Good Learning
–
Analyzing Meetings of Sloan Fellows

Master's Thesis in Computer Science

submitted
by

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Übersicht

Gruppenarbeit wird heutzutage zunehmend wichtiger. Um Gruppenarbeit so effektiv wie möglich zu gestalten, ist es notwendig, die entscheidenden Faktoren erfolgreicher Gruppenarbeit zu verstehen. Die bisherige Forschung im Bereich der Gruppenarbeit beschränkt sich größtenteils auf Laborstudien. Mangel an Forschung bestehet im Hinblick auf Feldstudien. In dieser Arbeit wurden natürliche Daten von den Treffen der Arbeitsgruppen des Sloan Fellows Programs - einem umfassenden MBA Studiengang für bereits erfahrene Manager - aufgenommen und mithilfe fortgeschrittener Regressionsanalyse untersucht. Eine Vielzahl an verschiedenen Datentypen (Beteiligung, Demographie, Persönlichkeit, Leistung und Zufriedenheit) wurde kombiniert um ein umfassendes Verständnis von Gruppenarbeit zu erhalten. Die Daten offenbarten, dass Asiaten dazu tendieren, seltener zu sprechen, dass Extrovertierte dazu tendieren, häufiger zu sprechen, und dass Frauen dazu tendieren, kürzer zu sprechen. Außerdem zeigten die Daten auf, dass Gruppen mit einem höheren Grad an Gewissenhaftigkeit oder Offenheit im Hinblick auf Erfahrungen eine gleichmäßigere Verteilung der Beteiligung aller Gruppenmitglieder aufweisen. Es wurde gezeigt, dass die Beteiligung der einzelnen Gruppenmitglieder in positivem Zusammenhang mit der Leistung sowie der Zufriedenheit steht. Gegen Erwartungen wurde kein Zusammenhang zwischen der Gleichmäßigkeit der Verteilung der Beteiligung und der Leistung sowie der Zufriedenheit beobachtet. Des Weiteren wurde gezeigt, dass Feedback in Echtzeit den Gruppenmitgliedern dabei im Mittel hilft, ihr Verhalten anzupassen. Allerdings sind weitere Untersuchungen notwendig, um diese Erkenntnis zweifelsfrei zu beweisen. Entgegen vorheriger Erkenntnisse aus Laborstudien wurde die neue Hypothese aufgestellt, dass eine gleichmäßige Verteilung der Beteiligung in der Realität nicht notwendigerweise vorteilhaft ist. Obwohl die ersten Erkenntnisse dieser Arbeit die Hypothese stützen, ist eine detailliertere Untersuchung notwendig. Die vorliegende Arbeit deckt aufschlussreiche Muster sozialer Interaktionen auf und verleiht ein tiefgehendes Verständnis über Gruppenarbeit. Die Erkenntnisse sind insbesondere wertvoll, weil sie dazu genutzt werden können, Gruppenarbeit effektiver zu gestalten.

Abstract

Group collaboration is becoming increasingly important these days. In order to make group collaboration as effective as possible, it is crucial to understand the determinants of successful group collaboration. Researchers have focused on studying group collaboration in laboratory settings. Lack of research remains for real-life settings. In this work, genuine data were collected from unstructured out-of-class meetings of the Sloan Fellow program, an immersive MBA program for mid-career mangers, and the data were analyzed by means of advanced regression analysis. A wide range of different types of data (participation, demographic, personality, performance, and satisfaction data) was combined in order to get a broad understanding of group collaboration. The data revealed that Asians tend to speak less frequently, extroverts tend to speak more frequently, and women tend to have shorter turns. They further revealed that groups with a higher level of conscientiousness or openness to experience have a more balanced participation. Individual participation was shown to have a positive correlation with performance as well as satisfaction. Against expectations, no correlation was observed between the balance of participation and performance as well as satisfaction. Real-time feedback was shown to support group members adapting their behavior on average. More data will be required in order to prove this finding though. Against prior findings from laboratory settings, a novel hypothesis postulating that even participation is not necessarily beneficial in real-life settings was created. Although the first findings support the hypothesis, further investigation of the hypothesis will be required. The present work uncovers insightful patterns of social interactions and provides a deep understanding of group collaboration. The findings are particularly valuable because they can be used in order to improve the effectiveness of group collaboration.

Contents

Chapter 1

Introduction

"More hands make for lighter work."

"Two heads are better than one."

"The more the merrier."

These adages reveal the high potential of group collaboration. Group collaboration is the key to success in most realms of work and life. For that reason, it is becoming increasingly important these days. Working together in groups can foster creativity and innovations through diverse thinking and collective ideas. It can complement strengths and compensate weaknesses of individuals from different fields of expertise. By sharing information among all group members, it can maximize the level of knowledge for each of the group members. Involvement and responsibilities within the group can cause the group members to be more enthusiastic and motivated. However, group collaboration is challenging as well. It requires the group members to resolve conflicts, to commit to other group members, and to communicate effectively.

In order to make group collaboration as effective as possible, it is crucial to understand the determinants of successful group collaboration. The research area of organizational behavior has investigated methods for improving the effectiveness of group collaboration and for dealing with group sub-optimality, i.e. groups tend to perform better than individuals but not as well as they could [Ker04]. In particular, group dynamics have been the focus of most studies in literature. They have been shown to be a key factor affecting the performance and the satisfaction of groups [Sha71]. Group dynamics are defined as the activities, processes, operations, changes, interdependencies, and interrelationships transpiring in social groups [Sha71]. Hall and Watson [Hal70] have discovered that group performance can be improved by simply instructing the group members to participate and engage more in the conversation. Another study from Woolley et al.

[Woo10] has shown that group performance is dependent on the social skills of the group members rather than on their individual performances. The authors have further stated that groups perform better if the conversation reflects more group members' ideas and if participation is evenly distributed among the group members. Dong and Pentland [Don10] have discussed and quantified the relationship between group performance and group dynamics. They have particularly figured out that groups perform better if the group members have a higher level of activity in their conversation. Dong et al. [Don12b] have further proposed a method for automatically predicting the group performance. They have been able to predict the group performance with notably high accuracy merely based on measures of group dynamics. Pentland [Pen12] has analyzed the relationship between group performance and group dynamics based on genuine data collected in financial organizations. He has identified that communication patterns are the most important predictor of group performance and that they are even more important than individual achievements of the group members.

Prior studies have consistently proven group dynamics to be a major indicator of the effectiveness of group collaboration. However, group dynamics were measured differently in different studies. Traditional approaches involved human observers, video recording, or retrospective questionnaires. In addition, electronic sensing devices have emerged. In contrast to traditional approaches, they are more detailed and accurate. They are not biased by subjective perceptions and they additionally allow for providing real-time feedback to the group members. For example, Bergstrom and Karahalios [Ber07] used microphones and visualized the interaction of the group members on table tops. Similarly, DiMicco et al. [DiM07] visualized the speaking times of the group members on large displays. In particular, the Human Dynamics Group of the MIT Media Lab has developed a wide range of different wearable systems and mobile frameworks for studying group dynamics [Cho02, Pen05, Kim08, OO10, Pen10, Pen14, Led16]. The systems are capable of capturing face-to-face interactions, non-linguistic audio data, as well as physical proximity to others. They provide real-time feedback by visualizing the amount of participation of all group members and the balance of participation among all group members. Olguin et al. own a patent (Appendix A.1) on a similar system providing feedback on a wide range of different measures of group dynamics. Another system patented by Chandrasekaran et al. (Appendix A.2) gives feedback on the style of communication. Finally, Chu et al. own a patent (Appendix A.3) on a system causing an alert in case of violations of predefined conversation rules. Independent of the type of feedback, feedback has been proven to support group members adapting their behavior. Dependent on the type of feedback, this might lead to higher performance and satisfaction of the groups. [Smi59, DiM07, Kim08].

In addition to group dynamics, characteristics of the individual group members have been studied in order to understand the determinants of successful group collaboration. In this connection, personality traits have been of particular interest. Tosi et al. [Tos00] have developed an accepted model describing the following five different personality traits, referred to as Big-Five personality dimensions:

- *Agreeableness:* Being tolerant, trusting, generous, warm, kind, good-natured, and less likely to be aggressive, rude, and thoughtless.
- *Conscientiousness:* Being responsible, dependable, organized, persistent, punctual, hard working, purposful, and mindful to details.
- *Emotional Stability:* Being resilient, tough, confident, not easily upset, and less prone to experiencing negative reactions.
- *Extraversion:* Being sociable, liking to be with others, energetic, talkative, active, assertive, dominant, and forceful.
- *Openness to Experience:* Being imaginative, creative, adventerous, curious, cultured, open-minded, having broad interests and tending to be self-sufficient.

