sum_{b=1}^{B} CCIT_b(\mathbf{x})$

CHAPTER V:
GENERAL CONCLUSIONS AND DIRECTIONS FOR FUTURE RESEARCH

GENERAL CONCLUSIONS AND DIRECTIONS FOR FUTURE RESEARCH

1. GENERAL CONCLUSIONS

The main body of this work, Chapter II, III and IV, presents results on their own and contributes to one research objective, i.e. the creation of a framework that allows community managers to proactively reduce inferior member participation, while dealing effectively with the data-rich environment. As visualized in Figure 2, the framework consists of four steps: 1) identify potential inferior member participation, 2) understand why they participate inferiorly, 3) design an appropriate contact strategy, 4) monitor and evaluate the results. Each chapter focuses on one or more of the steps, represents and independent study and presents results that allow to validate this proactive inferior member management framework. Chapter II investigates the first two steps by exploring the signaling role of a self-interest oriented and positive emotional writing style of important community actors for inferior member participation identification. Chapter III focuses on the first step by exploring the potential benefit of multi-label classifiers and label information to improve the predictive performance of proactive inferior member participation identification. Chapter IV examines step one, three and four by relying on a field experiment and investigating whether a proactive motivational e-mail campaign can be used to reduce inferior member participation. The remainder of this section discusses the most important findings and conclusions for each chapter.

Chapter II explores the signaling role of community actors' writing style for inferior member participation identification. The findings are four fold. First, the results indicate that a community member's self-interest-oriented writing style does not give insight into future inferior participation quantity, nor quality. Second, moderator's self-interest-oriented writing style signals a higher level of inferior member participation quality, while the community's self-interest-oriented writing style signals less inferior member participation quality. Self-interest-oriented writing styles of the moderator and the community do not help in identifying a member's inferior participation quantity. Third, the findings indicate that community member's positive emotional writing style signals less inferior member participation quantity and quality. Fourth, the moderator's positive emotional writing style signals less inferior member participation quality, whereas no significant relationship is found with inferior participation quantity. The community's use of a positive emotional writing style indicates less inferior member participation quantity and quality.

Chapter II proves the ability of the linguistic style of several community actors to identify inferior member participation and understand the conditions that signal the unconstructive behavior. There are three important conclusions. First, this study reveals the subtle signaling role of language-use drivers in ICs and proves that automated text analysis is an effective mechanism in a big data environment to identify future inferior member participation. Second, it reveals the signaling role of self-interest-oriented and positive emotional writing styles. Exploring these writing styles allows to understand the patterns that signal future inferior member participation. It shows that community managers who struggle with their IC must realize that in addition to what people say, how they say it gives insights into the IC's viability. Third, this study reveals the external influence of the moderator and the community on inferior member participation through the use of self-interest-oriented and positive emotional writing styles. This indicates that community managers should not only pay attention to the individual community member, but be aware of their own writing style and community language as these have an important influence on members' subsequent participation.

Chapter III explores whether the predictive performance of prediction models for proactive identification of inferior member participation can be improved by using the multi-label (ML) prediction methodology as opposed to the scenario of training independent models for each independent label, i.e. the Binarly Relevance (BR) approach. This study takes into account several ML classifiers: three problem transformation (PT) methods (BR, CC, Stacking), three Algorithm Adaptation (AA) methods (ML-kNN, IBLR, AdaBoost.MH) and four Ensemble methods (HOMER, CBMLC, RAkEL, ECC). We explore kNN and AdaBoost as the single label (SL) base classifiers for PT and AA methods. The predictive performance of the ML methods is evaluated using the example-based specificity (ES) and subset accuracy (SA) metrics. There are five important findings. First, in comparison to BR, CC is superior as the PT method for both SL classifiers kNN (only ES) and AdaBoost perform significantly better. There is no definite answer for Stacking compared to BR as the method performs significantly better for ES, but worse for SA, when the kNN approach represents the SL classifier and there is equal rank performance when it is built upon AdaBoost. Second, in comparison to BR, the kNN adaptation IBLR is superior for all evaluation metrics, as opposed to the adaptation ML-kNN which has inconclusive and insignificant results. The AdaBoost adaptation AdaBoost.MH is significantly superior (only ES) to BR. Third, in comparison to Stacking, only ES results are significant and show that HOMER for both SL classifiers and CBMLC for AdaBoost perform worse. In comparison to CC, HOMER and CBMLC (only for AdaBoost) also perform worse.

