FACTORS THAT AFFECT GROUP GENERATIVE COLLABORATIONS IN ENTERPRISE SOCIAL MEDIA

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ABSTRACT

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Innovation is closely linked to a company's ability to survive and thrive. As a result, companies are becoming increasingly interested in group generative collaborations – the conception of novel ideas and solutions through group exchanges. This exploratory study investigates the prevalence of generative collaborations in ESM-based groups and identifies antecedents of such collaborations in groups. Additionally, the nature (i.e. language) of these collaborations is explored. A mixed methods approach is employed for this study, comprised of a content analysis of text-based data from an ESM platform, building a machine learning classifier model, and a predictive regression model. The results of this exploratory study show that approximately 44% of exchanges on an ESM platform contain elements of generative collaborations. Furthermore, the predictive negative binomial regression model illustrates that a group's visibility (closed or open), the bonding and bridging behaviors of group members, and the size of a group are significant antecedents for group generative collaborations. These outcomes are valuable insights that help advance our theoretical understanding of ESM-based group generative collaborations and could also help improve these collaboration behaviors in the context of ESM platforms, and possibly beyond.

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INTRODUCTION

In the last few years, Enterprise Social Media (ESM) have become an omnipresent workplace IT tool. ESM are web-based platforms that aid organizations to conduct internal corporate business processes and objectives, by allowing users to communicate, network, organize, leverage information capital, and collaborate. ESM are encouraging knowledge sharing within the workplace by making it simpler to find and work with people with mutual interests and complementary expertise (Leonardi, 2014). These platforms are also equipped with affordances that have the potential to foster group generative collaborations – the co-creation of novel ideas and solutions through group exchanges (Avital & Te'eni, 2009). ESM offer a unique opportunity for researchers interested in studying online team behaviors. Visibility, a unique affordance of ESM, allows all contributions and activities to the platform to become visible to anyone, enhancing not only the possibilities for employees to access knowledge and ideas from anywhere in the organization, but also the availability of such data for investigation. This opportunity to observe how people collaborate is not only an opportunity to improve the theoretical understanding of the nature of group exchanges occurring in ESM, but also a chance to improve these types of exchanges in the context of ESM platforms, and potentially beyond. As the root-cause of innovation (Avital & Te'eni, 2009), generative collaborations are of particular interest for companies, given the direct link between their ability to innovate and their chance to survive and thrive (Cowen, 2011; Abernathy & Clark, 1985). The objective of this study is to examine the forms of generative collaborations that occur in Enterprise Social Media and identify the factors that predict their success. To do this, I pose two research questions:

RQ1: What types of generative collaborations occur in ESM?

RQ2: What are the antecedents to the generative collaborations that occur in ESM?

To conduct this study, I will be utilizing data that contains thread messages from a multinational organization that uses an ESM platform for internal corporate processes. This data set includes a total of over 20,000 messages from various groups on the platform. Given its exploratory nature, a subset of 2,230 messages were used for the purpose of this study.

I operationalize the forms of generative collaborations from Tsoukas's (2009) research on conceptual change, where the author identifies three distinct types of creativity (i.e., generativity): reframing, expansion, and combination. Additionally, to identify antecedents of generative collaborations, I will implement the forms of generative collaborations as a dependent variables, and I will be incorporating characteristics of groups found in ESM (as independent variables); including their size (number of members), their privacy setting (i.e., whether they are open (visible to network) or closed (invisible to network) groups), and various network measures (e.g., particularly the bridging and bonding structures of the group network).

LITERATURE REVIEW

Given the exploratory nature of this study, hypotheses are not proposed. The objective is to gain an understanding of the landscape of group generative collaborations in ESM platforms. Specifically, to explore the prevalence of the three types of group generative collaborations that are present on ESM platforms, and the antecedents for their success. Additionally, the study aims to offer new heuristics (i.e. in the form of linguistic indicators) for investigating these behaviors among users of ESM.

Generativity

According to Avital and Te'eni (2009), generativity is the capacity to create, originate, or produce. The concept of generativity originated in 1950 when psychoanalyst Erikson coined the term while developing a theory for stages of psychosocial development (Erikson, 1950). Since then, it has been a notion that is repeatedly used in social science and humanities to refer to the diverse forms of creative development and social change. Van Osch and Avital (2010) defined the generative capacity found in virtual teams as collaborations between team members working together to create, originate, or produce ideas and solutions. In addition to the creation of novel ideas and solutions generative collaborations have other effects, such as forming associations or expanding one's network, gathering knowledge on different perspectives, and other diverse forms of creativity stimulants, that become evident to team members (Tsoukas, 2009). In identifying ways of producing novel conceptualizations, Tsoukas (2009) defines the different forms of group generative collaborations that can be inferred from creative cognition research (Dunbar, 1997; Frinke, Ward, & Smith, 1992): combination, expansion, and reframing. Combination refers to combining concepts that already exist in new ways. Expansion involves expanding the use of an existing concept from its core use to match a new situation. Reframing takes place when an existing concept is deconstructed, and reconstructed, to fit a new situation, often by challenging the status quo (Van Osch & Avital, 2010). Due to the process of conceptual change that reframing follows, it is the most disruptive form of group generativity.

Group generative collaborations are an important attraction for companies when deciding to implement an ESM platform. Over time, as new knowledge from either of the three generativity types becomes applied to new products and services, competitive consequences arise for an organization (Henderson & Clark, 1990; Abernathy & Clark, 1985). Cowen (2011) discusses the need for innovative solutions to improve the competitiveness of the American economy in the global marketplace. The U.S. economy greatly benefits from corporate generativity. Breakthrough solutions are more likely to occur because of generative collaborations, which increase the likelihood of innovation (Tsoukas, 2009). Corporate generativity has social benefits as well, that could apply to society at large. These social benefits include innovations that cut costs and save money, and the discovery of new and useful products, services, and solutions, that are applicable to a variety of societal needs. Applications of these innovations would include customer technologies, or technological advances in health and education. Hence, corporate generativity, and more specifically the generativity that occurs in groups, is a worthwhile topic to investigate due to its importance in the American economy, and the survival of companies in general.

Many of the parameters that impact the quality of knowledge exchanged between two parties on an ESM platform are likely to influence the success of generative collaborations. Such parameters would include identifying relevant groups, cooperation behaviors, and the strength of relationships in a network. Previous research on social capital has suggested that strongly bonded social groups that possess enhanced intellectual and social capital (Tsai & Goshal, 1998) are important to promoting group generativity (Harvey, 2014).

Enterprise Social Media and Generative Collaborations

In recent years, research on Enterprise Social Media (ESM) has proliferated. ESM are an IT tool equipped with a compatible set of affordances (Leonardi, Huysman, & Steinfield, 2013) for collaborations to occur and could potentially foster generative collaborations – the creation of novel ideas and solutions (Avital & Te'eni, 2009). They enable users to perform various internal business processes such as communicating, networking, organizing, leveraging information capital, and many other activities (Leonardi, Huysman, & Steinfield, 2013).

Thus far, the literature has lacked an understanding of the role that social media play within organizations, and more specifically for the ways social media can aid with internal business objectives. Most of the studies published on ESM have been conducted by scholars in the domain of computer-supported cooperative work (CSCW) and human-computer interaction (HCI), where the focus has been on specific technologies. Examples of such studies are ones by Brzozowski (2009) and DiMicco, Geyer, & Dugan (2008) on Hewlett Packard's WaterCooler ESM tool, and IBM's Beehive ESM tool, respectively. Though both studies were supportive of ESM's potential to positively impact organizations, the focus was on agendas in the domains of CSCW and HCI. Hence, extant research produced mostly descriptive and self-report accounts of how individuals use ESM, which have limited value in terms of producing unobtrusive insights into the team-level use of ESM. Additionally, these studies have paid little attention to the strategic implications of these tools. A possible cause for this absence is that scholars in the domain of management and organization have not begun to consider and examine ESM (Leonardi, Huysman, & Steinfield, 2013). Furthermore, Information Systems (IS) scholars have only recently begun to examine ESM; their focus, however, has mainly remained on how the use of ESM aids knowledge management (Kane G. C., 2015; Von Krogh, 2012; Leonardi, 2014; Beck, Pahlke, & Seebach, 2014). This underscores a need to investigate strategic implications beyond knowledge management, such as understanding the extent to which generative collaborations occur with ESM.

The limited empirical evidence that exists suggests that ESM offer other opportunities that might be valuable from a strategic point of view, such as people sensemaking and building and maintaining social capital. People sensemaking is a mental model of who a person is, based on the information available on ESM (DiMicco, Geyer, & Dugan, 2008; DiMicco, Hollenbach, Pandolfo, & Bender, 2007); this is a concept that is important for users leveraging associations between people. Furthermore, ESM support creating transactive memory systems – sharing, supporting, and maintaining of knowledge within a team - (Leonardi, Huysman, & Steinfield, 2013; Leonardi, 2014), strengthen boundary work (Holtzblatt & Tierney, 2011; Majchrzak, Faraj, Kane, & Azad, 2013), and promote effective knowledge management – a process of organizing, maintaining and sharing knowledge within an organization - (Kane G. C., 2017). These aforementioned impacts of ESM could be important in promoting generative collaborations.

In particular given that group generativity in the context of ESM is textually co-constructed (Burt, 1992; North, 2007) and thus embedded in the network of relationships of the ESM, social network theory sheds light onto various aspects of the nature of the relationships that develop in ESM and which play a role in the enactment of group generativity (c.f., Perry-Smith & Shalley, 2003). This would include the sharing of knowledge that is challenging to obtain on other platforms that do not possess the same affordances as ESM, and the free flow of various diverse perspectives that are combined in group blogs and group discussions. Thus, it is suggested that the landscape of the network (i.e. the inter-connectedness of group members between each other) plays an important role in enhancing group generative collaborations (c.f., Perry-Smith & Shalley, 2003). There are several aspects of the network that could affect group generative collaborations. First, the diversity of the network that groups have access to (by virtue of the network structures of its members) – members of one group can also belong to another group; there is an overall variation of members between and within groups. Moreover, beyond the diversity of the network structures, the social network literature has produced two opposing views (Kijkuit & Van Den Ende, 2007). The first is based on 'structural holes' theory (Burt, Structural Holes, 1992). Most scholars in the network literature that have focused on creativity and knowledge sharing have built on this or similar lines of reasoning (Burt, 2004;Cummings, 2004;Perry-Smith & Shalley, 2003). This view proclaims that a *bridging* network gives access to non-redundant contacts and therewith generates informational benefits. The second view, which was first introduced by (Coleman, 1988) stresses the importance of social cohesion or *bonding*. In this bonding network structure, benefits for idea generation, creativity, and knowledge exchange stem from trust, support, coordinated action, and clear expectations (Coleman, 1988; Obstfeld, 2005; Reagans & Zuckerman, 2001). These two distinct forms of network structures—bridging and bonding—have been widely studied in the context of online groups (Kim, Jarvenpaa, & Gu, 2018) as critical antecedents to the way in which groups collaborate (Adler & Kwon, 2002; Burt, 2000; Ellison, Steinfield, & Lampe, 2007; Kim, Jarvenpaa, & Gu, 2018; Reagans & Zuckerman, 2001) and therefore are important aspects to study in an investigation of ESM-based groups.