Researchers have studied the relationship between the Big-Five personality dimensions and the effectiveness of groups. They have both explored common characteristics of high performing group members [Kic97, Dri06, Pen10] as well as the composition of high performing groups [Kic97, Hal05, Mat08]. Other researches have again focused on demographic characteristics such as gender, age, and ethnicity [Sat82, Rid92, Jon99, Pen10, Kar12, Onn14, Lev15]. Understanding the relationship between the characteristics of individual group members and the effectiveness of groups helps improving the performance as well as the satisfaction.

In order to study the determinants of successful group collaboration, researchers have almost entirely chosen laboratory studies. Groups were composed by the researchers and they were asked to perform predefined tasks such as brainstorming tasks, problem solving tasks, or decision making tasks. Although laboratory studies allow for better controlling for confounding factors, they are limited in their validity. Due to the artificial setting of the study, group members might behave unnatural and the findings of the study cannot simply by generalized to the real world. The purpose of this work is to investigate group collaboration in a naturalistic study and to prove or disprove prior findings from literature in real-life settings. For that purpose, data are collected and analyzed from unstructured out-of-class meetings of the Sloan Fellows program, an immersive MBA program for mid-career managers. Furthermore, a wide range of different types of data are combined in order to obtain a broad understanding of group collaboration. The data are participation data, demographic data, personality data, performance data, as well as satisfaction data. The data are particularly valuable because they are collected from a large amount of participants over a large amount of time. Different research questions are approached by means of the data and advanced regression analysis. In order to deeply understand group collaboration, factors affecting participation are analyzed. The relationship between participation and performance as well as satisfaction is analyzed in order to obtain determinants of successful group collaboration. Furthermore, it is investigated whether real-time feedback can improve participation and in turn performance and satisfaction. Finally, a novel hypothesis is created in contrast to prior findings form literature. It is postulated that even participation might be indeed beneficial in laboratory settings but not necessarily in the real world. The reasoning for this hypothesis as well as its analysis are covered as well.

The work is structured as follows: Chapter 2 covers the applied methods from data collection to data processing and cleansing and finally to data modeling and evaluation. Chapter 3 presents the corresponding results and Chapter 4 discusses both the methods and results. In addition, conclusions are drawn from the results in this chapter. Finally, Chapter 5 summarizes the most important findings and gives an outlook on possible future directions of this work.

Chapter 2

Methods

The purpose of this work is to deeply understand participation in group collaboration as well as its correlation with performance and satisfaction. Furthermore, it is investigated whether real-time feedback can improve participation and in turn also performance and satisfaction. Finally, a novel hypothesis with respect to group collaboration is created and analyzed. The methods used for approaching this purpose are covered in this chapter. In order to have a basis for data analysis, data were collected in a first step and processed and cleansed in the subsequent steps. The data were finally modeled and evaluated in order to gain major insights into group collaboration.

2.1 Data Collection

Data were collected from the MIT Sloan Fellows class of 2016/17. The MIT Sloan Fellows program as well as the participating students, the system and surveys used in the study, and also the study protocol are introduced in this section.

2.1.1 Sloan Fellows Program

Program and Participants

The Sloan Fellows program is a 12-month full-time graduate business program in management and leadership for elite mid-career professionals. It grew out of grants from Generals Motors Chairman Alfred P. Sloan, who aimed to optimally prepare experienced managers and entrepreneurs for leadership positions. Only the MIT Sloan School of Management, the Standford Graduate School of Business, and the London Business School offer the program linked to a Master of Business Administration (MBA) or a Master of Science in Management [oM17].

The Sloan Fellows program is considered to be the most prestigious and elite business program in the world. Admission criteria are rigorous and only outstanding professionals with work experience of at least eight years are considered. One hundred and five of the 110 students of the MIT Sloan Fellows class of 2016/17 participated in the study, therefrom 33 females and 72 males. They came from 35 different countries and had an average age of 37.41 ± 4.45 years (mean $\pm$ standard deviation) as well as an average work experience of 13.78 ± 4.24 years. All participants gave written informed consent about their participation in the study.

Curriculum

The MIT Sloan Fellows program starts with the summer term in June. The first weeks focus on introducing the students to the program. Furthermore, events on team building and coaching are scheduled in order to build a strong foundation for group collaboration.

Core courses are scheduled in the remaining weeks of the summer term. These courses are intended to bring all students to the same level of knowledge in the key disciplines. In the first half of the summer term, the Sloan Fellows attend the courses ”Financial Accounting”, ”Marketing and Strategy”, and ”Data, Models and Decisions”. In the second half of the summer term, they attend the courses ”Applied Economics for Managers”, ”Financial Management”, and ”Management of Supply Networks for Products and Services”. Each course consists of sessions, recitations, individual and group assignments, as well as a final exam or project.

The fall term, the independent activities period (IAP), and the spring term integrate core courses, electives, and a thesis. These terms have no bearing on this work. Therefore, no more information is given about them.

Study Groups

Great importance is attached to group collaboration in the MIT Sloan Fellows program. As mentioned before, events on team building and coaching are provided in order to build a strong foundation for group collaboration. Above, the Sloan Fellows are assigned to study groups of four or five students each before the program starts. These groups are consistent over the whole program and the students within these groups regularly meet in order to study and work on the courses together. They are free in how often and how long they meet.

The group formation is done by administrators of the MIT Sloan School of Management. They try to optimally bring together students by using the following loose guidelines:

1. There is not only one student of a different gender in a group. The group has either only students of one gender or at least two students per gender.

2. The students within a group have similar ages.

3. The students within a group are diverse in terms of ethnicity, personality, and expertise.

With the first guideline, the administrators try to assure that all students feel comfortable in their group. With the second guideline, they try to simplify finding appointments within their group. The administrators assume that students with a similar age are at a similar point of life (e.g., being married, having children) and therefore have similar daily routines. With the third loose guideline, they intend to enrich group collaboration by different cultures, ways of thinking and acting, as well as knowledge and skills.

With regard to the MIT Sloan Fellows class of 2016/17, the participants were assigned to 22 study groups. Five of theses groups involved four members only, the remaining 17 groups involved five members.

2.1.2 Open Badges

The system used in this study is called Open Badges. It is a modular open-source system for collecting and monitoring social interaction data from people engaged in real-life settings. Open Badges has been developed by Lederman et al. [Led16] and can be found on `https://github.com/HumanDynamics/OpenBadge/`. The system consists of custom hardware badges that collect data, a base station that pulls and processes the data, and a visualization that provides real-time feedback on conversation dynamics by means of the data.

The badges, which are shown in Figure 2.1, are simple, light, and low-cost wearables. They fit in a standard plastic name tag holder and are designed to be worn around the neck. Core of the minimalistic circuit of the badges is the nRF51822, a 16MHz ARM Cortex-M0 microcontroller with integrated Bluetooth Low Energy (BLE). It runs the open-source code and transmits recorded data to the base station. Further components of the badges are an analog MEMS microphone, an amplifier, a low-pass filter, flash memory, a voltage regulator, a coin cell battery holder, a power switch, a button, and several capacitors, resistors, and LEDs. Using a single CR2032 coin cell battery, the badges can operate for a couple of days [Led16].

The badges are capable of measuring voice activity, proximity to other badges, and location (using location beacons). However, only voice activity was measured in this work. The microphone was sampled at a frequency of 8000 Hz and the amplitude was averaged every 50 ms. Only

Figure 2.1: Custom Hardware Badges. With a dimension of 3 cm × 7 cm, the badges are small enough to fit in a standard plastic name tag holder and designed to be worn around the neck. Image source: `http://www.rhythm.mit.edu/open-badge/`

non-linguistic audio or volume data were collected hence. The raw volume data were used for data analysis. Furthermore, one purpose of this work was to examine whether and how feedback affects conversation dynamics. Therefore, the base station and the visualization of the Open Badges system were implemented in an Android application, whose open-source code can be found on GitHub as well. The application pulled and processed the collected data and gave real-time feedback by visualizing the conversation dynamics as shown in Figure 2.2. The participants of a meeting are drawn around a round-table and a ball in the middle of the round-table as well as lines from the participants to the ball represent the balance of participation of all participants and the amount of participation of individual participants, respectively.