Fourth, the ensemble methods of ML-kNN do not differ in rank performance. For IBLR, CBMLC and HOMER (only ES) have inferior performance. In comparison to AdaBoost.MH, HOMER and CBMLC (only SA) perform worse. Fifth, overall comparison shows that CC and IBLR are the top performing classifiers for kNN, as opposed to CC and AdaBoost.MH as the top performing classifiers for AdaBoost.

Chapter III proves the benefit of multi-label classification methodology to improve prediction performance. There are three important conclusions. First, when looking to adopt the ML classification methodology in ICs, it's always useful to explore PT and AA methods as some of them will lead a better modeling performance than training independent models in a BR approach. When having already identified a good prediction model for traditional SL settings, it's better to transform the ML problem first by going for the CC problem transformation method and then training the SL model of choice on the multiple chained SL problems. When looking for ML classifiers that adapt SL classifiers, for kNN, it's better to use the IBLR adaption and for AdaBoost to go for AdaBoost.MH. Second, plugging these PT or AA methods into an ensemble to increase prediction performance is not a good strategy as they always lead to inferior prediction performance. Third, evaluating these models according to example-based specificity and subset accuracy allow community moderators to evaluate how safe it is to ignore predicted non-inferior participation behavior and the overall ability to make correct predictions.

Chapter IV explores the viability of a proactive motivational e-mail campaign to proactively reduce inferior member participation and uses a field experiment to evaluate the impact. There are four important findings. First, the proactive untargeted e-mail, using all motivational elements obtains a higher inferior member participation rate as opposed to the strategy of sending no e-mail at all. Second, the proactive targeted e-mail with a hedonic and social motivational element performs worse to the scenario of no e-mail, while a proactive targeted e-mail with a cognitive motivational element allows to reduce inferior member participation in ICs. When 20% of the most persuadable members are treated, the inferior member participation rate can be reduced with 1,29%, while targeting the top 40% results in a reduction of the IMP rate by 2,97%. Third, in the untargeted approach, all motivational elements create e-mails that perform worse than sending no e-mail at all. In the targeted approach, both e-mails with hedonic and social elements are not able to positively influence individuals, while the e-mail with cognitive element allows to reduce future inferior member participation. Fourth, a member’s self-interest oriented writing style cannot be used to see whether they must be targeted or not. With regards to a positive emotional writing, the more positive emotional words are used in a member's community language, the higher the likelihood that he can be motivated using a proactive targeted e-mail with a cognitive motivational message.

Chapter IV proves the ability of a proactive motivational e-mail to reduce inferior member participation using a business case. There are three important conclusions. First, when pursuing a proactive motivational e-mail campaign, a targeted treatment scope should be favored over an untargeted approach. While an untargeted proactive e-mail increases the inferior member participation rate, a targeted proactive e-mail using uplift models allows to identify those individuals that can be positively influenced. By selecting the top 40% of most persuadable members, the inferior member participation rate can be reduced by 2.97%. Second, when choosing a motivational message to include in the e-mail campaign, exploiting members' hedonic and social motivation do not allow to reduce inferior member participation, while a cognitive motivational message allows to meet the intended campaign purpose. Third, when observing members' community behavior, moderators should not pay attention to members' self-interest oriented writing style, however, a positive emotional writing style indicates the member profile that can be motivated using a motivational e-mail.

2. LIMITATIONS AND DIRECTIONS FOR FUTURE RESEARCH

Despite the added value of this work, it is not without limitations. In each chapter, the limitations with respect to the particular study are explained in detail. This section lists the overall limitations across the different chapters and directions for future research.