In addition, due to the dependency on the affordance of a social media platform allowing for such team creativity to occur, team creativity is a function of employing the right tools and promoting the right behaviors for such collaborations to occur. Examples of promoting 'right' behaviors would include encouraging users to interact with a collaborative mindset; helping others in the community, actively seeking information or helping provide information, or acknowledging others' contributions and many more.

Thus, it is apparent that ESM possess the criteria to support team-level generative collaborations. ESM can afford the identification of relevant information, individuals, and contributors. Additionally, they create a wider awareness and broaden contribution in creative processes. They may also spark the creative disruptions of existing concepts and work practices as necessary, to support the creation of novel concepts. Yet, the studies so far do not offer information on where, when, why, and how these benefits may occur, the ways that ESM can aid generative collaborations for larger groups, and how to promote the right behaviors in teams for group generativity. Hence, it is of paramount importance to examine the effect of ESM on generative collaborations. Such research is significant because it includes extending the existing ESM and organizational literatures by deepening our theoretical understanding of the multilevel antecedents of generative collaborations in ESM using the unparalleled amounts of archival data from a real-world ESM.

DATA

This study will utilize data from an ESM tool used by a multi-national organization. The organization focuses on conducting research and consulting in the domain of human-computer interaction, where their objective is to build technology and furnishing products for a variety of clients from corporate offices, healthcare, educational institutions, and government institutions. The case organization has over 11,000 employees, in over 80 locations around the world.

The case organization launched an ESM tool in January 2012. The ESM is based on a platform called Jive, an industry leader in the market for corporate collaboration and communication technologies[1]. The case organization's product development and client consulting are supported through global collaborative teams. The majority of these teams are virtual in nature and heavily rely on tools such as email, Google Docs, or Skype, etc. The ESM tool integrates various communication modalities (i.e. private chat, group blogs, discussion boards) and the goal for overall implementation was to replace the plethora of tools used by groups and offer them an umbrella tool. By offering a single integrative platform, the intention of senior management was to create enhanced opportunities for supporting connections, communications, and collaborations within and between employee groups.

At the time of data collection for this study, the ESM had a stable base of 10,000 users, which were accumulated over five years since its launch. Ninety-one percent (9,000) of the users are members of groups, who participate regularly in group discussions and activities. This makes the use of this data a suitable case study to investigate the types of generativity that occur in ESM, and the antecedents of generative collaborations that occur in ESM.

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[1] The case organization has recently migrated to a new platform called Igloo. In this study, the focus remains on the data from the Jive platform; the platform migration did not affect this study.

The data corpus has more than 20,000 messages from groups on the platform. Given the exploratory nature of this study approximately 10% will be used as training data, with the intent for the remaining 90% to be used in the future to validate a machine learning classifier model. The total data corpus contains 1,075 groups, and 2,745 unique users. Within the 10% sub-sample for the training data, 114 groups and 500 unique users are included. Figures 1 to 4 describe the groups included in this sample.

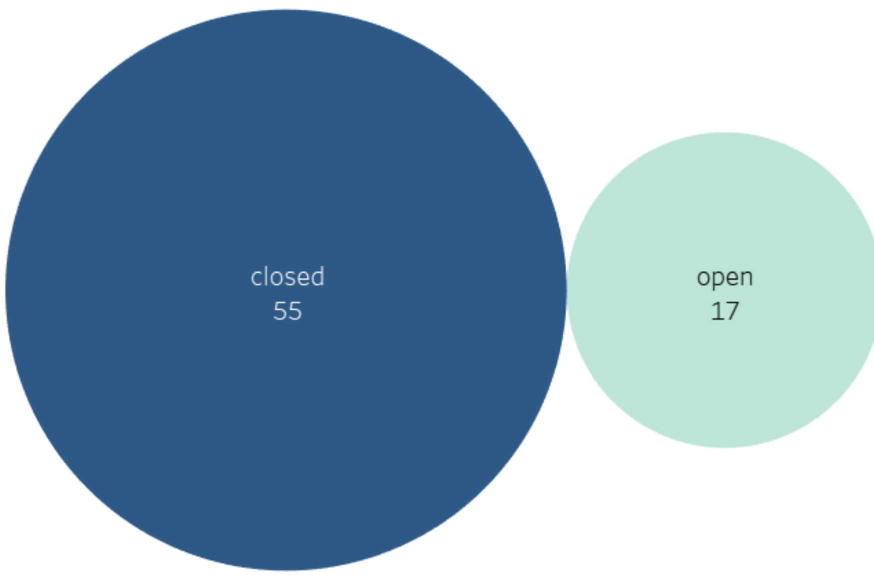

Figure 1: Average Group Size by Group Visibility

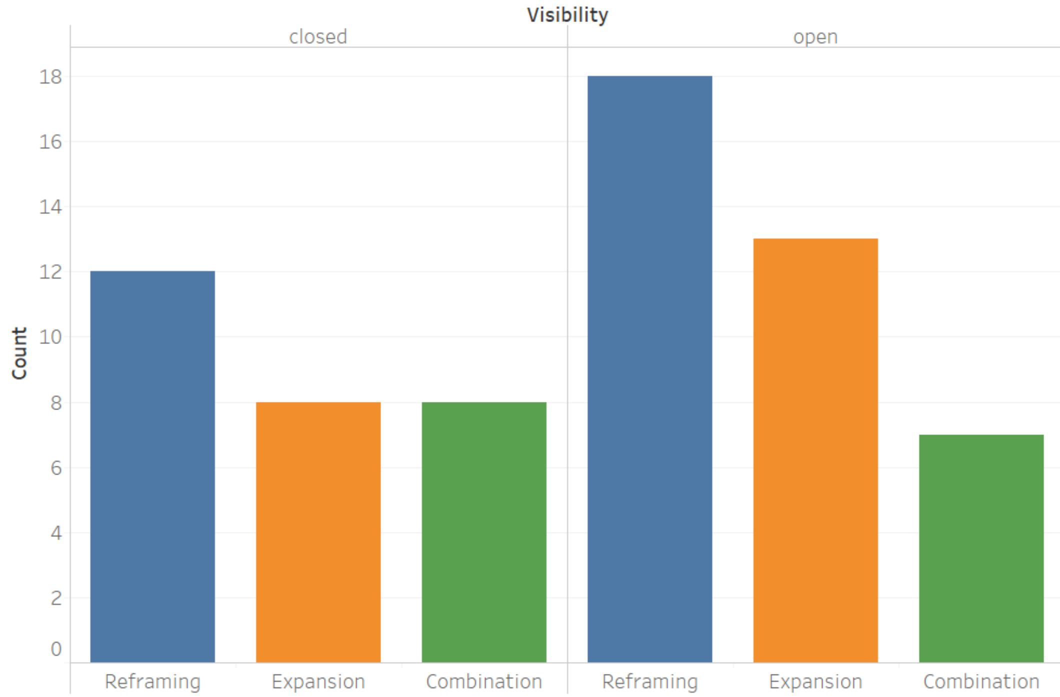

Figure 2: Distribution of Group Generativity Type by Group Visibility

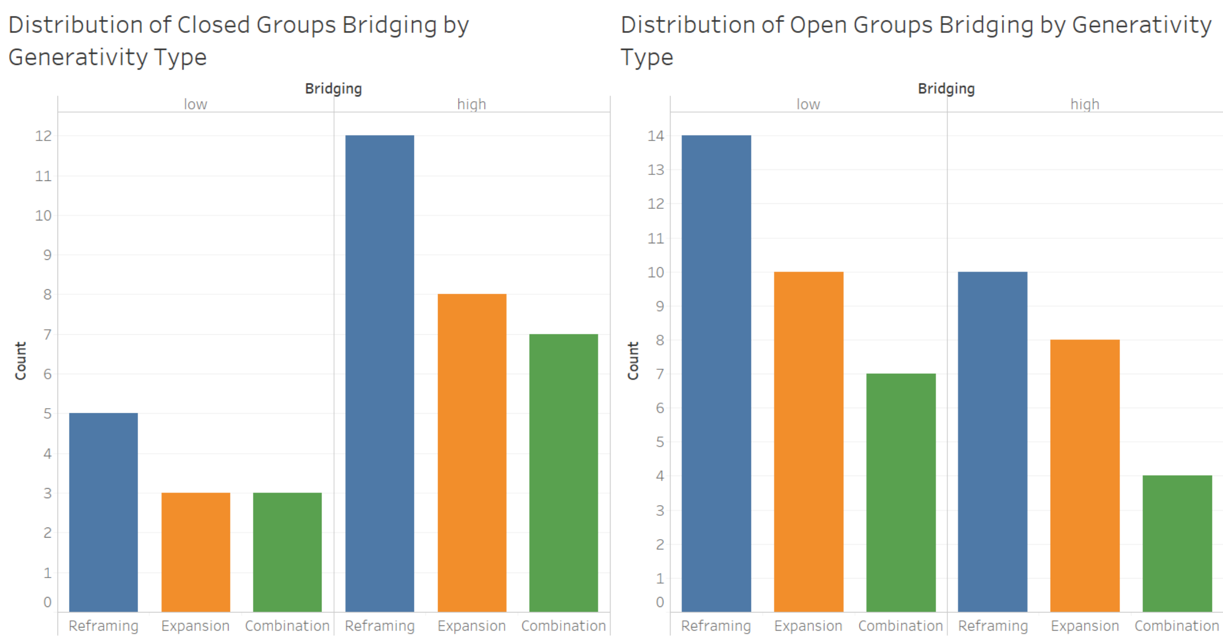

Figure 3: Distribution of Group Generativity by Group Bridging

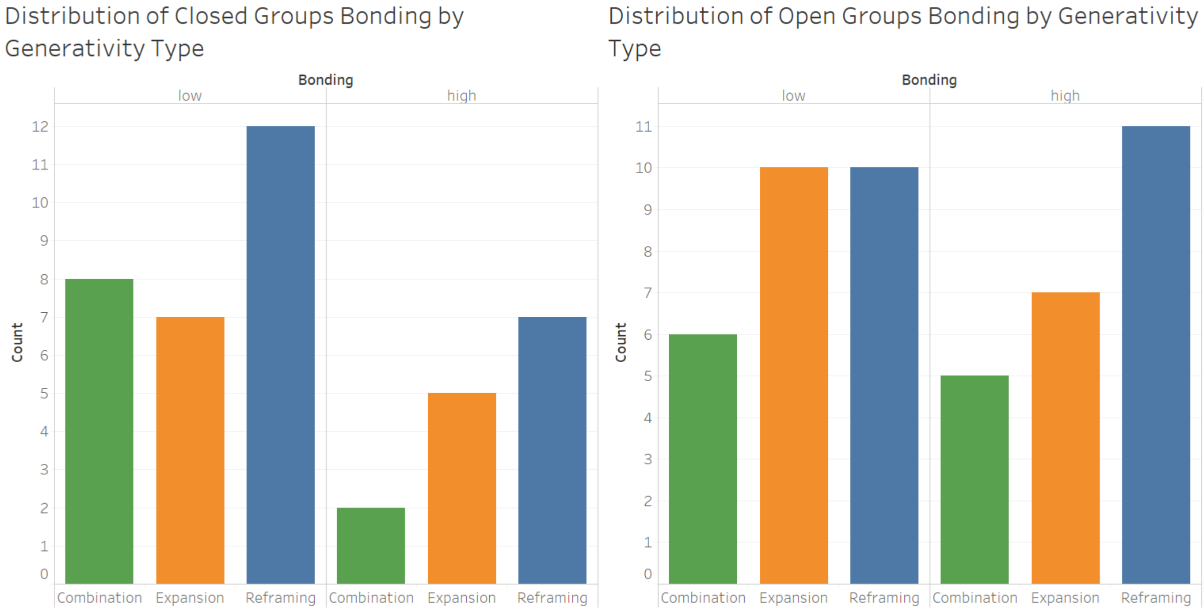

Figure 4: Distribution of Group Generativity by Group Bonding

METHODS

This study calls for the use of a mixed methods approach. The approach can be broken down into three components: a manual content analysis, the development and implementation of a machine learning classifier model, and a predictive regression model. The first research question, which explores the prevalence of the different types of generative collaborations occurring on ESM platforms, is addressed through the manual content analysis as well as the development and implementation of a machine learning classifier model. Discovering the antecedents of generative collaborations, which is posed in the second research question, is addressed through the implementation of the predictive regression model. As an additional outcome from this study, linguistic indicators (keywords in the data) will be extracted to improve our understanding of the linguistic nature of these collaborations.