2.1.3 Surveys

In addition to Open Badges, three different surveys were used for data collection. First, the participants were asked to fill out a demographic survey. This survey contained questions about gender, age, ethnicity, academic major and degree, as well as work experience and industry. The survey can be found in Appendix B.1.

Second, the Ten-Item Personality Inventory (TIPI) [Gos03] was used to get insights into the personality of the Sloan Fellows. TIPI is a brief measure of the Big-Five personality domains agreeableness, conscientiousness, emotional stability, extraversion, and openness to experiences, which were introduced in Section 1. It contains two items for each of the five personality dimensions. Each item is rated on a seven-point scale ranging from one (disagree strongly) to

Figure 2.2: Round-Table Visualization. Participants of a meeting are drawn around a round-table. Balance of participation and amount of participation are visualized by means of a ball in the middle of the round-table as well as lines from the ball to the participants, respectively. Image source: `http://www.rhythm.mit.edu/open-badge/`

seven (agree strongly). The items as well as the scale can be found in [Gos03]. Although TIPI is considered to be inferior to longer measures of the Big-Five personality dimensions, it has been shown to be an adequate measure when brevity has priority and when personality is not the primary topic of interest [Gos03].

Third and last, the participants were asked to fill out a weekly satisfaction survey. The survey covered questions about the satisfaction with the outcome of the meetings, the process used in the meetings, the perceived value of the own perspective to the meetings, as well as the comfortability in sharing the own perspective in the meetings. Each question was answered with a seven-point scale ranging from one (extremely satisfied) to seven (extremely dissatisfied). Furthermore, the participants were able to share stories and other experiences in free text. The survey can be found in Appendix B.2. The students were only asked to fill out the survey once a week in order minimally bother them and to increase their compliance.

2.1.4 Study Protocol

Data were collected over four weeks in the first half of the summer term from June 13, 2016 to July 10, 2016. Prior to that interval, the MIT Sloan Fellows of 2016/17 were introduced to the study as well as the system usage. In order to allow them for data acquisition, they were provided with the hardware badges as well as an Android smartphone with the app installed. Furthermore, the participants gave written informed consent about their participation in the study and filled out the demographic survey as well as TIPI.

During the four weeks of data collection, the Sloan Fellows were asked to use the badges and the app in every meeting. At the beginning of each meeting, all members of a study group switched on their badges and selected a moderator. The moderator started the app. He was responsible for using the app as well as for observing the visualization and encouraging members to contribute. At the end of each meeting, the moderator stopped the app and all members switched off their badges. The Sloan Fellows were encouraged to periodically rotate the moderator so that all of them gathered moderator experience. Once a week, the Sloan Fellows were requested to fill out the satisfaction survey. Furthermore, they had to change the batteries of the badges as needed. In order to support the Sloan Fellows with the system usage, researchers of the study were personally available for at least one hour per day and available by mail around the clock.

One purpose of the study was to investigate the effect of the round-table visualization on conversation dynamics. Therefore, a crossover study design with an ABBA pattern was chosen and the visualization was only enabled in week two and three, and disabled in week one and four. Due to constraints of the Sloan Fellows program, a control/trial study design was not possible and for that reason, the ABBA pattern was the same for all students participating in the study.

After the four weeks of data collection, the MIT Sloan School of Management additionally supplied performance data in form of grades. Taken together, data were collected from 105 Sloan Fellows in 22 groups. The number of meetings amounted to 363 and their total duration summed up to 523.18 hours. Furthermore, five different types of data were acquired: Volume data, demographic data, personality data, satisfaction data, as well as performance data.

2.2 Data Processing

The raw volume output of the hardware badges was used for data analysis. Prior to modeling the data, they were processed in order to detect voice activity as well as turn taking behavior. The algorithms used for data processing were implemented in Python.

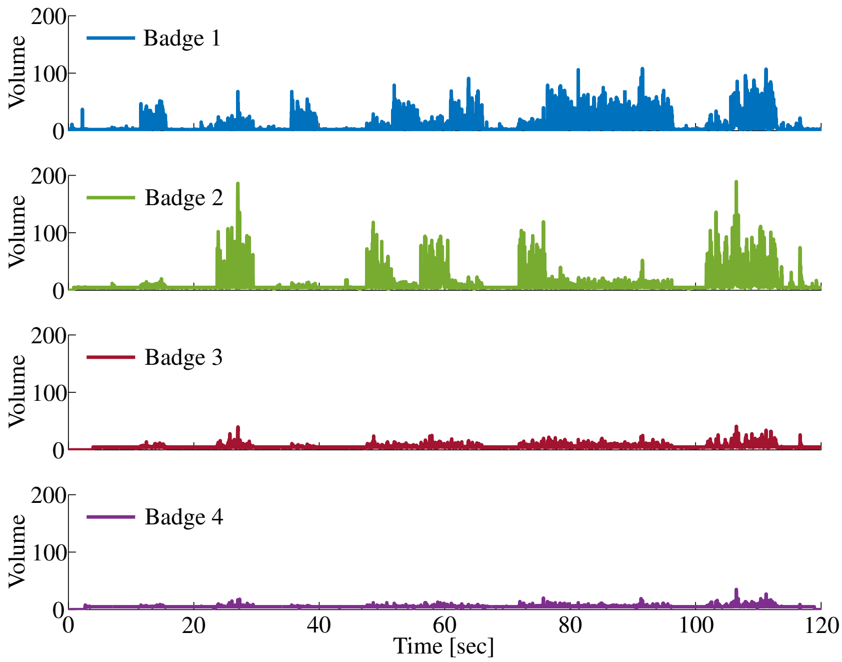


Figure 2.3: Raw Volume Signal. Exemplary volume signal obtained from the hardware badges, where only the wearers of Badge 1 and Badge 2 are speaking.

2.2.1 Voice Activity

Volume data were used to detect whether the badge wearer was speaking or not. For that purpose, a voice activity detection (VAD) algorithm was applied. The volume signal obtained from the hardware badges, which is exemplified in Figure 2.3, was assumed to consist of four components:

1. The badge wearer's speech,
2. attenuated speech from other speakers than the badge wearer,
3. a badge specific constant offset, and
4. environmental noise.

In order to detect the active speaker, a clipping value was applied to the signal in a first step. The clipping value was the maximum value of the volume above which the signal was assumed to have non-speech external noise. It was set to 120 and bounded the signal above. The clipping value was determined experimentally.

In a second step, the badge specific constant offset was removed. Therefore, the offset was estimated by computing the median of the signal over a sliding window with sufficiently large size and by subtracting the estimate. The window size was set to two minutes. The exemplary processed volume signal after clipping values greater than 120 and removing the badge specific constant offset can be found in Figure 2.4.

Third, the signal power was computed over a sliding window with a size of one second and a threshold was applied to decide whether the badge wearer was speaking (signal power greater than the threshold) or not (signal power lower or equal to the threshold). The signal power was computed using Equation 2.1, where P_n is the power of signal x at sample n and where w is the window size. The resulting signal can be seen in Figure 2.5.

$$P_n = \frac{1}{w} \sum_{i=n-w+1}^{n} x_i^2 \tag{2.1}$$

The threshold was determined in two steps. In a first step, an exemplary dataset collected in the operating environment where no badge wearer was speaking was used in order to compute a threshold for the environmental noise power. Therefore, the signal power of each badge in the dataset was computed as before. Assuming a gaussian distribution for the signal power, the threshold for each badge was set to $\mu_P + 2\sigma_P$, where μ_P is the mean and σ_P the standard deviation of the computed power signal. The final threshold for the environmental noise power was chosen as the maximum threshold of all badges.

In a second step, another exemplary dataset collected in the operating environment where only one badge wearer was speaking was used in order to compute a threshold for the attenuated speech power. The minimum distance between any two badge wearers was assumed to be three feet or 91.44 cm. Again, the signal power of each badge was computed as before. After ignoring signal samples lower or equal to the threshold for the environmental noise power, the threshold for the attenuated speech power was computed by $\mu_P + 2\sigma_P$ again. The maximum threshold of all badges was finally used to decide whether a badge wearer was speaking or not. It came up to a value of 45 in this work.