In Chapter II, III and IV, the sample consists of ICs that are all private communities. This private characteristic consists of community members who can only enter the community based on invitation or selection and community contributions to be invisible for outside individuals. However, other types of communities also exist, such as open ICs and user-regulated ICs (e.g., Bagozzi & Dholakia, 2006). In this dissertation, I only focus on the private ICs as dynamics and policy in the other type of communities could differ and answers to the research questions of this dissertation could be completely different. However, as these communities are also threatened by inferior member participation and big data characteristics, it is important to explore in future research how the inferior member participation management framework could be applied to those communities.

In Chapter II, III and IV, the members that participate in the ICs of the sample are not regular individuals. These community members were carefully selected and invited to join the IC on the basis of extensive usage experience, which was traceable in internal transactional databases, or by answers to an intake survey that demonstrated their deep knowledge of the focal topic. As a consequence, these members have favorable characteristics for community participation. In literature, there is a whole research stream on lead user theory (von Hippel, 2005) and the huge added value to consult them in innovation processes due to their innovative behavior (Schreier & Prügl, 2008). Despite it is important to explore general community management tactics for inferior member participation reduction, which was the focus of this dissertation, it is interesting to examine how these results apply to lead users in particular. Due to their different characteristics, they could potentially need other treatment tactics when they would not be motivated anymore. Therefore, I encourage future research to investigate how the inferior member participation management framework applies to lead users.

In Chapter II and IV, the findings indicate that community actors' linguistic style use allows to identify members who will participate inferiorly and members whose behavior can be positively influenced using an e-mail campaign, respectively. As text is the most straightforward approach for members to express themselves, this dissertation focuses only on textual posts and relies on automated text analysis to explore the benefit of linguistic style use. However, several IC frameworks allow members to contribute to innovation tasks in a non-textual way. Members can, for example, post images, videos, or audio snippets. As such content-rich contribution types are becoming increasingly popular, research is encouraged that finds ways to extract relevant meaning from non-textual cues and, thereby, supports innovation processes through image, video, or audio mining.

In Chapter II, III and IV, analytical models are used to make predictions about future member participation. These prediction models are constructed by leveraging data mining tools on IC data. However, they are not the only approach to take a look in the future. In particular, alternative prediction strategies also exist, including moderators' individual judgements, members' self-reported behaviors, and managerial heuristics. As in the end the moderator will most likely use a hybrid approach of all types of prediction strategies, an extensive comparison between these approaches could increase understanding of which prediction strategy works the best for which purpose. These decision strategies can be compared using the effort/accuracy framework proposed by Payne, Bettman and Johnson (1993). The basic hypothesis of that framework is that the strategy used to make a prediction has the goal of being as accurate as possible with the aim of limiting cognitive efforts. Therefore, this dissertation leaves the question of a detailed accuracy comparison open for future investigation in an IC context.

This dissertation explores several methodologies to construct the prediction models. In particular, Chapter II relies on multi-level regression to indicate that we can proactively identify future inferior member participation, Chapter III proves the benefit of the multi-label classification methodology to improve prediction performance and Chapter IV uses causal conditional inference trees as the uplift model to identify whether members can be most likely positively influenced. As the prediction performance of the models determines the success of the treatment campaign to target and treat the right individuals, future research must continue to explore new approaches that can improve predictive performance. In literature many suggestions exist such as by improvements on data, algorithms, algorithm tuning and ensembles. Therefore, I encourage future research to explore new improvements.

This dissertation introduces a framework to proactively reduce inferior member participation. Chapter IVs demonstrates this by using a motivational e-mail campaign. Despite an e-mail campaign is a commonly used approach for member engagement, other techniques also exist such as socialization tactics (Liao, Huang, & Xiao, 2017), financial rewards and individual attention. However, all of these approaches can also be used in a proactive context where the moderator anticipates on future expected inferior member participation. As this dissertation reveals the viability of a proactive e-mail campaign for IC management, future research must explore the potential benefit of other engagement techniques in a proactive context.