Content Analysis

A content analysis is a method that attempts to "quantitatively summarize different messages" (Wrench, 2019). This method involves hiring "coders" (or sometimes referred to as "annotators") who will tag different messages from the group threads in the data as one of the three types of generativity – namely: combination, expansion, and reframing – or as non-generative, if applicable (See Appendix B for Coding Manual).

Four business analytics students were recruited as coders. The coders were shown the entire thread from which messages originated from, so that they are able to accurately evaluate whether any of the forms of generativity are present based not only on the individual message but also on a contextual understanding of the entire conversation of which the message belongs to.

To streamline the process, the coders attended three meeting sessions (see Table 1 for timeline details), explained as follows. In the first session, they were introduced to the topic of group generative collaborations on enterprise social media platforms; this included discussing the definitions as well as examples of the three typologies. The coders were also shown the coding manual for the first time (see Appendix A for first version). Qualtrics, a survey tool, was used to record the coders' annotations. Figure 5 is a screen capture of the survey the coders used to annotate messages. First, the Thread ID is shown, then the subject of the thread, followed by the message ID and the message text. Each ID must be ticked, to ensure the coders have viewed and read the information associated.

Date	Task	Description
May 22nd	Introduction & First Training	Introduced coders to the topic of interest, showed them the coding manual and coding scheme, and provided practice threads to try annotating for the first time. Debriefed on the practice threads. Assigned a small batch of threads to annotate as 'homework' for the second session.
May 23rd	Second Training & Debrief	Calculated inter-coder reliability from the 'homework'. Debriefed and discussed the annotations from the homework. Agreed on edits for the coding manual. Assigned another batch as 'homework' for the third session.
May 29th	Third Training & Debrief	Calculated inter-coder reliability from the 'homework'. Debriefed and discussed the annotations from the homework. Agreed on last edits to the coding manual.

Table 1: Content Analysis Training Timeline

The data was preprocessed in preparation for the Qualtrics surveys. This included removing HTML metadata and ensuring the punctuation and grammar of the text was preserved. Once the data was preprocessed, it was saved into a file that could be imported to Qualtrics to

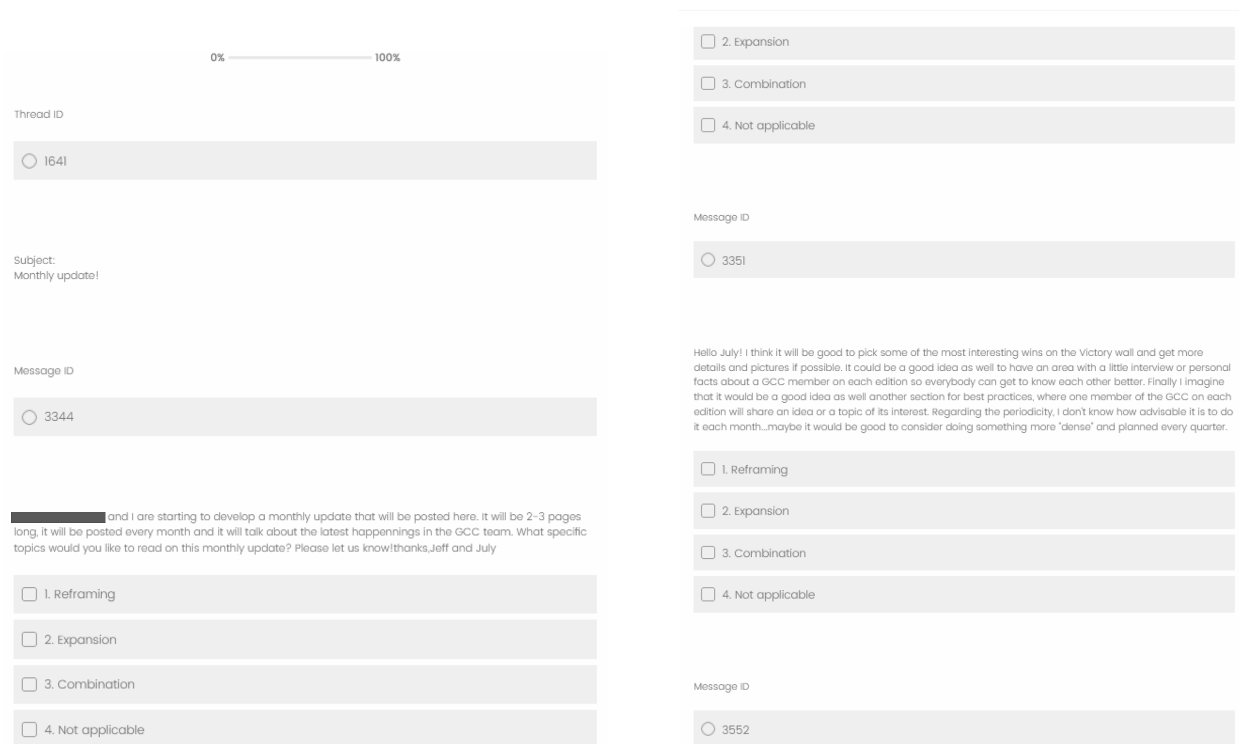

Figure 5: Qualtrics Example Survey

automatically generate a survey, where each thread is displayed on a single page, along with the messages associated with the thread, and the response options for each component of the thread (multiple choice answers, etc.). Survey settings were tweaked so that it is compulsory to tick the boxes for the Thread ID and Message ID. This not only helped to record this information for data analysis later, but also focused the coders attention on the overall Thread topic, which could aid with the contextual understanding of the thread. Additionally, for the category choices the coders are given, additional settings were used so that coders would select at least one category, but no more than two categories for each message they were annotating.

During the first training session, the students were able to practice the coding process by independently annotating 6 threads, which varied in length – between 3 to 10 messages. This allowed to coders to become familiar with the process of annotating messages and identifying the instances of each of the generativity types. Following the annotation, the disagreements were discussed and resolved by exploring why a particular category was most applicable. Next, the coders were given another set of 10 threads to complete as practice prior to the second session. This second training set would serve as data to measure the inter-coder reliability using Krippendorf's alpha. The results showed that the inter-coder reliability was not satisfactory yet, thus a third training set would be given to the coders to improve their inter-coder reliability.

During the second training session, the coders had a chance to discuss any disagreements in their annotations and improve their understanding of the typologies. In this second training and debriefing session, it was also evident that some amendments had to be made to the coding manual, such as adding some clarifications for the annotation instructions and rules. Due to the observation that the coders found messages that contained more than one category, the coding manual was revised, so that a message can be labelled as at least one category, but no more than two categories – with an additional rule, that a message cannot contain a label for one of the types of generativity, and at the same time a label for "Not applicable" (see Appendix B for the second and final version). The third training set proved to help the coders practice, and we were able to conclude with an inter-coder reliability using Krippendorff's alpha[2], which is an appropriate reliability measure for multi-label data.

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[2] Krippendorff's alpha is typically considered satisfactory at a threshold of 0.5 and above. In this study however, due to the multiclass and multilabel nature of the data, the complexity of inter-reliability between coders is higher. Thus, the alpha scores produced at nearly ~0.5 were considered satisfactory enough for the purposes of this exploratory study.

Coder pair	Krippendorff's alpha	Percentage Disagreement
C1, C3	0.454	49%
C2, C4	0.493	51%

Table 2: Inter-Coder Reliability Highest Pairs

According to the inter-coder reliability results, it was best to split the four coders into two groups. According to Krippendorff's alpha for each of the coders, I was able to identify the pairs of coders that would generate the most reliable annotations (see Table 2).

In the final component of the content analysis, each of the two groups were given 100 threads to annotate. The 100 threads were split into four batches of 25 threads. This helped the coders with managing their time spent on each batch of 25 threads and made the overall process of annotating more manageable. Once the two groups of coders had completed annotating their batches, the data was cleaned and processed. It was expected that the coders would still have some disagreement between them. To handle these disagreements in their annotations, the two coders that seemed to have the highest reliability (according to Krippendorff's alpha) were considered the *primary* coders. Their annotations would hold precedence. However, due to biases that may exist from any coder, regardless of their reliability score, the messages that the coders had disagreements in were re-examined and re-labelled where necessary. It was a priority to ensure the training data for the next step, the machine learning classifier, was reliably labelled.

Machine-learning Classified Model

Given the large data corpus, annotating all the content manually is a significant undertaking and would limit the scalability of this study to possible other data sources in the future. Building a machine learning classifier helps to facilitate the automatic classification of data from the ESM data corpus. The strategy for building and training the classifier is shown in Figure 6.

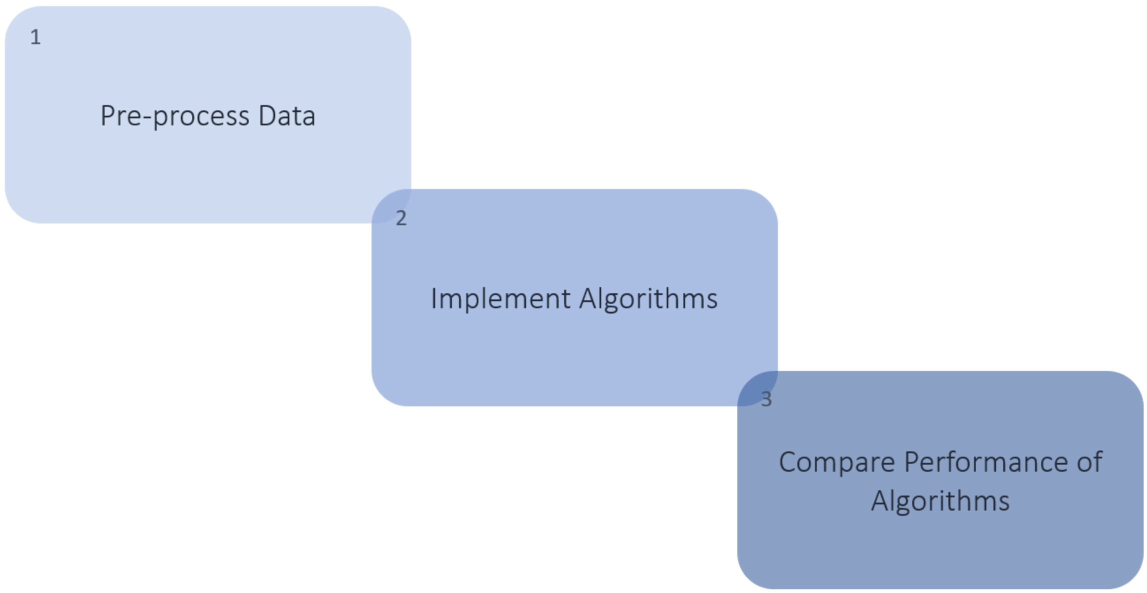

Figure 6: Machine Learning Classifier Steps

The data that resulted from the manual content analysis is considered a multiclass and multilabel dataset. The data contains four different categories of labeled data (multiclass) and each message in the data can be classified as at least one of these categories, or at most two (multilabel). Considering this, the first step before following the strategy to build a machine learning classifier, is to analyze the data distribution. It was evident that the data was slightly imbalanced as there were approximately 500 cases of generative content under the reframing category, and just over 1,000 cases of "not applicable" (i.e., approximately half the training data). To ensure the machine learning model has enough positive (i.e. generative) cases, the "not applicable" cases were cut down to approximately 90. The data from a social media platform will rarely be perfectly balanced as the real exchanges do not have a set balanced pattern of behaviors. Nevertheless, the data is suitable to run a classifier model for each of the categories, separately, since different classifier algorithms work better for different generativity types; in addition, this would ensure the highest performance. This decision to run the classifiers separately for each of the categories did not affect the cases in the data that had more than one label (i.e. the multilabel observations). Such cases are represented as positive for each of the two classes present, in their own separate dataset. For example, if a message has both expansion and combination categories, only expansion will be included for the classifier handling expansion positive data, and the same would apply for the combination classifier.