The VAD algorithm used in this study assumed that only one badge wearer was speaking at any time. This assumption was made in order to make the algorithm more robust and to avoid false positives due to attenuated speech of nearby speakers or spikes in environmental noise. If more than one speaker was detected in the previous step, the speaker with the highest volume was chosen in the last step of the VAD algorithm. Figure 2.6 exemplifies the final output of the VAD algorithm, i.e. the voice activity of all badge wearers.

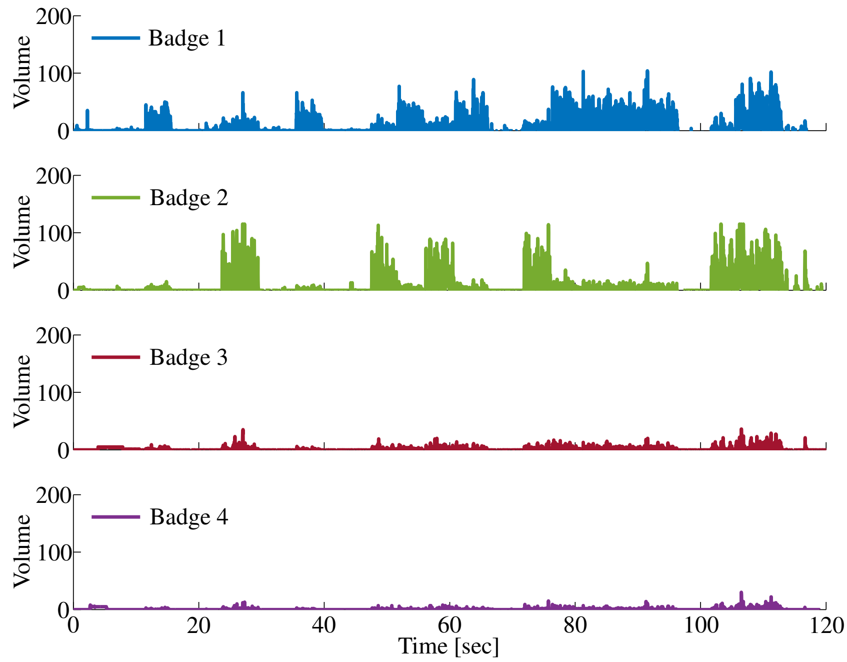


Figure 2.4: Processed Volume Signal. Signal values above 120 are clipped and the badge specific constant offset is removed from the signal.

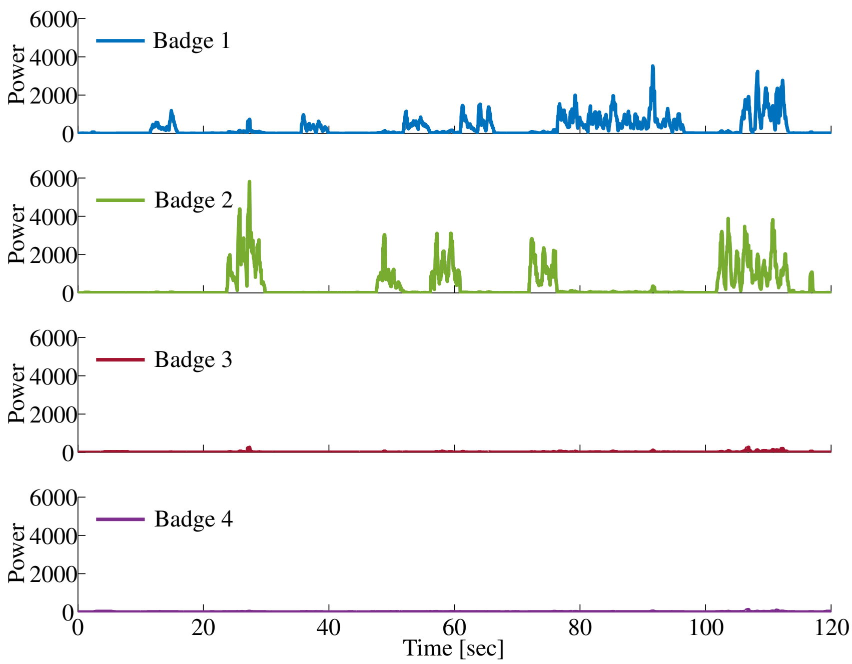


Figure 2.5: Power Signal. The power signal is computed based on the processed volume signal exemplified in Figure 2.4 using Equation 2.1. A threshold is applied to the power signal in order to decide whether the badge wearer is speaking or not.

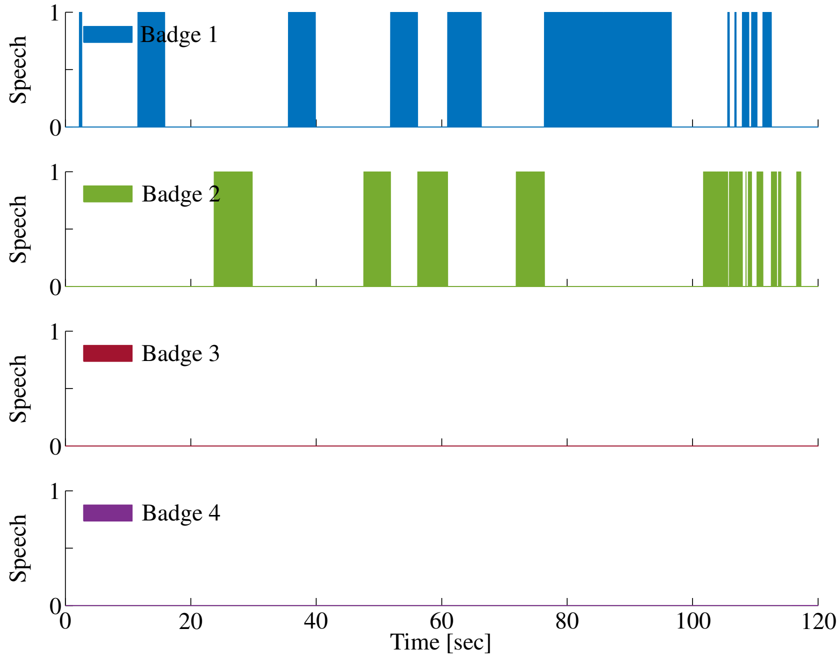


Figure 2.6: Voice Activity. A value of one indicates that a badge wearer is speaking, a value of zero indicates that the badge wearer is silent.

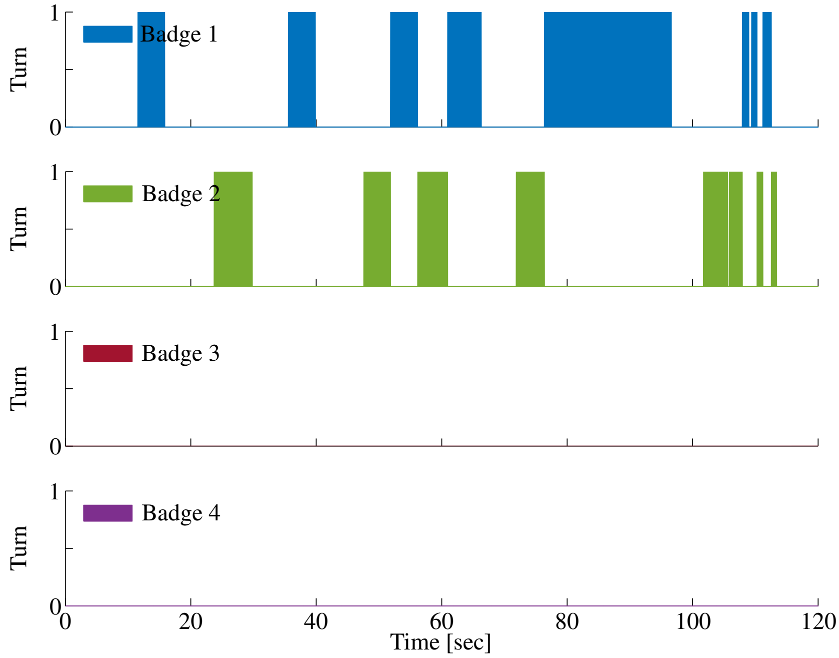


Figure 2.7: Turn Taking Behavior. Regarding the voice activity in Figure 2.6, speaking intervals shorter than two seconds are discarded and pauses shorter than half a second are filled.