This dissertation introduces CRM strategies to ICs to proactively reduce inferior member participation, while effectively dealing with the data-rich environment. This data-driven and model based approach allows community managers to manage the IC objectively, cost effectively and in a future-oriented manner. As this dissertation reveals the huge benefits of the proactive inferior member participation management framework for ICs, a logical consequence is to implement these approaches into ICs. However, it is important for companies to be aware of the technical and organizational challenges when adopting CRM projects (Goodhue, Wixom, & Watson, 2002). As these ideas can only realize their full potential when properly implemented or adopted, I encourage future research to explore how companies and community managers can properly implement and utilize these strategies in ICs.

This dissertation aims to tackle the problem of IMP in ICs. The purpose of this dissertation is to provide a framework for community managers to identify IMP in ICs, predict and prevent it. However, one can argue that it is not a good practice to aim to proactively convert future "bad contributors" as their motivation will never be the same (as if they had earlier). Therefore, a valuable direction for future research is to explore how moderators, before members even enter the community and contribute, could identify and predict which members would be valuable contributors in the community itself. As a consequence, only members would enter the community that have high chances to be good contributors, potentially resulting in better interactions and more positive innovation outcomes.

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CONCLUSIONS GÉNÉRALES

1. CONCLUSIONS GÉNÉRALES

Le corps principal de ce travail, à savoir les chapitres II, III et IV, présente les résultats et contribue à l'unique objectif de cette recherche, à savoir la création d'un cadre qui permettra aux animateurs de communautés de réduire proactivement la faible participation des membres tout en gérant efficacement l'environnement riche en données. Comme indiqué sur la figure 1, ce cadre comprend quatre étapes : 1) identifier la faible participation potentielle des membres, 2) comprendre les causes de cette faible participation, 3) établir une stratégie de communication appropriée, 4) surveiller et évaluer les résultats. Chaque chapitre se concentre sur une ou plusieurs de ces étapes, étudie et représente de façon indépendante les résultats qui permettent de valider ce cadre de gestion proactive de la faible participation des membres. Le chapitre II étudie les deux premières étapes en étudiant le rôle important du style d'écriture émotionnel et positif orienté vers l'intérêt personnel des acteurs communautaires dans l'identification de la faible participation des membres. Le chapitre III se concentre sur la première étape en étudiant l'avantage potentiel des classifieurs multi-label et le rôle des informations de labels dans l'amélioration de la performance prédictive de l'identification proactive de la faible participation des membres. Quant au chapitre IV, il examine les étapes une, trois et quatre en s'appuyant sur une expérience de terrain et en cherchant à savoir s'il serait possible d'avoir recous à une campagne de motivation par e-mail pour réduire la faible participation des membres. Le reste de cette section traite l'ensemble des constatations et des conclusions les plus importantes de chaque chapitre.

Le chapitre II étudie le rôle important du style d'écriture des acteurs de communautés dans l'identification de la faible participation des membres. Les résultats sont au nombre de quatre. Premièrement, ils indiquent que le style d'écriture orienté vers l'intérêt personnel d'un membre de la communauté ne donne pas un aperçu de la quantité des faibles participations potentielles, ni de leur qualité. Deuxièmement, le style d'écriture orienté vers l'intérêt personnel du modérateur montre un niveau plus élevé de qualité de la faible participation des membres, alors que le style d'écriture orienté vers l'intérêt personnel de la communauté montre moins de qualité de cette faible participation. Les styles d'écriture orientés vers l'intérêt personnel du modérateur et de la communauté n'aident pas à identifier la quantité de la faible participation d'un membre. Troisièmement, les résultats indiquent que le style d'écriture émotionnel et positif des membres de la communauté indique une quantité et une qualité inférieures de la faible participation des membres. Quatrièmement, le style d'écriture émotionnel et positif du modérateur montre une moindre qualité de faible participation chez les membres, alors que rien n'est prouvé en rapport avec la quantité de cette faible participation. L'utilisation par la communauté d'un style d'écriture émotionnel et positif montre une quantité et une qualité de la faible participation des membres très inférieures.