Moving forward with the strategy for building a classifier, the first task is to preprocess the data. This includes removing punctuation, special characters, stop words, and other special symbols from the text data. Next, the text data is converted to its lower-case format. Subsequently, the text is split by words, and lemmatized - a technique that is used to reduce words to their base form: “dogs” is reduced to “dog”. Following lemmatization, the features (i.e. keywords) are extracted from the text using the ‘bag of words’ method, where the text is converted and represented by the number of times that any and each word appears, in order to describe their occurrence. Finally, TF-IDF (Term Frequency – Inverse Document Frequency) is implemented to describe the occurrence of words in the data, and to transform the data from text to vector form (i.e. from characters to numerical form) - which the machine learning model can process.

The second task is to implement different algorithms in order to find the one that performs best. For this task, the data is split into training and testing sets. Since the classifiers will handle each category separately, the data is split into a training and testing set for *each* of the categories. The training set used in each classifier will allow the algorithm to learn how to classify the text containing elements of the specific category (i.e. generative category) it is trying to classify, or a lack thereof. The testing set will be used by the model to check its performance at (in)correctly classifying the data. To measure the performance of the algorithms implemented, performance measures such as precision, recall, f-1 score, accuracy, and AUC (Area Under the Curve) are generated. The algorithms that were implemented include: Logistic Regression, Random Forest, and Naïve Bayes. To help with the imbalanced nature of the data, the ADASYN (Adaptive Synthetic) oversampling method was added to the classifier. Oversampling is a method that is used to balance classes. The ADASYN oversampling method will shift the weight of the class (i.e. category) distribution so that the minority classes (i.e. classes that have few observations) that are a challenge for the classifier to detect have an increased importance in the dataset.

Regression Model

The third component of my approach is building a regression model. The aim was to identify the antecedents of generative collaborations.

As aforementioned, I would be using group characteristics to predict each type of group generativity. Namely, the visibility of a group (open or closed) , the bonding (density of the network of group members), the bridging of the group (Zafarani, Abbasi, & Liu, 2014) and the diversity of the group (in the network) (Zafarani, Abbasi, & Liu, 2014). Following existing practices in the ESM literature that have shown that group visibility often moderates the effects

Table 3: Regression Models Variable List

Level of Analysis	Variablie	Variable Type
Group Level	Form of Generative Collaboration	Dependent Variable
Group Level	Group Visibility	Independent Variable
Group Level	Group Bonding	Independent Variable
Group Level	Group Bridging	Independent Variable
Group Level	Group Network Diversity	Independent Variable
Group Level	Group Size	Control Variable

Variable	Definition	Representation in Regression Model
Generativity Type	One of the three types of generativity; reframing, expansion, or combination. Measured for each group by the distinct count of messages that contain a type of generativity.	The total number of observations for each type of generativity,for each group.
Bonding	The structure of a group. A measure for the inter-connectedness of the group members. Calculated using density network measure.	Split by the mean of all observations. 1 = low bonding 2 = high bonding
Bridging	The network structure between groups. A measure for the inter-connectedness of different groups, based on members. Calculated using the closeness (network measure) between members in different groups.	Split by the mean of all observations. 1 = low bridging 2 = high bridging
Diversity	The similarities of members positions in a network within a group. A measure that determines how diversly inter-connected group members are. Calculated using the Jaccard Index.	Split by the mean of all observations. 1 = low diversity 2 = high diversity
Visibility	Whether a group is open (i.e. visibile to the entire platform's network) or closed (i.e. visibile only to members of the group.	1 = open group 0 = closed group

Table 4: Operationalization of Group Level Variables

of network variables (Van Osch & Steinfield, 2018), interaction terms were added to the models to explore the interaction effect of group visibility with bonding and bridging.

To build the regression models for each category, negative binomial regression was applied. The use this type of regression model is typical for when a dependent variable is a count variable (see Table 4). The dependent variable for each generativity type is the count of the instances it occurs in messages within the group. Additionally, this regression model is appropriate for the over-dispersed nature of the data – considering the distribution of instances of combination in the 10% sample that was labelled (displayed in Figure 7).

$$Generativity\ Type \sim Group\ Visiblity + Group\ Bonding + Group\ Bridging + Group\ Diversity\ Index + Group\ Size + Group\ Bonding\ \times Group\ Visibility$$

Model 1: Negative Binomial Regression Model with Bonding and Group Visibility Interaction Terms

$$Generativity\ Type \sim Group\ Visiblity + Group\ Bonding + Group\ Bridging + Group\ Diversity\ Index + Group\ Size + Group\ Bridging\ \times Group\ Visibility$$

Model 2: Negative Binomial Regression Model with Bridging and Group Visibility Interaction Terms

Preparing the data for the regression model involved aggregating the data from the individual level to the group level. The messages in the sample from the content analysis are individual level data, as each message is associated with a user. Aggregating the data to the group level resulted in a new data set of 79 groups with 7 variables – where one variable was a control variable and one was the dependent variable (see Table 3 for list of variables, and Table 4 for operationalization of variables). A dataset of this size is considered small for a regression model that involves a count datatype dependent variable, and thus obtaining statistical significance can be a challenge. To alleviate this issue, the bridging, bonding, and diversity variables were all split by the mean of the total observations in each variable.

Linguistic Indicators

An additional outcome, and component, in my approach to this study is to extract the linguistic indicators of each type of generativity from the data. A “linguistic indicator” refers to the words in the text data. Using the best performing machine learning classifier model for each category of generativity, I have identified keywords that are present for each of the categories. It is likely that these sets of words are used by the models to distinguish the different types of generative activity.

This set of language can be used to evaluate how likely it is that a message in a group thread contains elements of a specific type of generativity; and thus, could potentially be a root-cause of innovation. This generates an additional valuable outcome from this research that could inform future semantic analysis aimed at identifying and classifying generative collaborations in text data.

Proof of Concept

In 2019 a preliminary study was conducted, which explored the generative versus non-generative collaborations in 209 group thread exchanges. This study can serve as a proof of concept for the method explained above.

More specifically, the study included a content analysis, the development of a machine learning classifier model, and feature importances (i.e. linguistic indicators). The sample of data used for the preliminary study was pulled from the same data corpus that was used for this research. Approximately 1% of the data was used for manual labeling (content analysis). Next, several algorithms were implemented to select a machine-learning classifier model; the performance of these algorithms was compared in order to find the algorithm that is best suited for classifying generative vs non generative collaborations. The algorithms implemented included: Random Forest, Adaptive Boosting, Naïve Bayes, Support-Vector Machine (SVM), and Logistic Regression. The performance measures used to compare the algorithms were the f-1 score, the accuracy, and the Area Under the Curve (AUC). The Random Forest algorithm was the best performing model, with a 76% accuracy score. The last step in this preliminary study was extracting the feature importances. Using the Random Forest classifier model, the top 20 important features (or keywords) were extracted. These features are the linguistic indicators that help to identify instances of generative collaborations.

The results from this study produced valuable insights. The implementation of a machine learning classifier model has shown that the Random Forest algorithm is well suited for this type of text-based classification problem. Additionally, from the top 20 important features, terms such as “work”, “business”, “project”, or “product”, are essential linguistic indicators of the nature of group generative collaborations. Furthermore, for this preliminary study, the sample of data used contained 28% generative collaborations, and 72% non-generative collaborations. This preliminary study’s outcomes were published in two conferences: SIGHCI 2019, and HCII 2020. Though the sample of data used for this preliminary study was small, it does show promise of the feasibility for the use of machine learning to reliably distinguish the generative and non-generative group collaborations.

RESULTS

Content Analysis

The content analysis conducted for this study was a helpful indicator of not only the distribution (see Figure 7) of the different categories of generativity (and lack thereof), but also a valuable source for new heuristics to explore the prevalence of these behaviors on ESM.

Looking closer, it is evident that while the divide between the applicable and not applicable content in the data is almost equal, it is a significant improvement from previous content analysis conducted as a proof of concept study. In that preliminary study, where the categories of generativity were collapsed to two categories (generative vs non-generative), 28% of the data was labelled as generative. In this study, where more data was sampled for the content analysis, the data that includes some form of generative content is approximately 44% of the sample.

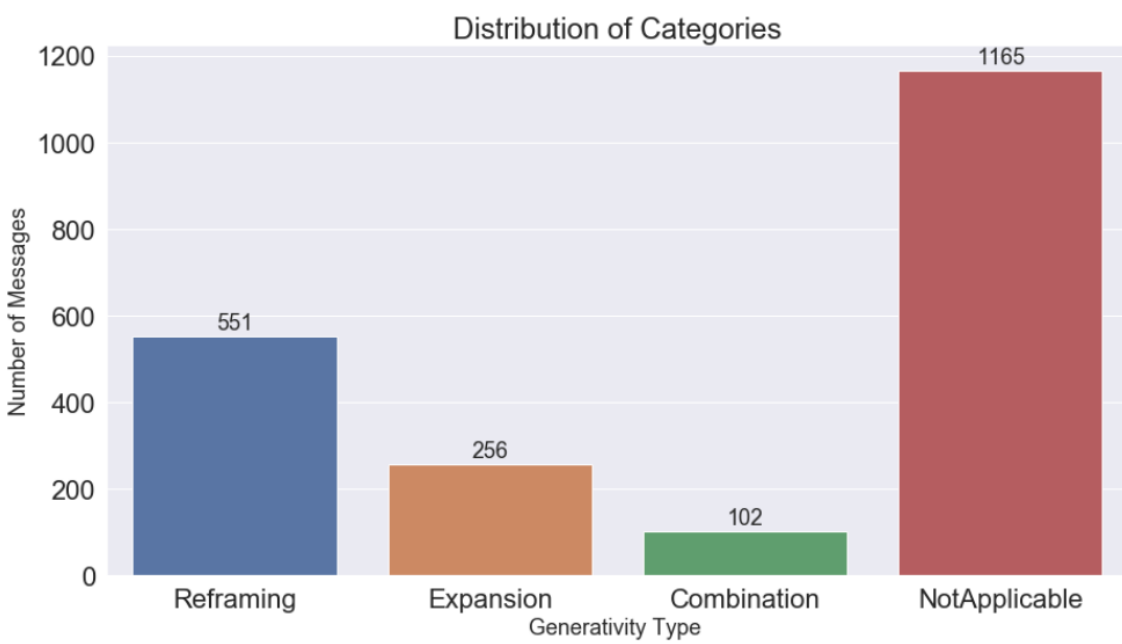

Figure 7: Distribution of Categories of Generativity from the Content Analysis

The following example of Reframing is a quote from a message in a thread about cloud storage use. The employee who wrote the message is describing the use of cloud storage as more than a way to share data with others – essentially reconstructing the concept of cloud storage as a means to store and backup files on their personal computer, for safe keeping, and as a way to access files at work and at home. The portion of the message that indicates that this message can be categorized as reframing is underlined:

> "[...] personal cloud storage is about <u>more than the need to share data with external parties. I use it primarily as an easy backup for files on my pc that I would hate to lose, and as way to share files between multiple devices that use my work pc and my home pc.</u> For example services like google drive Dropbox and SkyDrive let me map a folder on my pc hard drive to a cloud storage location that is kept constantly synchronized so I can access these files from any of my devices, and I can also be sure that even if my pc hard drive completely fails - which has happened to me in the past – I won't lose those files."