2.2.2 Turn Taking

On the basis of the voice activity obtained in the previous step, the turn taking behavior of the badge wearers was computed. A turn is customly defined as a speaking interval which indicates a contribution to the conversation by the badge wearer. A badge wearer is said to have a turn if he or she speaks for a minimum of two seconds. Furthermore, a pause in the speaking interval is restricted to be a maximum of half a second. Given the output of the VAD algorithm, the turn taking behavior was computed by filling pauses in speaking intervals shorter than half a second and by discarding speaking intervals shorter that two seconds. The turn taking behavior is visualized in Figure 2.7. In the further process of analyzing the data, the turn taking behavior allowed for computing features of participation of the badge wearers such as the number of turns, the average length of turns, as well as the total length of turns, also referred to as airtime.

2.3 Data Cleansing

Not all of the collected data could be used for analysis. After data processing, data cleansing was performed in order to detect and remove irrelevant or incorrect samples and to proceed with a clean dataset only. Data cleansing was performed using Python again.

2.3.1 Irrelevant Data

One group opted out after a few days of the study. The data of this group were removed. Furthermore, there were a number of meetings where not all group members were present. Conversation dynamics were presumed to be different in meetings with considerably less members though. For that reason, meetings with only one or two present members were removed as well.

2.3.2 Incorrect Data

Some groups had difficulties in using the badges and the app. They accidentally created meetings that actually did not exist. In order to remove non-existing meetings, all meetings shorter than five minutes or longer than 200 minutes were discarded. The turn taking behavior, which was computed previously, was additionally used to detect non-existing meetings. Meetings with a total airtime shorter than one minute were removed as well.

After accomplishing data cleansing, data of 100 Sloan Fellows in 21 groups remained. The number of meetings in the consistent dataset amounted to 233 and the total duration of these meetings summed up to 344.11 hours.

2.4 Data Modeling

After collecting, processing, and cleansing data, the resulting dataset was examined in order to gain new insights into successful group collaboration. Group dynamics have been shown to be a key factor affecting both performance and satisfaction of groups [Sha71, Mye00]. Therefore, the study focused on understanding group dynamics by revealing factors having an impact on the amount and manner of participation in group collaboration. The real-world data were further used to examine the correlation of participation with performance and satisfaction in non-laboratory settings. Finally, the effect of giving feedback using the round-table visualization and a novel hypothesis with respect to group collaboration were investigatedt.

Data modeling was accomplished by means of advanced regression analysis. Dependent and independent variables were computed in Python and their relationship was modeled in R. The used dependent and independent variables, the specific approaches, as well as the formalizations of the models are covered in this section. Basic knowledge on regression analysis is assumed though and can be found in [Dra14] for instance.

2.4.1 Individual Participation

Factors affecting the amount and manner of individual participation were examined first. They were considered to be of great importance for the purpose of deeply understanding group collaboration and building a strong foundation for improving group collaboration. No hypothesis was made on potential factors and an exploratory approach was chosen in this part of the analysis. It is introduced in the following.

Dependent Variables

For the purpose of revealing factors affecting participation on individual level, three different measures were used as dependent variables. First, the *percentage of turns* was computed by dividing the number of turns of a group member by the total number of turns of the group. Second, the *percentage of airtime* was computed by dividing the airtime of a group member by the total airtime of the group, and third, the average *length of turns* was computed by dividing the airtime of a group member by the number of turns of the group member.

The three measures were computed per meeting and member. The unit of interest in this part of the analysis was members though. Therefore, the measures were aggregated over all meetings using mean. Furthermore, no more complex measures were used as dependent variables in order to keep the models simple and robust in terms of potential inaccuracy of the VAD algorithm.

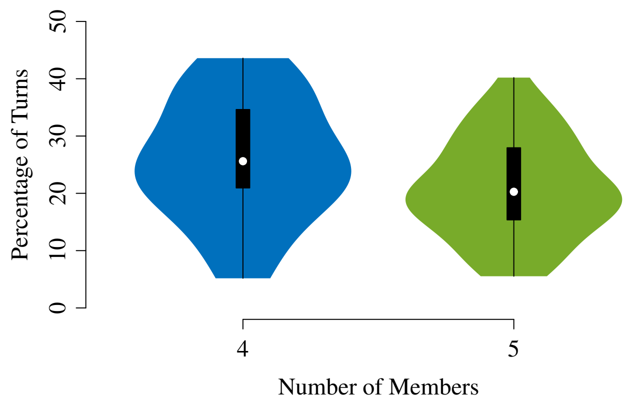


Figure 2.8: Distribution of Percentage of Turns. Violin plots for the distribution of percentage of turns with regard to four and five group members.

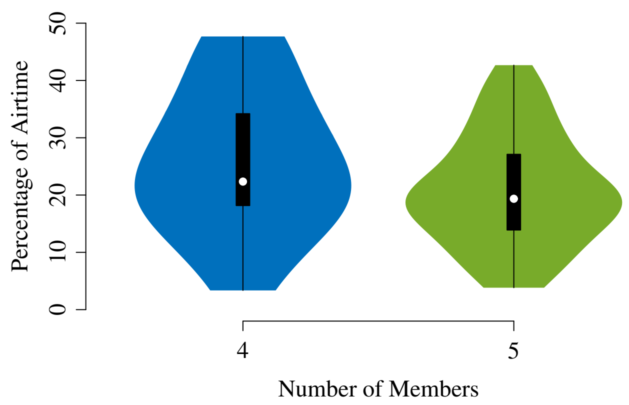


Figure 2.9: Distribution of Percentage of Airtime. Violin plots for the distribution of percentage of airtime with regard to four and five group members.

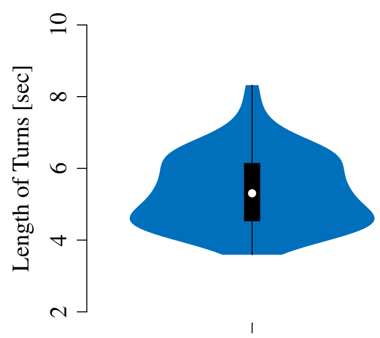


Figure 2.10: Distribution of Length of Turns. Violin plot for the distribution of length of turns.

Table 2.1: Dependent Variables for Analysis of Individual Participation. Index i denotes the participant and index j the group of the respective participant.

Variable	Symbol	Resolution	Type
Percentage of turns	p_{ij}	Member	Continuous
Percentage of airtime	p_{ij}	Member	Continuous
Length of turns	p_{ij}	Member	Continuous

The distribution of percentage of turns, percentage of airtime, and length of turns can be found in Figure 2.8, Figure 2.9, and Figure 2.10, respectively. Violin plots were chosen for visualization. They are a combination of box plots, which show the median (white dot) and interquartile range (black box), as well as kernel density plots. Furthermore, an overview on the used dependent variables is given in Table 2.1.

Independent Variables

The data obtained from the demographic survey as well as TIPI were used as independent variables. Variables about *gender*, *age* (in years), *ethnicity*, and *work experience* (in years) of the participants were extracted from the demographic survey. With respect to ethnicity, the 35 different countries of the participants were assigned to the regions Africa, Asia, Europe, Middle East, North America, Oceania, South America, and South Asia. The eight different regions were further mapped onto seven dummy variables, where Europe was chosen as reference because it was the median region regarding the three dependent variables. In addition to the data obtained from the demographic survey, the *Big-Five personality dimensions* agreeableness, conscientiousness, emotional stability, extraversion, and openness to experiences were extracted from TIPI. The values of the personality variables ranged from one (does not apply) to seven (fully applies). Table 2.2 lists all independent variables used in this part of the analysis.

With regard to the distribution of the independent variables, 31 participants were female and the remaining 69 participants were male. They had an average age of 37.15 $\pm$ 4.38 years (mean $\pm$ standard deviation) and an average work experience of 13.18 $\pm$ 4.21 years. The frequency of ethnicities as well as the distribution of the Big-Five personality dimensions is visualized in Figure 2.11 and Figure 2.12, respectively.

The dependent variables percentage of turns and percentage of airtime strongly dependent on the number of members in a group. For instance, balanced participation corresponds to 25% in groups with four members whereas it corresponds to 20% in groups with five members. In order to account for different percentages due to different numbers of members, the number of

Table 2.2: Set of Independent Variables for Analysis of Individual Participation. Only the variables listed in the table were used that were selected by LASSO. Index i denotes the participant and index k the respective independent variable of the set.