Le chapitre II prouve la capacité du style linguistique des différents acteurs de communauté à identifier la faible participation des membres et à comprendre les situations qui dévoilent un comportement non constructif. Il y a trois conclusions importantes. Premièrement, cette étude révèle le rôle subtil et très important de l’utilisation du language dans les CI et prouve que l'analyse automatisée de texte est un mécanisme efficace dans un environnement big data pour identifier la faible participation potentielle des membres. Deuxièmement, elle révèle le rôle importat des styles d'écriture émotionnels et positifs orientés vers l'intérêt personnel. Étudier ces styles d'écriture permet de comprendre les modèles qui indiquent la faibe participation potentielle des membres. Cela montre que les animateurs de communauté qui luttent avec leur CI doivent réaliser qu'en plus de ce que les gens disent, la manière dont ils le disent donne une idée sur la viabilité de leur CI. Troisièmement, cette étude révèle l'influence externe du modérateur et de la communauté sur la faible participation des membres à travers l'utilisation de styles d'écriture émotionnels et positifs orientés vers l'intérêt personnel. Ceci indique que les animateurs de communauté ne doivent pas seulement prêter attention aux différents membres de la communauté, mais doivent être conscients de leur propre style d'écriture et de leur langage communautaire, car ils ont une influence importante sur l’éventuelle participation des membres.

Le chapitre III étudie la possibilité d’améliorer la performance prédictive des modèles de prédiction dans l’identification de façon proactive de la faible participation des membres en utilisant la méthode de prédiction multi-label (ML) par opposition au scénario de dressage de modèles indépendants pour chaque label comme le cas de la pertinence binaire (BR). Plusieurs classifieurs ML sont à considérer pour cette recherche : trois méthodes de transformation de problème (PT) : (BR, CC, Stacking), trois méthodes d'adaptation d'algorithme (AA) : (ML-kNN, IBLR, AdaBoost.MH) et quatre méthodes d'ensemble (HOMER, CBMLC, RAkEL, ECC). Nous étudierons kNN et AdaBoost en tant que classifieurs de base à label unique (SL) pour les méthodes PT et AA. La performance prédictive des méthodes ML est évaluée à l'aide des métriques « example-based specificity » (ES) et « subset accuracy » (SA). Cinq résultats importants en résultent : premièrement, en tant que méthode PT, CC est meilleure en la comparant à BR, les deux classifieurs SL à savoir kNN (ES uniquement) et AdaBoost se comportent nettement mieux. Il n'y a pas de réponse précise à la comparaison du Stacking par rapport au BR, car la méthode fonctionne significativement mieux pour ES, mais pas autant pour SA lorsque l'approche kNN représente le classifieur SL tandis que les performances sont égales quand elle est construite sur AdaBoost.

Deuxièmement, par rapport à BR, l'IBLR, une adaptation de kNN, est la meilleure entre toutes les métriques d'évaluation, par opposition à l'adaptation ML-kNN qui a des résultats non concluants et insignifiants. AdaBoost.MH, qui est une adaptation d'AdaBoost est largement mieux (ES uniquement) que BR. Troisièmement, par rapport au Stacking, seuls les résultats ES sont significatifs et montrent que HOMER pour les classifieurs SL et CBMLC pour AdaBoost sont moins performants. En comparaison avec CC, HOMER et CBMLC (seulement pour AdaBoost) fonctionnent également moins bien. Quatrièmement, les méthodes d'ensemble de ML-kNN ne diffèrent pas en ce qui concerne les questions de performance. Concerant IBLR, CBMLC et HOMER (ES uniquement) ont des performances inférieures. En comparaison avec AdaBoost.MH, HOMER et CBMLC (seulement SA) fonctionnent moins bien. Cinquièmement, la comparaison globale montre que CC et IBLR sont les classifieurs les plus performants pour kNN, tandis que CC et AdaBoost.MH sont les classifieurs les plus performants pour AdaBoost.