In the following example of expansion, the employee who wrote the message is discussing with colleagues the process of new product creation. Here, the employee is expanding the use of a quote they mention, to fit the topic of discussion in the thread:

> "[…on managing product creation…] This reminds me of Samuel Johnson famous quote: "knowledge is of two kinds: we know a subject ourselves or we know where we can find information on it". <u>Taking this quote a step further, and looking at the [case organization] family as whole</u>, I'm 6 months in and can't tell you how many times people in this company have made me look good in front of customers. We have so many knowledgeable individuals and the fact that anyone and everyone is willing to pull together at a moment's notice is impressive to colleagues, but truly amazing to the customer."

The example of combination below is from an employee contributing to a thread about gamification. The employee has agreed with their colleague's thoughts on gamification, and moves on to combine what was mentioned by the colleague into a new idea for implementing gamification theory:

"Mike, I really like the connection you made to gamification. I've been thinking about the same thing. Drive really describes why certain elements of game theory work as well as they do. Maybe gamification game theory helps one think through how to apply the concepts. If one were to take an element of performance such as Mapp objective or maybe dimension of the ITCDPP, and structure it as more of a game, how might that look? keeping in mind a game does not always mean video game, but can come in different varieties, such as group oriented vs. solo and tangible real vs. virtual group. Tangible baseball solo, tangible bowling, group virtual world of war craft solo, virtual pac man. Games also tend to have meaningful status, and an intrinsic reward component. How might this be built into the mechanics of such a game?"

The language included in each of the categories in the labeled data sample, at first glance, can be seen in Figures 8 to 10. It can be observed from the overlap in words that there is not enough distinction between each type of generativity. This observation supports the use of a machine learning classifier model for this research; manually distinguishing the linguistic patterns of each type of generativity and then classifying the rest of the more than 20,000 messages in the data corpus would be a tedious task and could result in error.

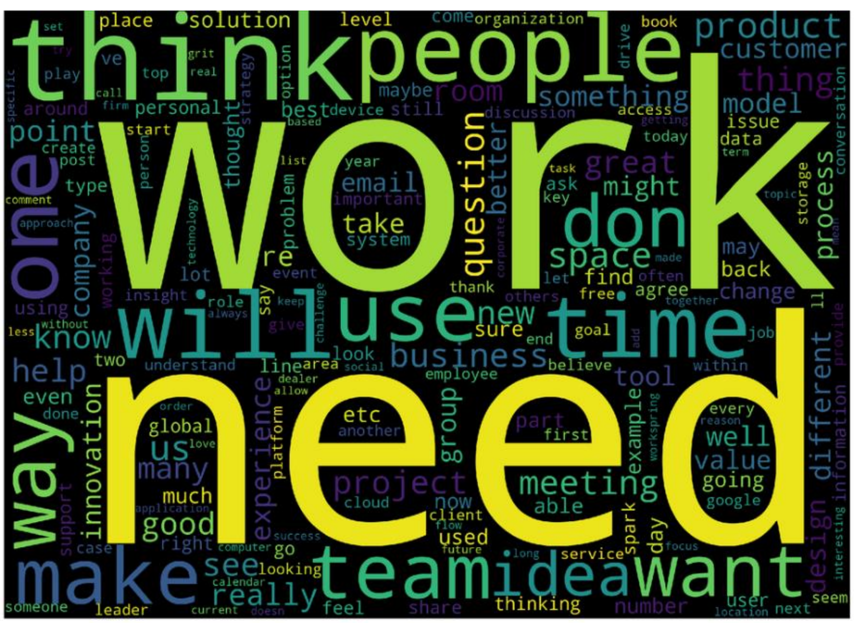

Figure 8: Reframing Word Cloud with Content Analysis Data

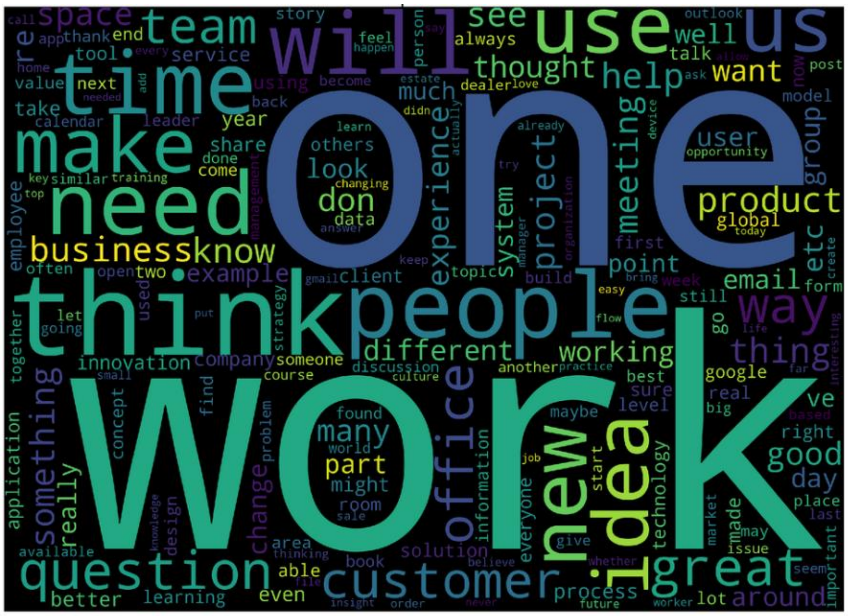

Figure 10: Expansion Word Cloud with Content Analysis Data

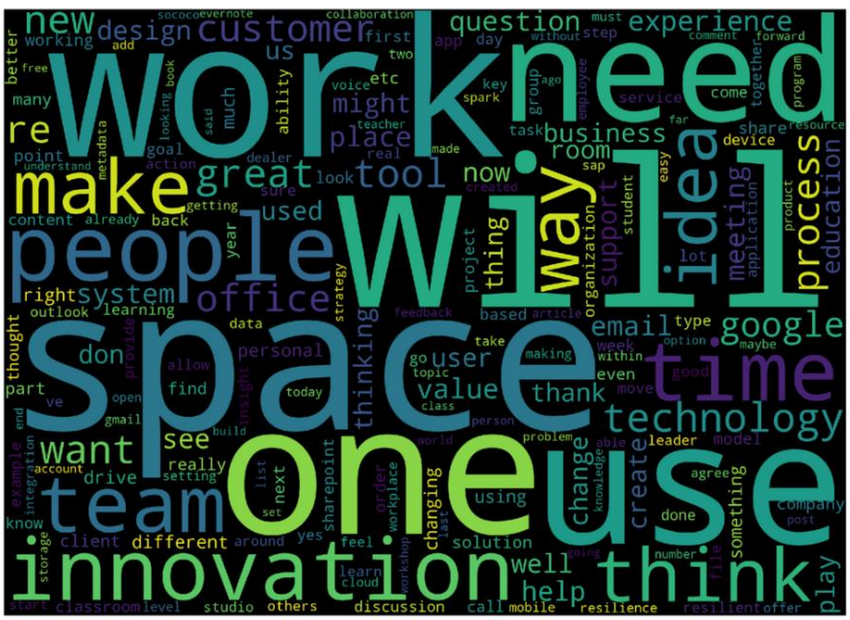

Figure 9: Combination Word Cloud with Content Analysis Data

Machine Learning

The results show that the best performing classifiers can accurately reflect the distribution of the data. This is evident from the accuracy the f-1 scores display for positive and negative cases of each of the categories of generativity. The percentage that is classified as negative (i.e.

0, meaning ‘not applicable’) is approximately the same as the portion of the data that is not relevant. The prevalence of the types of generativity can be reflected in the classifier models’ performance.

Models were selected for each type of generativity by comparing the f-1 scores of each classifier for each category of generativity. Additionally, the overall accuracy was also taken into consideration. The precision and recall scores for the classifiers were considered as tie-breaker scores; if two models seemed to perform almost as well as each other, the precision and recall scores were used to decide which model should be selected. The reliability of the classifiers was the highest priority. Approaching the selection of the classifier models this way ensures that the models are compared with appropriate measures, giving precedence to the scores (f-1 score and overall accuracy) that are most important.

Reframing Classifier Model

The classifier model that performed best at correctly classifying cases of reframing in the data was the Logistic Regression model. Table 5 displays the results for the logistic regression model; results for the other two models implemented can be found in Appendix C.

Logistic Regression				
	Precision	**Recall**	**f-1 score**	**Accuracy**
0	61%	43%	50%	65%
1	66%	81%	73%	

Table 5: Reframing Logistic Regression Classifier Model Results

The logistic regression model has 73% accuracy (f-1 score positive) at correctly classifying instances of Reframing. Moreover, the classifier’s recall score is promising, as it shows that 81% of the data that is relevant to positive cases of reframing are correctly classified by the model. Concluding that Logistic Regression is the model that performs best at classifying data that contains reframing, the linguistic indicators that the model uses to distinguish these cases were obtained (see Figure 11). This set of language is important for the model to identify the cases that contain elements of reframing, as opposed to the cases that do not.