Variable	Symbol	Resolution	Type
Female	x_{ik}	Member	Dummy
Age	x_{ik}	Member	Continuous
Africa	x_{ik}	Member	Dummy
Asia	x_{ik}	Member	Dummy
Middle East	x_{ik}	Member	Dummy
North America	x_{ik}	Member	Dummy
Oceania	x_{ik}	Member	Dummy
South America	x_{ik}	Member	Dummy
South Asia	x_{ik}	Member	Dummy
Agreeableness	x_{ik}	Member	Continuous
Conscientiousness	x_{ik}	Member	Continuous
Emotional stability	x_{ik}	Member	Continuous
Extraverstion	x_{ik}	Member	Continuous
Openness to experience	x_{ik}	Member	Continuous
Work experience	x_{ik}	Member	Continuous
Five-member group	x_{ik}	Member	Dummy

members was added to the set of independent variables as well. Since there were only groups with four or five members, it was added as a dummy variable. With regard to the distribution, five groups involved four members and the remaining 16 groups involved five mebers.

The continuous independent variables were standardized using the z-score, also referred to as standard score [Has09]. The z-score x^* of a raw score x is computed by means of Equation 2.2, where μ is the mean and σ the standard deviation of the variable.

$$x^* = \frac{x - \mu}{\sigma} \tag{2.2}$$

The z-score rescales the variables to have a mean of zero and a standard deviation of one. It indicates differences from the mean of the original variable in number of standard deviations [Has09]. Standardizing continuous independent variables using the z-score has several advantages. In this work, it was especially used in order to make the interpretation of the regression results easier. Standardized coefficients serve as a standard effect size. They make it possible to compare variables that are measured in different units of measurement.

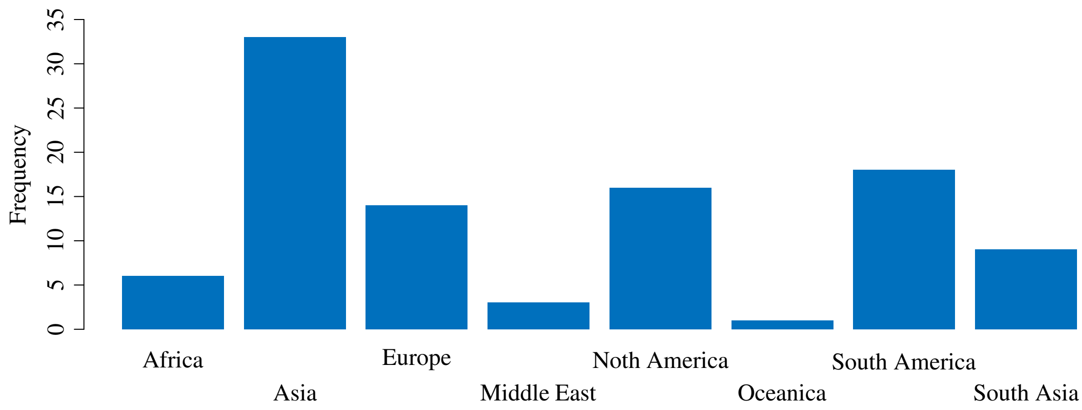


Figure 2.11: Distribution of Ethnicity. Bar plot for the frequency of participants coming from Africa, Asia, Europe, Middle East, North America, Oceania, South America, and South Asia.

Variable Selection

An exploratory approach was used in this part of the analysis. Potential factors affecting individual participation were not known beforehand and a variety of independent variables was considered hence. For the purpose of interpretation, it is beneficial to exhibit the strongest effects and to omit minor variables though [Has09]. Therefore, LASSO was applied for variable selection. LASSO [Tib96] is short for Least Absolute Shrinkage and Selection Operator. It is a penalized least squares method imposing an L_1 penalty on the regression coefficients. The optimization problem of LASSO is expressed in Equation 2.3 [Tib96], where y_i is the dependent variable evaluated at an observation i, where x_{ik} are the independent variables, and where β_0 and β_k are the intercept and the coefficients of the independent variables, respectively.

$$\begin{aligned} \hat{\beta}^{lasso} &= \underset{\beta}{\text{argmin}} \sum_{i=1}^{N} (y_i - \beta_0 - \sum_{k=1}^{p} \beta_k x_{ik})^2 \\ &\text{subject to} \sum_{k=1}^{p} |\beta_k| \leq t \end{aligned} \tag{2.3}$$

Due to the nature of the L_1 penalty, the regression coefficients shrink towards zero. Making t sufficiently small even causes some of them to be exactly zero. For that reason, LASSO performs a continous variable selection. The LASSO optimization problem can be rewritten in Lagrangian form. In this connection, the Lagrangian multiplier $\lambda \geq 0$ controls the amount of shrinkage as

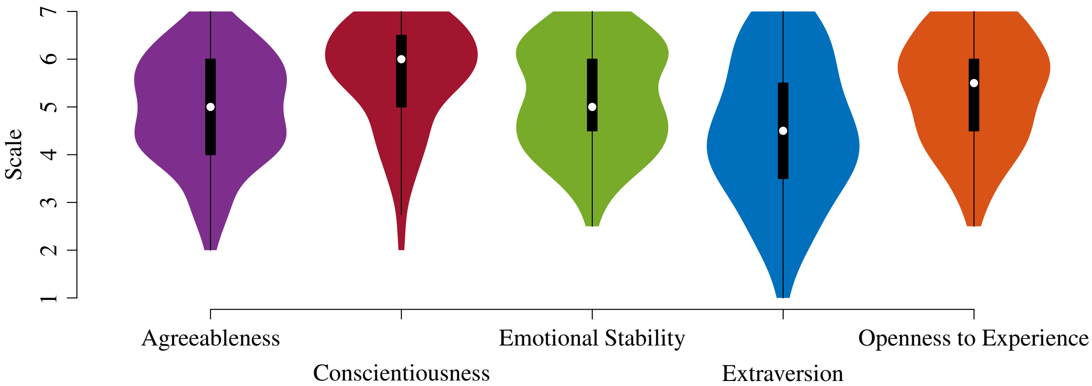


Figure 2.12: Distribution of Big-Five Personality Dimensions. Violin plots for the distribution of agreeableness, conscientiousness, emotional stability, extraversion, and openness to experience on a scale ranging from one (does not apply) to seven (fully applies).

well as the number of variables selected. The larger the value of λ, the greater the amount of shrinkage and the smaller the number of variables selected by LASSO.

$$\hat{\beta}^{lasso} = \underset{\beta}{\operatorname{argmin}} \left\{ \frac{1}{2} \sum_{i=1}^{N} (y_i - \beta_0 - \sum_{k=1}^{p} \beta_k x_{ik})^2 + \lambda \sum_{k=1}^{p} |\beta_k| \right\} \tag{2.4}$$

LASSO was chosen over discrete variable selection methods as for instance Stepwise Selection or Best Subset Selection because it has less variance [Has09]. Furthermore, it was particularly beneficial in this work since correlated variables do not pose a problem to the method. Regarding the variables used in this work, some of them such as age and work experience or ethnicity and the Big-Five personality dimensions are unavoidably correlated. Another advantage of LASSO over discrete variable selection methods is that it can be applied in situations with a large number of variables, even if the number exceeds the number of samples in the dataset. This was valuable for the exploratory approach in particular.

The Lagrangian multiplier or shrinkage parameter λ was determined by means of a 10-fold cross-validation. The value of λ was chosen that minimized the mean squared error (MSE) of the cross-validation. Furthermore, the number of members in a group was forced to be in the selected subset of independent variables for the dependent variables percentage of turns and percentage of airtime in order to account for different percentages due to different numbers of members. In R, the described procedure of selecting variables was implemented by means of the functions `glmnet` and `cv.glment` of the `glmnet` package [Fri10].