Le chapitre III prouve l’avantage de la méthode de classification multi-label pour améliorer les performances de prédiction. Il y a trois conclusions importantes. Tout d'abord, lorsqu'on cherche à adopter la méthode de classification ML dans les CI, il est toujours utile d’étudier les méthodes PT et AA car certaines d'entre elles conduiront à une meilleure performance de modélisation que le fait de dresser des modèles indépendants dans une approche BR. Lorsqu’un bon modèle de prédiction pour les paramètres SL traditionnels est identifié, il est préférable de commencer par transformer le problème ML en appliquant la méthode de transformation du problème CC, puis en appliquant le modèle SL choisi sur les différents problèmes SL enchaînés. Lorsque on cherche des classifieurs ML qui adaptent les classifieurs SL, il vaut mieux utiliser l'adaptation IBLR pour kNN et AdaBoost pour AdaBoost.MH. Deuxièmement, intégrer les méthodes PT ou AA dans un ensemble pour augmenter les performances de prédiction n'est pas une bonne stratégie car elles conduisent toujours à des performances de prédiction inférieures. Troisièmement, l'évaluation de ces modèles selon les métriques «

example-based specificity » (ES) et « subset accuracy » (SA) permet aux modérateurs de la communauté de savoir à quel point il serait prudent d'ignorer le comportement prévu de la participation non faible et la capacité globale de faire des prédictions correctes. Le chapitre IV étudie la viabilité d'une campagne de motivation par courriel proactif dans le processus de la réduction proactive de la faible participation des membres et utilise une expérience sur le terrain pour évaluer l'impact. Il y a quatre résultats importants. Tout d'abord, le courrier électronique proactif non ciblé, utilisant tous les éléments de motivation, réalise un taux de faible participation des membres plus élevé que la stratégie consistant à ne pas envoyer d'e-mail du tout. Deuxièmement, l'e-mail ciblé proactif avec un élément motivationnel hédoniste et social est pire que le scénario sans e-mail, tandis qu'un e-mail ciblé proactif avec un élément motivationnel cognitif permet de réduire la faible participation des membres dans les CI. Lorsque 20 % des membres les plus susceptibles d'être persuadés sont traités, le taux de faible participation des membres peut être réduit de 1,29 %, tandis que cibler les meilleurs 40 % des membres les plus susceptibles d'être persuadés entraîne une réduction du taux de cette faible participation de 2,97 %. Troisièmement, dans l'approche non ciblée, tous les éléments de motivation créent des e-mails qui sont moins performants que l'absence d'envoi d'e-mails. Dans l'approche ciblée, les e-mails avec des éléments hédoniques et sociaux ne sont pas capables d'influencer positivement les individus, tandis que les e-mails avec des éléments cognitifs permettent de réduire la faible participation éventuelle des membres. Quatrièmement, le style d'écriture orienté vers l'intérêt personnel d'un membre ne peut pas être utilisé pour voir s'il doit être ciblé ou non. En ce qui concerne une écriture émotionnelle positive, plus les mots émotionnels positifs sont utilisés dans le langage d'un membre de communauté, plus il est susceptible d'être motivé en utilisant un e-mail ciblé proactif avec un message cognitif de motivation.