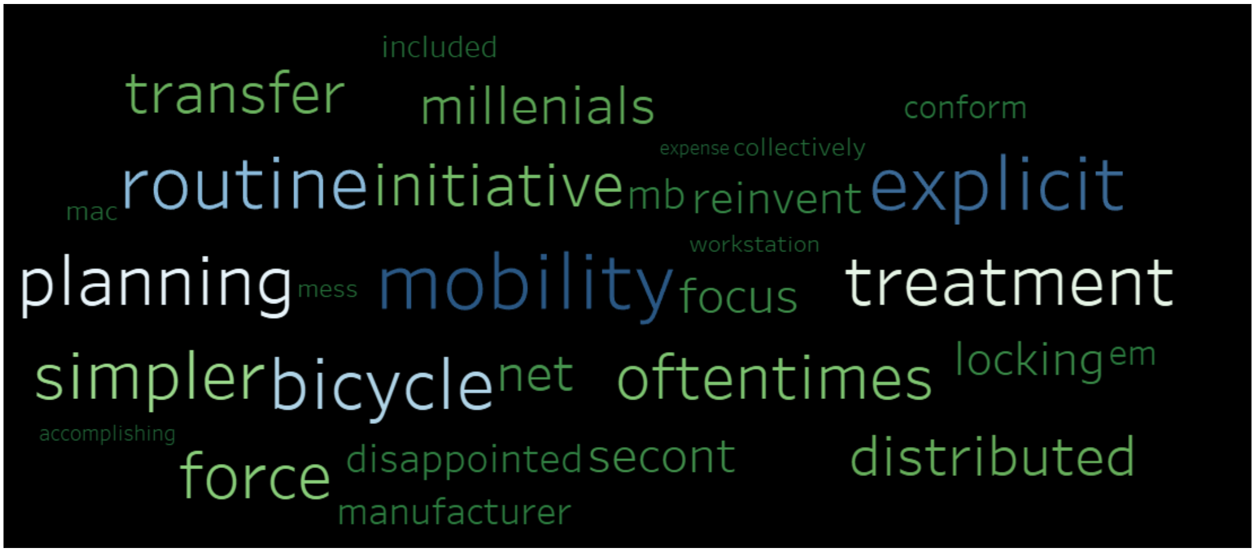

Figure 11: Reframing Machine Learning Model Linguistic Indicators

Expansion Classifier Model

The same process was followed for selecting the classifier that performs best at classifying instances of expansion. Table 6 displays the results from the Random Forest classifier, which performed better than Logistic Regression and Naïve Bayes at correctly classifying the data (see Appendix C for results for the other two models).

	Random Forest			
	Precision	Recall	f-1 score	Accuracy
0	76%	78%	77%	66%
1	37%	35%	36%	

Table 6: Expansion Random Forest Classifier Model Results

The random forest model has 36% accuracy (f-1 positive score) at correctly classifying instances of expansion. Though this performance may seem low at first, the distribution of the data that contains expansion is lower than reframing, combination, and 'not applicable' combined. Thus, the model can only produce a certain level of accuracy with such few instances of positive cases. Moreover, the overall accuracy of the model is 66%, indicating the reliability of the classifier. From this perspective, this model is promising for future improvement with data that includes more instances of expansion. The linguistic indicators produced by this model were also generated, as these can be a helpful approximation of the set of language that is found in instances of expansion.

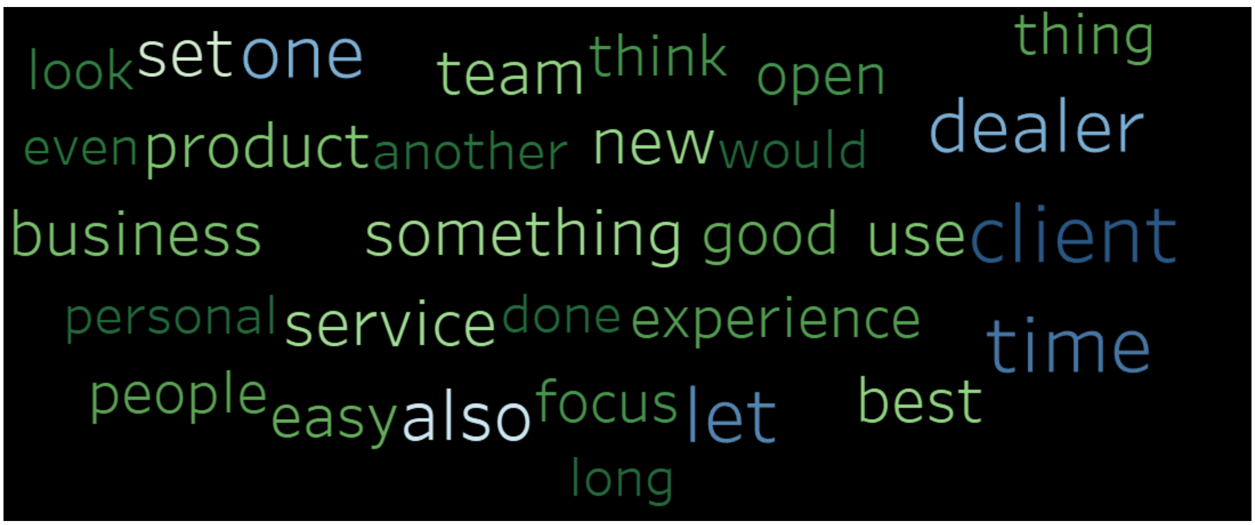

Figure 12: Expansion Machine Learning Model Linguistic Indicators

Combination Classifier Model

Finally, the process to selecting the classifier model for combination was the same as the process for reframing and expansion. Combination had the smallest amount of positive cases (i.e. prevalence) in the data. Thus, the results were similar to those of the classifiers implemented for expansion. The f-1 score accuracy at correctly classifying the data for combination can seem low at first; however, it is a reflection of the low amount of cases in the data that pertain to combination. Table 7 displays the results from the Naïve Bayes classifier, which performed better classifications than the other two models implemented for this type of generativity (see Appendix C for results from other models implemented).

Naïve Bayes				
	Precision	Recall	f-1 score	Accuracy
0	92%	70%	79%	68%
1	17%	50%	25%	

Table 7: Combination Naive Bayes Classifier Model Results

Similarly, to the expansion random forest model, the low accuracy for correctly classifying positive data (positive f-1 score) is a reflection of the number of cases of combination present in the data. The overall accuracy of the model is 68%, which indicates a dependable model for classifying cases of combination in the text data. The Naïve Bayes model would be well suited to classify instances of combination. The linguistic indicators, which are an approximation of the language present in cases of combination, can be seen in Figure 13.

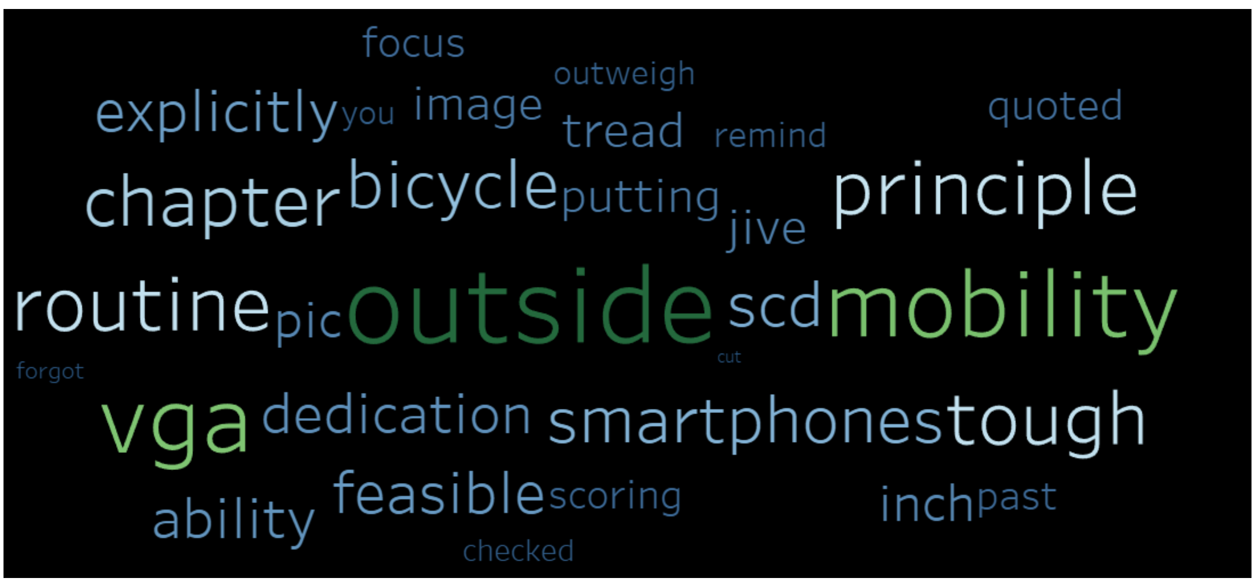

Figure 13: Combination Machine Learning Model Linguistic Indicators

Regression Models

Two models were created for each type of group generative collaboration. Model 1 includes bonding and group visibility as interaction terms, whereas model 2 includes bridging and group visibility as interaction terms. Tables 8 to 10 show the different estimates for each of the independent variables (generativity types); an asterisk next to the estimate indicates statistical significance.

After implementing both Poisson and Negative Binomial regression, with and without interaction terms, the results showed that a Negative Binomial regression with interaction terms

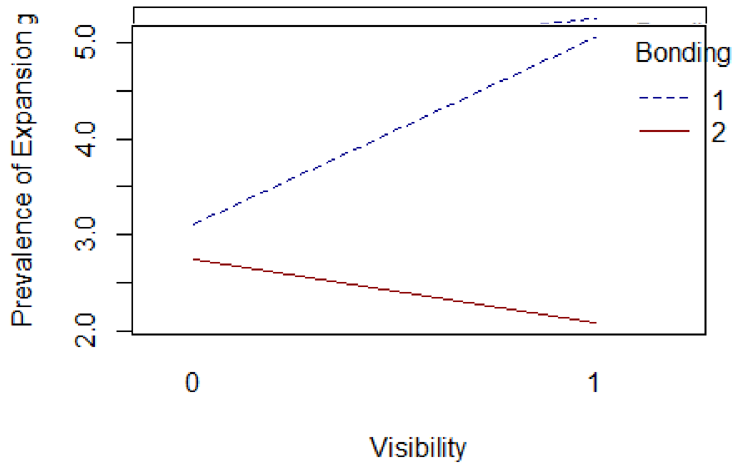

Figure 14: Reframing Interaction Plot

Figure 15: Expansion Interaction Plot

(see Figures 14 to 15, interaction plots) would be the best approach (see Tables 9 to 11 for results).

Model 1 Estimates			Model 2 Estimates		
Intercept	1.30369	**	Intercept	1.435556	***
Visibility (closed)	0.25912		Visibility (closed)	0.156097	
Bonding	0.04699		Bonding	0.132446	
Bridging	0.0875		Bridging	-0.006304	
Diversity	0.58355	*	Diversity	0.572516	*
Size	0.53833	***	Size	0.59568	***
Bridging	-0.18707		Bonding	0.587353	.
Visibility (closed) x Bridging	0.32892		Visibility (closed) x Bonding	-0.925464	**

Signif. codes: 0 "***", 0.001 "**", 0.01 "*" , 0.05 "." , 0.1 ""

Table 8: Reframing Model 1 & 2 Estimates

Reframing Models

Table 9 displays the results for the two models built for the reframing generativity type.

In both model 1 and model 2, group size is statistically significant. An increase in the size of an ESM group can increase the prevalence of reframing. Moreover, an increase in the diversity of an ESM group's network can also increase the prevalence of reframing.

Model 1 includes the 'bridging and group visibility' interaction term, which is not statistically significant for any change in the prevalence of reframing for an ESM group. In Model 2 however, an increase in the bonding behavior of a closed group, will increase the prevalence of reframing for that group.

Expansion Models

Similarly to the models created for reframing, group size and group diversity are important indicators of the prevalence of expansion in an ESM group. Bonding is a strong antecedent of the prevalence of expansion for a closed group. That is, if a closed group displays lower levels of bonding, the amount of expansion increases.