Linear Regression Model

After applying LASSO, a linear regression model was fitted for each dependent variable using the respective selected set of independent variables. The model was fitted using Equation 2.5, where p_{ij} is one of the introduced measures of participation with regard to student i of group j, where x_{ik} are the respective selected independent variables, and where β_0 is the intercept, β_k the coefficients, and e_{ij} the residuals of the linear regression model.

$$\begin{aligned} p_{ij} &= \beta_0 + \left(\sum_{k=1}^{p} \beta_k x_{ik}\right) + e_{ij} \\ e_{ij} &\sim \mathcal{N}(0, \sigma^2) \end{aligned} \tag{2.5}$$

The residuals are assumed to follow a normal or Gaussian distribution with zero as mean and σ^2 as the variance of residuals. All the other variables in the model are constant. Thus, the variance of observations corresponds to the variance of residuals [Bro15].

$$\operatorname{var}(p_{ij}) = \operatorname{var}(e_{ij}) = \sigma^2 \tag{2.6}$$

In a linear regression model, all observations are further assumed to be uncorrelated. Therefore, the covariance for any pair of observations is zero [Bro15].

$$\operatorname{cov}(p_{ij}, p_{i'j'}) = \operatorname{cov}(e_{ij}, e_{i'j'}) = \begin{cases} \sigma^2 & \text{if } i = i' \\ 0 & \text{otherwise} \end{cases} \tag{2.7}$$

The ordinary linear regression model was implemented using the function `lm` of the standard statistical R package `stats`.

Covariance Pattern Model

It was noted that all observations in a linear regression model are assumed to be uncorrelated. With regard to the measures of individual participation, this assumption is violated for the percentage of turns and the percentage of airtime. Within a group, the percentages of all members sum up to one. If one group member speaks more, the others accordingly speak less. For that reason, the observations are negatively correlated within groups. Assumption violations diminish both validity and reliability of the results though [Sai10]. Therefore, another model was applied in order verify or falsify the results from the linear regression model.

The common approach in case of correlated observations are Linear Mixed Models (LMMs) [Bro15, Wes14]. They will be introduced in detail in Section 2.4.3. With LMMs, the covariance for any pair of observations is implicitly specified by adding variables, so-called random effects, that are assumed to be drawn from a normal or Gaussian distribution as well. The covariance includes both variance components of the residuals as well as the random effects for that reason. The latter allow for correlated observations. However, variance components are non-negative by definition and negative variance components are considered to be an underestimate of a small or zero variance component. Thus, LMMs are not suitable for negative correlations between observations and cannot be applied in this part of the analysis [Bro15].

In this work, covariance pattern models were used in order to account for correlated observations. Covariance pattern models are some kind of a redefinition of LMMs. The random effects are omitted and the covariance structure allowing for correlated observations is explicitly defined in the covariance of residuals. Depending on the chosen pattern of the covariance structure, both positive and negative correlations between observations are permissible [Bro15]. In this case, the Compound Symmetry covariance pattern defined in Equation 2.8 was chosen. The covariance is equal to zero in case of observations from different groups (i.e. $j \neq j'$) and it is unequal to zero in case of observations from the same group (i.e. $j = j'$). Thus, observations from the same group have a constant correlation ρ, whereas observations from different groups are uncorrelated. The parameter ρ allows for negative correlations in this connection [Bro15].

$$\operatorname{cov}(p_{ij}, p_{i'j'}) = \operatorname{cov}(e_{ij}, e_{i'j'}) = \begin{cases} \sigma^2 & \text{if } i = i' \\ \rho\sigma^2 & \text{if } i \neq i' \text{ and } j = j' \\ 0 & \text{otherwise} \end{cases} \tag{2.8}$$

Apart from the explicitly specified covariance structure, the model formalization remains the same as in Equation 2.5. The model was fitted using function `gls` of the `nlme` package [Pin17].

Extended Model

In order to further deepen the understanding of the relationship among the variables, the covariance pattern model from the previous step was extended by interaction terms. Interaction terms indicate whether the impact of one independent variable on the dependent variable in turn depends on the value of another independent variable. In this study, interaction terms were only added for main effects, i.e. independent variables that were both shown to be significant and to have a considerable effect size. The interaction terms were created by multiplying the main effects and they were added to model as depicted in Equation 2.9, where m is the number of revealed main effects in the previous step.

$$
\begin{aligned}
p_{ij} &= \beta_0 + \left(\sum_{k=1}^{p} \beta_k x_{ik}\right) + \left(\sum_{k=1}^{m} \sum_{\substack{l=1 \\ l>k}}^{m} \beta_{kl} x_{ik} x_{il}\right) + e_{ij} \\
e_{ij} &\sim \mathcal{N}(0, \sigma^2)
\end{aligned}
\tag{2.9}
$$

All independent variables selected by LASSO remained in the model in order to avoid confounding. Furthermore, the continuous variables were standardized before multiplying them in the interaction terms in order to make the results interpretable [Aik91, Jac03].

2.4.2 Balance of Participation

In addition to factors affecting participation on individual level, factors affecting participation on group level were examined. They were of particular interest in order to derive recommendations on composing successful groups. Again, no hypothesis was made on potential factors and the research question was approached in an exploratory manner.

Depedent Variables

The balance of participation in a group was of major interest in this part of the analysis. It was shown to be an indicator for successful group collaboration in a wide range of studies [Don12a, Don12b, Pen12]. The *Herfindahl index*, also known as Herfindahl-Hirschman index (HHI), was used as a measure of balance of participation [Hir64]. It is a commonly accepted measure of market concentration in economics and can be calculated using Equation 2.10 [Hir16]. In this application, s_i is the share of participation of a group member i measured in terms of turns or airtime. N is the number of members in the group furthermore.

$$h = \sum_{i=1}^{N} s_i^2 \tag{2.10}$$

The values of HHI range from $\frac{1}{N}$ to N and are dependent of the number of group members N hence. In order to obtain a measure of balance of participation which is independent of N, HHI was normalized by means of Equation 2.11 [Hir16]. The equation assumes $N > 1$. If $N = 1$, the normalized HHI h^* is set to one.

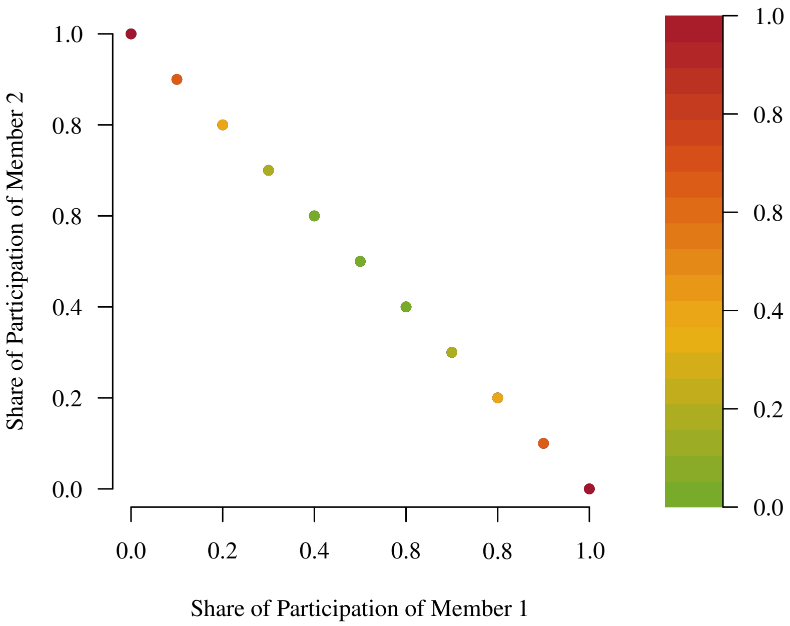


Figure 2.13: Normalized Herfindahl Index. Visualization of exemplary values of the normalized HHI in case of two group members. The higher the balance of participation, the lower the normalized HHI.

$$h^* = \frac{h - \frac{1}{N}}{1 - \frac{1}{N}} \tag{2.11}$$

The values of the normalized HHI h^* range from zero to one, where the value decreases as the balance of participation increases. The maximum balance of participation, which is given by a participation share of $\frac{1}{N}$ for each group member, corresponds to a value of zero. In order to deepen the understanding of the normalized HHI, a visualization of exemplary values in case of two group members is given in Figure 2.13. The normalized HHI was calculated both in terms of turns and airtime and the two measures were used as dependent variables. The measures were calculated per meeting and group and aggregated over all meetings using mean. Thus, one observation was available per group. The distribution of the normalized HHIs both in terms of turns and airtime can be seen in Figure 2.14. Furthermore, an overview of the used dependent variables in this part of the analysis can be found in Table 2.3.