Le chapitre IV prouve la capacité d'un e-mail de motivation proactif à réduire la faible participation des membres grâce à une étude de cas. Il y a trois conclusions importantes. Tout d'abord, dans le cadre d'une campagne de mailing proactif et motivationnel, un traitement ciblé devrait être privilégié par rapport à une approche non ciblée. Alors qu'un e-mail proactif non ciblé augmente le taux de la faible participation des membres, un e-mail proactif ciblé utilisant des modèles uplift (levier en français) permet d'identifier les individus qui sont susceptibles d'être positivement influencés. En sélectionnant les meilleurs 40 % des membres les plus susceptibles d'être persuadés, le taux de la faible participation des membres peut être réduit de 2,97 %. Deuxièmement, lors du choix d'un message de motivation à inclure dans la campagne de mailing, exploiter la motivation hédonique et sociale des membres ne permet pas de réduire la faible participation des membres, tandis qu'un message cognitif de motivation permet d'atteindre le but recherché. Troisièmement, en observant le comportement des membres de la communauté, les modérateurs ne devraient pas prêter attention au style d'écriture orienté vers l'intérêt personnel des membres, cependant, un style émotionnel positif indique le profil du membre susceptible d'être motivé en utilisant un e-mail de motivation.

2. LIMITES ET ORIENTATIONS FUTURES DE LA RECHERCHE

Malgré l'énorme valeur ajoutée de ce travail, il n'est pas sans limites. Dans chaque chapitre, les limites relatives à cette étude sont expliquées en détail. Cette section dresse la liste des limites globales au niveau des différents chapitres et les orientations futures de la recherche.

Dans les chapitres II, III et IV, l'échantillon est constitué de CI qui sont toutes des communautés privées. Cette caractéristique privée consiste en des membres de la communauté qui ne peuvent entrer dans la communauté qu'avec une invitation ou par le biais d'une sélection, les contributions de cette communauté sont alors invisibles pour les personnes extérieures. Cependant, d'autres types de communautés existent également, tels que les CI ouvertes et les CI contrôlées par l'utilisateur (par exemple, Bagozzi & Dholakia, 2006). Dans cette thèse, je me concentre uniquement sur les CI privées car la dynamique et la politique dans les autres types de communautés pourraient différer et les réponses aux questions de recherche de cette thèse pourraient être complètement différentes. Cependant, puisque ces communautés sont également menacées par une faible participation des membres et des caractéristiques de big data, il est important d'étudier dans de futures recherches comment le cadre de gestion de la faible participation des membres pourrait s'appliquer à ces types de communautés.

Au niveau des chapitres II, III et IV, les membres qui participent aux CI de l'échantillon ne sont pas des personnes ordinaires. Ces membres de communauté ont été soigneusement sélectionnés et invités à rejoindre la CI sur la base d'une longue expérience d'utilisation, dont la traçablilité est dans des bases de données transactionnelles internes, ou sur la base des réponses à une enquête d'admission qui démontrait leur connaissance approfondie du sujet principal. En conséquence, ces membres ont des particularités favorables à la participation communautaire. En littérature, il y a tout un courant de recherche sur la théorie des utilisateurs pilotes (von Hippel, 2005) et l'énorme valeur ajoutée de les consulter dans les processus d'innovation en raison de leur comportement innovant (Schreier & Prügl, 2008). Bien qu'il soit important d'étudier les tactiques générales de gestion de la communauté pour la réduction de la faible participation des membres, ce qui était l'objet de cette thèse, il est intéressant d'examiner comment ces résultats s'appliquent aux utilisateurs potentiels en particulier. En raison de leurs différentes particularités, il pourrait avoir besoin d'autres tactiques de traitement quand ils ne seraient plus motivés. Par conséquent, j'encourage les recherches futures à examiner comment le cadre de gestion de la faible participation des membres s'applique aux utilisateurs pilotes.

Dans les chapitres II et IV, les résultats indiquent que l'utilisation du style linguistique des acteurs communautaires permet d'identifier les membres qui participeront de manière faible et les membres dont le comportement peut être influencé positivement par une campagne de mailing, respectivement. Comme le texte est le moyen le plus directe pour les membres de s'exprimer, cette thèse se concentre uniquement sur les messages textuels et s'appuie sur l'analyse automatisée de texte pour étudier les avantages de l'utilisation de style linguistique. Cependant, plusieurs cadres de CI permettent aux membres de contribuer aux tâches d'innovation de manière non textuelle. Les membres peuvent, par exemple, publier des images, des vidéos ou des extraits audio. Au fur et à mesure que de tels types de contributions sont de plus en plus populaires, on encourage la recherche à chercher des moyens d'extraire les significations non textuelles et, par conséquent, soutenir les processus d'innovation par l'image, la vidéo ou l'audio.