Model 1 Estimates		
Intercept	0.09390	
Visibility (closed)	0.65355	
Bonding	-0.25443	
Bridging	0.40085	
Diversity	0.67739	*
Size	0.48611	**
Bridging	-0.02372	
Visibility (closed) x Bridging	-0.18512	

Model 2 Estimates		
Intercept	0.5236	
Visibility (closed)	0.5259	
Bonding	-0.1732	
Bridging	0.101	
Diversity	0.5832	.
Size	0.5611	***
Bonding	0.6149	.
Visibility (closed) x Bonding	-1.0624	**

Signif. codes: 0 "***", 0.001 "**", 0.01 "*" , 0.05 "." , 0.1 ""

Table 9: Expansion Model 1 & 2 Estimates

Model 1 Estimates			Model 2 Estimates		
Intercept	-0.2604		Intercept	0.3161	
Visibility (closed)	0.17781		Visibility (closed)	0.3095	
Bonding	-1.03283	*	Bonding	-0.9759	.
Bridging	-0.03742		Bridging	-0.6742	.
Diversity	1.05548	**	Diversity	0.7766	*
Size	0.23821		Size	0.2424	
Bridging	-0.27708		Bonding	0.1134	
Visibility (closed) x Bridging	-0.22086		Visibility (closed) x Bonding	-0.1873	

Signif. codes: 0 "***", 0.001 "**", 0.01 "*" , 0.05 "." , 0.1 ""

Table 10: Combination Model 1 & 2 Estimates

Combination Models

For both models for the combination type of generativity, a different pattern is evident. Though the diversity is also a significant antecedent for the prevalence of combination in a ESM group, the bonding behavior of a group in model 1 and 2, and the bridging behavior in model 2 are significant negative predictors of the prevalence of combination for group collaborations in ESM groups. The interaction terms, for both models 1 and 2 are not significant. This could be due to the small sample size, coupled with the few instances of combination in the groups included in this sample.

DISCUSSION

The continuously generated numerous traces of team behaviors make ESM a suitable context to study computer-mediated communication and group collaborations of different kinds. The knowledge-focused exchanges that are supported by ESM give reason to assume that generative collaborations can occur on these platforms.

Summary of Findings

Through pursuing RQ1 – prevalence of generative collaborations in ESM-based groups – two outcomes have been identified: finding a suitable machine learning classifier model for each of the three types of generativity, and an approximation for the extent to which these three types of generativity (reframing, expansion, and combination) occur in ESM-based groups. The results show that 44% percent of group collaborations in ESM show characteristics of being generative. Additionally, the findings show that the prevalence of each type of generativity is as follows: 60% Reframing, 28% Expansion, and 11% Combination[3].

Through pursuing RQ2 - identifying the antecedents of group generative collaborations - six regression models were created, one for each generativity type (as the dependent variable) and one per interaction term (for visibility with network structure) – the findings show that bridging, bonding, and the group visibility are the most significant indicators of group generativity. It can also be observed that the size of a group can influence the prevalence of the types of generativity. Other variables that were also incorporated in the regression model include the network diversity of a group, and the group size.

[3] Percentage breakdown from the 44% of data that contain elements of generative activity.

Implications

This opportunity to study team behaviors in an unobtrusive way, from a data source that has numerous traces of these behaviors, contributes to advancing the theoretical understanding of the nature of group collaborations and their antecedents in various ways. First, generative collaborations are prevalent in ESM, though some types are more prevalent than others. One assumption about this pattern is that the most prevalent for of group generativity – Reframing – is the most intuitive for groups to engage in when collaborating. This type of generative collaboration behavior is also the most disruptive. Thus, it could be that ESM encourages disruptive thinking because it affords to bring people together in non-traditional ways (i.e. outside of official organization teams). Secondly, there is an interesting implication derived from the predictive regression models. ESM literature has suggested that due to the affordance of visibility, any user can see anything on the platform, and any other user that is on the platform, and that this affordance leads to serendipitous exchanges – which are expected to drive benefits for teams and organizations. However, for reframing and expansion, the regression models developed show that closed groups seem to be more generative than open groups.

Beyond these possible theoretical implications, there are three practical implications associated with this study. By building a predictive regression model and identifying a machine learning classifier model suitable for classifying text data containing any of the three types of generative activity, there is an opportunity to develop a business analytics tool. Insights such as the level of generative activity, and the statistics that describe other employee activities on the ESM platform, would be useful to organizations. Managers and practitioners would also benefit from the proposed research, as it could help them improve their understanding of group generative collaborations. Lastly, and perhaps the most important practical implication of this research, is that it is a chance to improve the collaborations that occur in the context of ESM platforms, and possibly beyond them by understanding what the significant antecedents are of (each of the types of) generative collaborations. Specifically, the insight that closed groups seem to be more generative is interesting in light of recent workplace trends reinforcing openness and transparency, whether through IT usage—such as ESM tools aimed at increasing visibility of content and exchanges—or through open workplace design. The predictive model could aid with finding the blend of group characteristics that work best to foster generativity, while the set of language that is identified in this study related to generative collaborations, could also be a useful guide for organizations. However, more data must be sampled first for a second round of content analysis, and consequently the larger labelled data sample could aid in achieving these practical implications in the future.

Limitations & Future Research

The proposed research includes some limitations. Firstly, the biggest limitation of this study is the generalizability of the results. The data used is provided by an ESM platform, utilized by a multinational organization, which implies some similarities to a case-study. This limitation is mitigated by the fact that the data includes numerous teams (~10,000) that all possess diverse and distinct characteristics; although the data is derived from one organization, the level of analysis is the team and significant diversity exists at this level of analysis. The second limitation of this study is the use of archival data from one data source, namely ESM. It is likely that there are exchanges occurring outside of the ESM platforms, through other forms of communication, which therefore cannot be measured. Hence these exchanges cannot be taken into account in this study. Nevertheless, the dataset that has been used for this research is large, with enough diverse teams, such that there is sufficient variation to cover many instances, including teams that rely almost solely on the ESM for communication.

Though the machine learning models did not show high accuracy at correctly classifying instances of positive cases for each type of generativity, they accurately reflect the distribution of positive cases in the sample labelled data. This shows promise of using the Logistic Regression classifier model for classifying reframing, for using the Random Forest classifier model to classify instances of expansion, and for using the Naïve Bayes multinomial classifier model for classifying cases of combination. Moreover, the linguistic indicators, which show an approximation of the language present in the three different types of generativity can be used to create a new sample for a content analysis, where using these heuristics would allow for a more balanced sample to be labelled, thereby allowing the generation of better-performing machine-learning models in future studies.

Moreover, it is evident that more data is needed to further train each of the classifiers. The machine learning classifiers are run separately, for each generativity category. Thus, the linguistic indicators could overlap between the types of generativity. Obtaining more data would pave the way to improving the classifiers that were developed in this exploratory study -where linguistic indicators can be distinct for each type of generativity - and in addition, would also create an opportunity to build a machine learning classifier that could handle multi-class and multi-label classification in one model. Such a model would be considered a neural network, where the Multi-layer Perceptron (MLP) classifier algorithm would be implemented, as it can handle these complex dimensions of multiclass and multilabel data.

The regression models developed, which aimed to identify important antecedents for group generative collaborations (RQ2), are a valuable insight to further improve our understanding of how these variables can affect each of the types of generativity. In future research, with more data, these regression models can show further insight as to which antecedents are significant for the presence of each type of group generative collaborations. Lastly, with more data, achieving statistical significance will not be as challenging. Using the heuristics from this study, in future research I will be able to incorporate additional variables such as geographic distribution, content creation per group, and a second control variable, the task type of a group. Content creation of a group is important, as it might help us to explain the positive effect of group size as group size could be acting as a proxy for the amount of content a groups creates, which would likely affect the amount of generativity inherent in that content.

CONCLUSION

In recent years ESM have become an omnipresent I.T. tool for organizations. Yet, there is a lack of research on the implications of using ESM to their full potential, and when, why, how, and where their benefits may occur. The study of prevalence of generative collaborations in ESM-based groups, and the antecedents for these types of collaborations, are not yet explored in the literature. This exploratory research has shed some initial light on the prevalence of these generative collaborations in ESM-based group exchanges, the different types of such collaborations, as well as some group-level characteristics—specifically the interaction between a group's visibility setting and its bonding network structure—that drive these collaborations.

APPENDICES

APPENDIX A

Coding Manual

Introduction

Your task is to annotate pieces of content from discussion threads from online teams on an ESM (Enterprise Social Media) platform. Each thread will start with one post and may include one or more subsequent posts responding to the first post.

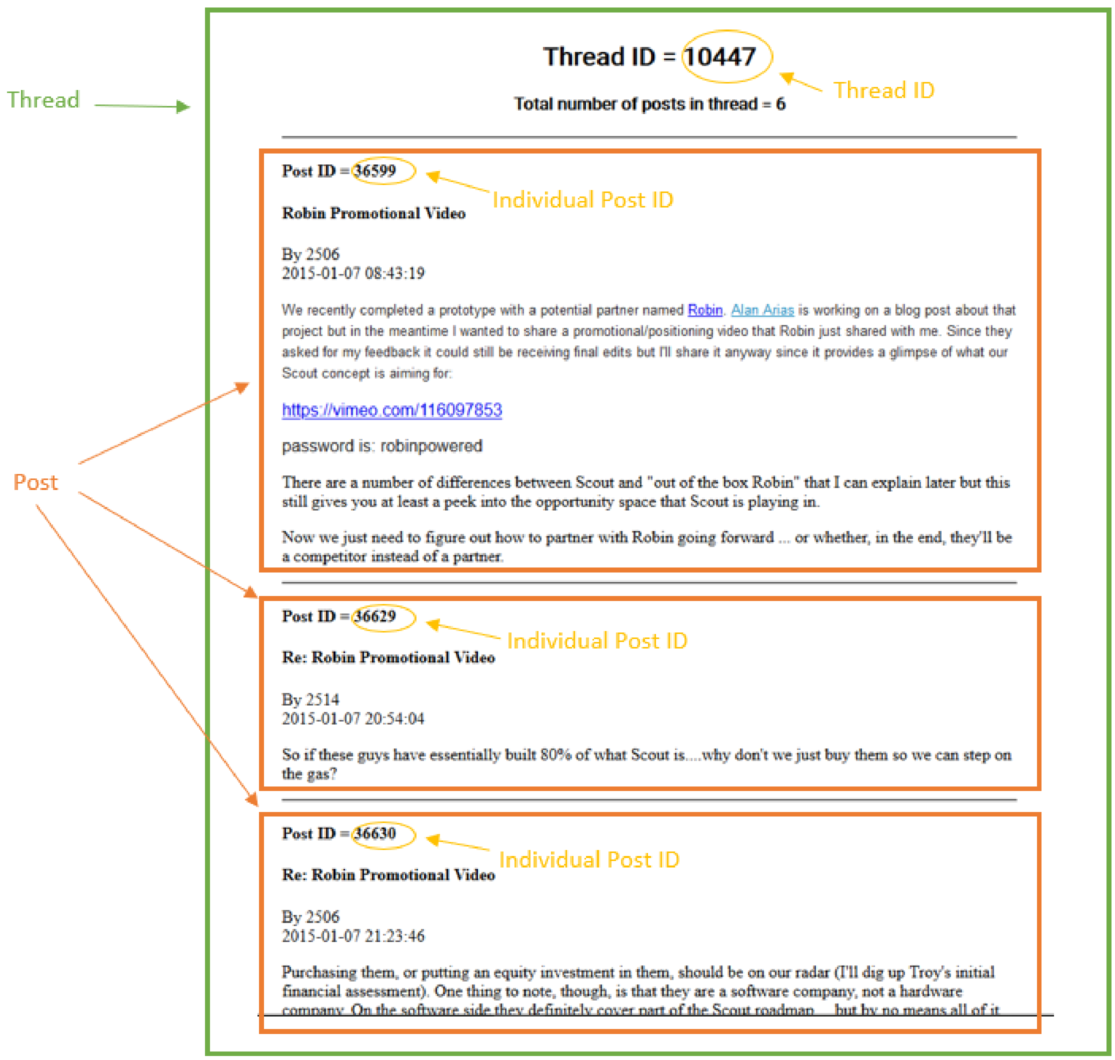

Figure 16: Example Thread

Annotating Idea Generation with Categories

A post contains an element of creating something novel through either reframing, expansion, or combination; if a post contains more than two categories, you should choose the category that is most dominant. Label accordingly for each type of idea generation (reframing = 1, expansion = 2, combination = 3, Not Applicable = 0).

Conceptual Reframing (code label: 1)

Reframing means reclassifying an object so that a new view of it emerges.

Reframing can be non-metaphoric or metaphoric.

Reframing usually involves arguing for the need to rethink the problem so a new view emerges or challenging the concept altogether by envisioning an alternate future state or otherwise alternative.

Example Post:

> "One of the things I started to think about after reading all of your thoughts was how augmented reality glasses might impact the social dimension of work positively or negatively. I couldn't help but think of WALL-E and the people that spent all day interacting with one another through screens and never directly. I found that a profoundly disturbing vision of the future, especially for a children's movie! One alternative to the WALL-E scenario would be the future state in which augmented reality glasses are used for specific tasks or activities that require a high degree of information process but relatively little social interaction...and thus far, most of the applications of augmented reality that I'm familiar with follow this pattern (flying a fighter jet, driving a car). A different future state might be one in which the information displayed via the glasses is designed to augment social interactions, and if that augmentation were done skillfully, the

enhancements to interaction might be beneficial enough as to outweigh any perceived negative impact on the texture of the human interaction."

Conceptual Expansion (code label: 2)

Posts focusing on extending the use of a concept beyond its core use to match a new situation. This may involve taking concepts developed for one context (for example, healthcare) and adapt it to another context (for example, education).

Example Post:

> "There has been some consideration for how techniques from online gaming could be applied to our new integration of social media technology to boost engagement?"

Conceptual Combination (code label: 3)

Posts focusing on developing a new concept by combining two or more existing concepts. Conceptual combination occurs primarily because novel combinations create new categories to describe or bring about changes in something familiar or existing (e.g., "Zionist Christians," "affordable luxury," "natural selection"). This may involve combining elements of two existing products and thereby creating a new one (e.g., merging the base of an existing desk with the counter of a meeting table to produce a meeting room table that can also be used as office space).

Example Post:

> "I have a couple thoughts rolling around for you to bash or build on for our "new" manager program: Aspiring leaders, Next Gen Leader, Emerging leaders"

Not Applicable (code label: 0)

Posts containing no elements of idea generation; they do not belong to any of the above categories.

Example Post:

“The [Organization Name] interns had the opportunity to participate in Chicago yesterday. It was great to see the organization show so full and have such an exciting buzz around it.”

APPENDIX B

Final Coding Manual

Introduction

Your task is to annotate pieces of content from discussion threads from online teams on

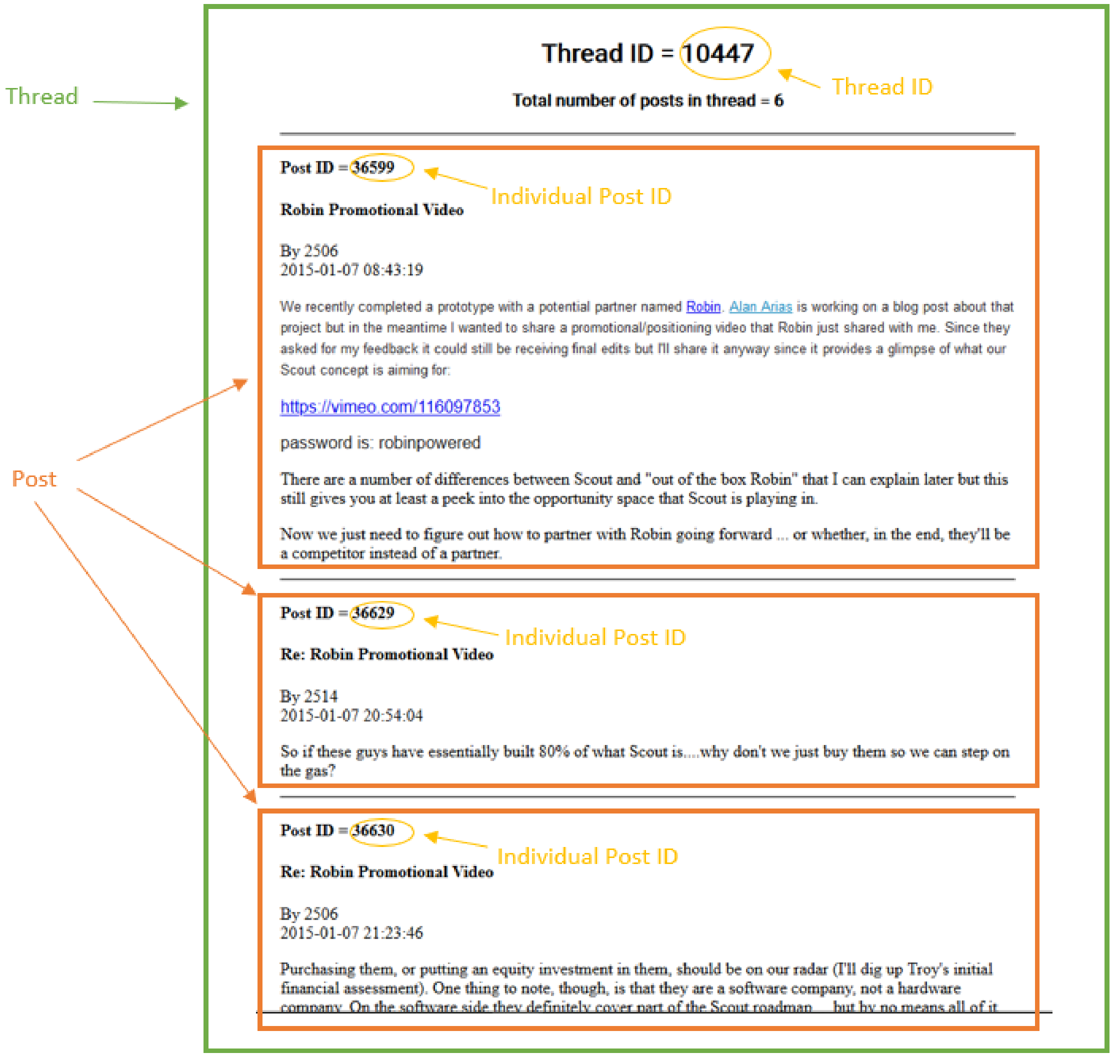

Figure 17: Example Thread for Final Coding Manual

an ESM (Enterprise Social Media) platform. Each thread will start with one message and may include one or more subsequent messages responding to the first message. The objective of annotating these messages is to develop an algorithm that can pick up idea generation.

Annotating Idea Generation with Categories

A message contains an element of creating something novel through either reframing, expansion, or combination. You must choose at least one category to label a message. If you are confident that a message contains elements of more than one category, you may choose up to two categories. An idea must be well developed to be labelled with any of the idea generation categories. If you observe that there is no new idea generation discussed, presented, or suggested in a message, you must label the message as 'not applicable' (do not label any messages as one of the categories and 'not applicable'). If a message contains an idea derived from a previous message, it must be considered at face value; the message still contains an idea. Label accordingly for each type of idea generation present in the message(s).

Conceptual Reframing

→ *An existing concept is deconstructed and reconstrued to fit a new situation, often by challenging the status quo.*

Reframing means reclassifying an object so that a new view of it emerges.

Reframing can be non-metaphoric or metaphoric.

Reframing usually involves arguing for the need to rethink the problem so a new view emerges or challenging the concept altogether by envisioning an alternate future state or otherwise alternative.

Example Message:

"One of the things I started to think about after reading all of your thoughts was how augmented reality glasses might impact the social dimension of work positively or negatively. I couldn't help but think of WALL-E and the people that spent all day interacting with one another through screens and never directly. I found that a profoundly disturbing vision of the future, especially for a children's movie! One alternative to the WALL-E scenario would be the future state in which augmented reality glasses are used for specific tasks or activities that require a high degree of information process but relatively little social interaction...and thus far, most of the applications of augmented reality that I'm familiar with follow this pattern (flying a fighter jet, driving a car). A different future state might be one in which the information displayed via the glasses is designed to augment social interactions, and if that augmentation were done skillfully, the enhancements to interaction might be beneficial enough as to outweigh any perceived negative impact on the texture of the human interaction."

Conceptual Expansion

→ *Expanding the use of an existing concept from its core use to match a new situation.*

Expansion involves transferring existing ideas to new contexts.

This may involve taking concepts developed for one context (for example, healthcare) and adapt it to another context (for example, education).

Example Message:

"There has been some consideration for how techniques from online gaming could be applied to our new integration of social media technology to boost engagement?"

Conceptual Combination

→ *Combining concepts that already exist in new ways.*

Merging existing ideas in new ways.

Conceptual combination occurs primarily because novel combinations create new categories to describe or bring about changes in something familiar or existing (e.g., "Zionist Christians," "affordable luxury," "natural selection"). This may involve combining elements of two existing products and thereby creating a new one (e.g., merging the base of an existing desk with the counter of a meeting table to produce a meeting room table that can also be used as office space).

Example Message:

"I have a couple thoughts rolling around for you to bash or build on for our "new" manager program:
Aspiring leaders
Next Gen Leader
Emerging leaders"

Not Applicable (code label: 0)

Messages containing no elements of idea generation; they do not belong to any of the above categories.

Example Message:

"The [Organization Name] interns had the opportunity to participate in Chicago yesterday. It was great to see the organization show so full and have such an exciting buzz around it."

APPENDIX C

Machine Learning Model Classifiers Results

Reframing

Random Forest

	Precision	Recall	f-1 score	Accuracy
0	46%	22%	30%	57%

Table 11: Reframing Random Forest Machine Learning Classifier Performance

Naïve Bayes

	Precision	Recall	f-1 score	Accuracy
0	58%	28%	38%	62%
1	63%	85%	72%	

Table 12: Reframing Naïve Bayes Machine Learning Classifier Performance

Expansion

Logistic Regression

	Precision	Recall	f-1 score	Accuracy
0	76%	93%	83%	73%
1	50%	19%	28%	

Table 13: Expansion Logistic Regression Machine Learning Classifier Performance

Naïve Bayes				
	Precision	Recall	f-1 score	Accuracy
0	77%	60%	68%	58%
1	33%	52%	40%	

Table 14: Expansion Naive Bayes Machine Learning Classifier Performance

Combination

Logistic Regression				
	Precision	Recall	f-1 score	Accuracy
0	90%	99%	94%	90%
1	60%	12%	21%	

Table 15: Combination Logistic Regression Machine Learning Classifier Performance

Random Forest				
	Precision	Recall	f-1 score	Accuracy
0	90%	93%	92%	85%
1	24%	18%	21%	

Table 16: Combination Random Forest Machine Learning Classifier Performance

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