Dans les chapitres II, III et IV, des modèles analytiques sont utilisés pour prédire la participation future des membres. Ces modèles de prédiction sont construits en tirant parti des outils d'exploration de données sur les données de la CI. Cependant, ils ne sont pas la seule approche. En particulier, des stratégies de prédiction alternatives existent également, y compris les jugements individuels des modérateurs, les comportements que les membres ont apportés en plus des heuristiques managériales. Puisqu'à la fin le modérateur utilisera très probablement une approche hybride de tous les types de stratégies de prédiction, une bonne comparaison de ces approches pourrait permettre de mieux comprendre quelle stratégie de prédiction fonctionne le mieux dans quel but. Ces stratégies de décision peuvent être comparées en utilisant la perspective effort / précision proposée par Payne, Bettman et Johnson (1993). L'hypothèse de base de cette perspective est que la stratégie utilisée pour faire une prédiction a pour but d'être aussi précise que possible dans le but de limiter les efforts cognitifs. Par conséquent, cette thèse laisse la question d'une comparaison de précision détaillée dans un contexte de CI ouverte pour une enquête future.

Cette thèse étudie plusieurs méthodologies pour construire les modèles de prédiction. En particulier, le chapitre II s'appuie sur la régression multi-niveaux pour indiquer que nous pouvons identifier proactivement la faible participation future des membres, le chapitre III prouve l'avantage de la méthodologie de classification multi-label pour améliorer les performances prédictives et le chapitre IV utilise les arbres d'inférence causale et conditionnelle comme modèle uplift pour déterminer si les membres peuvent être influencés positivement. Comme la performance prédictive des modèles détermine le succès de la campagne de traitement à cibler et traiter les bonnes personnes, les recherches futures doivent continuer à explorer de nouvelles approches qui peuvent améliorer la performance prédictive. Dans la littérature, de nombreuses suggestions existent, telles qu'en améliorant les données, les algorithmes, l'adaptation des algorithmes et les ensembles. Par conséquent, j'encourage la recherche future à étudier de nouvelles améliorations.

Cette thèse introduit un cadre pour réduire proactivement la faible participation des membres. Le chapitre III le prouve en utilisant une campagne de motivation par e-mail. Bien qu'une campagne de mailing soit une approche couramment utilisée pour la participation des membres, d'autres techniques existent, telles que les tactiques de socialisation (Liao, Huang et Xiao, 2017), les gratifications financières et l'attention particulière. Cependant, toutes ces approches peuvent également être utilisées dans un contexte proactif où le modérateur anticipe sur la faible participation éventuelle attendue des membres. Tandis que cette thèse révèle la viabilité d'une campagne de mailing proactif pour la gestion des CI, la recherche future doit explorer les avantages potentiels des autres techniques de participation dans un contexte proactif.

Cette thèse présente des stratégies de GRC dans les CI pour réduire de manière proactive la faible participation des membres, tout en traitant efficacement l'environnement riche en données. Cette approche fondée sur les données et les modèles permet aux animateurs de communauté de gérer la CI de manière objective, rentable et orientée vers l'avenir. Comme cette thèse révèle les énormes avantages du cadre de gestion proactive de la faible participation des membres au sein des CI, la conséquence logique est de mettre en œuvre ces approches dans les CI. Cependant, il est important que les entreprises soient conscientes des défis techniques et organisationnels qu'elles encontreront lors de l'adoption des projets de GRC (Goodhue, Wixom et Watson, 2002). Comme ces idées ne peuvent réaliser leur plein potentiel que lorsqu'elles sont correctement appliquées ou adoptées, j'encourage la recherche future à explorer comment les entreprises et les animateurs de communauté peuvent correctement mettre en œuvre et utiliser ces stratégies dans les CI.

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