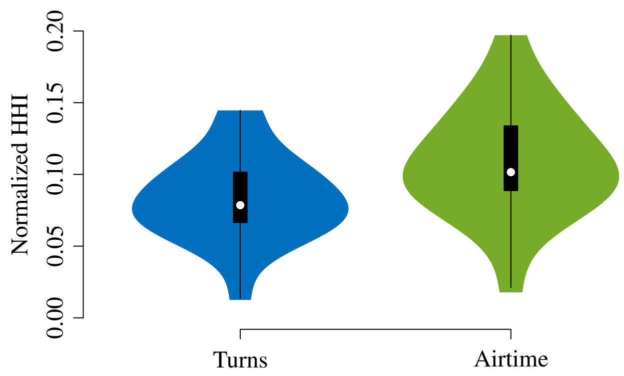


Figure 2.14: Distribution of Normalized Herfindahl Index. Violin plots for the normalized HHIs in terms of turns and airtime with repect to groups.

Indepedent Variables

With regard to the independent variables, both *level* and *diversity* of the demographic and personality data obtained from the surveys were considered as measures of group composition. Level indices were used in order to get insights into the joint degree of a group of having a certain characteristic or not. For the continuous variables age, work experience, and the Big-Five personality dimensions, median was chosen over mean because it is more robust in case of skewed data and because the data were assumed to be indeed skewed within a group [Hir16]. For the categorical variables gender and ethnicity, the proportion of each category was calculated.

Diversity indices were used in order to get insights into both richness and evenness of a group with respect to different characteristics. For the continuous variables, the variance coefficient was calculated by dividing the standard deviation by the mean of the respective variable [Hir16]. For the categorical variables, the Shannon index was chosen as diversity index. It is commonly used in ecology for the purpose of quantifying species populations [McP03]. The index is based on the entropy theory and measures the uncertainty of predicting a specific species. As more species a population has and as more they are evenly distributed in the population, the higher the uncertainty. In this application, the species correspond to the categories of the variables and the populations correspond to the groups. The Shannon index H is defined by Equation 2.12 [McP03], where p_i is the probability or relative frequency of category i in a group and where S is the total number of categories in the group. The values of the Shannon index H range from zero to $\ln(S)$, where the value increases as diversity increases.

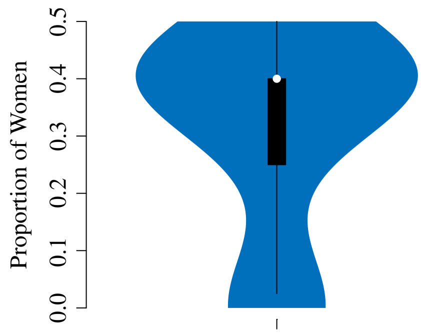


Figure 2.15: Distribution of Proportion of Women. Violin plot of the distribution of proportion of women with respect to groups.

$$H = -\sum_{i=1}^{S} p_i \ln(p_i) \tag{2.12}$$

An overview on all independent variables can be found in Table 2.4. As with the prior analysis, the continuous variables were standardized using the z-sore. The distribution of selected independent variables can be found in Figure 2.15 to Figure 2.17 furthermore.

Variable Selection

Common characteristics of groups with highly balanced participation were not known beforehand. Therefore, an exploratory approach was chosen and a large number of level and diversity indices were calculated in order to get insights into the composition of groups. With 24 calculated variables, the number of variables even exceeded the number of groups and samples in the dataset. It was indispensable to apply LASSO for variable selection hence. LASSO was applied as described in Section 2.4.1.

Linear Regression Model

For the purpose of analyzing participation on group level, the dataset consisted of one observation per group. The observations were not correlated and therefore, an ordinary linear regression model was permissible and no more complex model was required. The model was fitted for each of the two normalized HHIs h_j^* according to Equation 2.13, where only the independent variables x_{jk} were considered that were selected by LASSO in the previous step.

Table 2.3: Dependent Variables for Analysis of Balance of Participation. Index j denotes the respective group.

Variable	Symbol	Resolution	Type
Normalized HHI of turns	h_j^*	Group	Continuous
Normalized HHI of airtime	h_j^*	Group	Continuous

Table 2.4: Set of Independent Variables for Analysis of Balance of Participation. Only the variables listed in the table were used that were selected by LASSO. Index j denotes the group and index k the respective independent variable of the set.

Variable	Symbol	Resolution	Type
Proportion of females	x_{jk}	Group	Continuous
Shannon index of gender	x_{jk}	Group	Continuous
Median age	x_{jk}	Group	Continuous
Variance coefficient of age	x_{jk}	Group	Continuous
Proportion of students from Africa	x_{jk}	Group	Continuous
Proportion of students from Asia	x_{jk}	Group	Continuous
Proportion of students from Middle East	x_{jk}	Group	Continuous
Proportion of students from North America	x_{jk}	Group	Continuous
Proportion of students from Oceania	x_{jk}	Group	Continuous
Proportion of students from South America	x_{jk}	Group	Continuous
Proportion of students from South Asia	x_{jk}	Group	Continuous
Shannon index of ethnicity	x_{jk}	Group	Continuous
Median agreeableness	x_{jk}	Group	Continuous
Variance coefficient of agreeableness	x_{jk}	Group	Continuous
Median conscientiousness	x_{jk}	Group	Continuous
Variance coefficient of conscientiousness	x_{jk}	Group	Continuous
Median emotional stability	x_{jk}	Group	Continuous
Variance coefficient of emotional stability	x_{jk}	Group	Continuous
Median extraversion	x_{jk}	Group	Continuous
Variance coefficient of extraversion	x_{jk}	Group	Continuous
Median openness to experience	x_{jk}	Group	Continuous
Variance coefficient of openness to experience	x_{jk}	Group	Continuous
Median of work experience	x_{jk}	Group	Continuous
Variance coefficient of work experience	x_{jk}	Group	Continuous

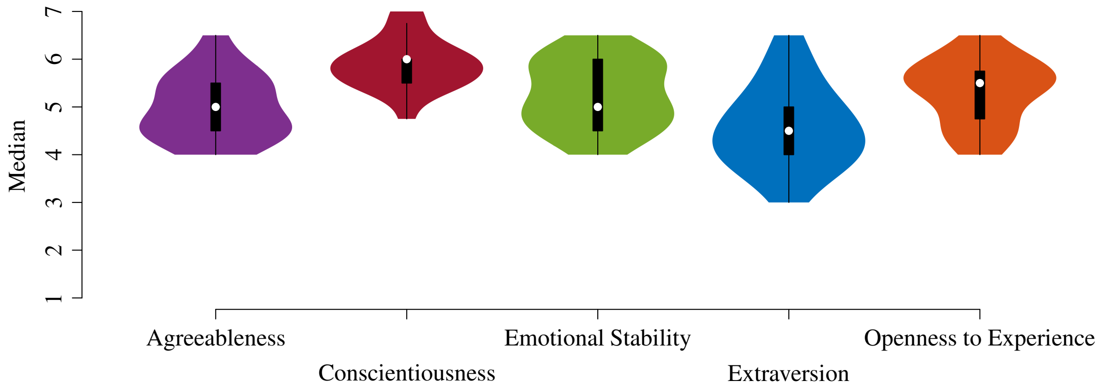


Figure 2.16: Distribution of Median of Big-Five Personality Dimensions. Violin plots of the median of agreeableness, conscientiousness, emotional stability, extraversion, and openness to experice with respect to groups.

$$\begin{aligned} h_j^* &= \beta_0 + \left(\sum_{k=1}^{p} \beta_k x_{jk}\right) + e_j \\ e_j &\sim \mathcal{N}(0, \sigma^2) \end{aligned} \tag{2.13}$$

Extended Model

Interaction terms were added to the linear regression model in order to expand the understanding of the relationship among the variables. The extension by interaction terms was accomplished as defined in Equation 2.14.

$$\begin{aligned} h_j^* &= \beta_0 + \left(\sum_{k=1}^{p} \beta_k x_{jk}\right) + \left(\sum_{k=1}^{m} \sum_{\substack{l=1 \\ l>k}}^{m} \beta_{kl} x_{jk} x_{jl}\right) + e_j \\ e_j &\sim \mathcal{N}(0, \sigma^2) \end{aligned} \tag{2.14}$$

2.4.3 Performance

Group dynamics were shown to be a key factor affecting performance in group collaboration [Sha71]. Furthermore, a high balance of participation was uncovered as an indicator for successful group collaboration [Pen12]. For that reason, two hypotheses were postulated.

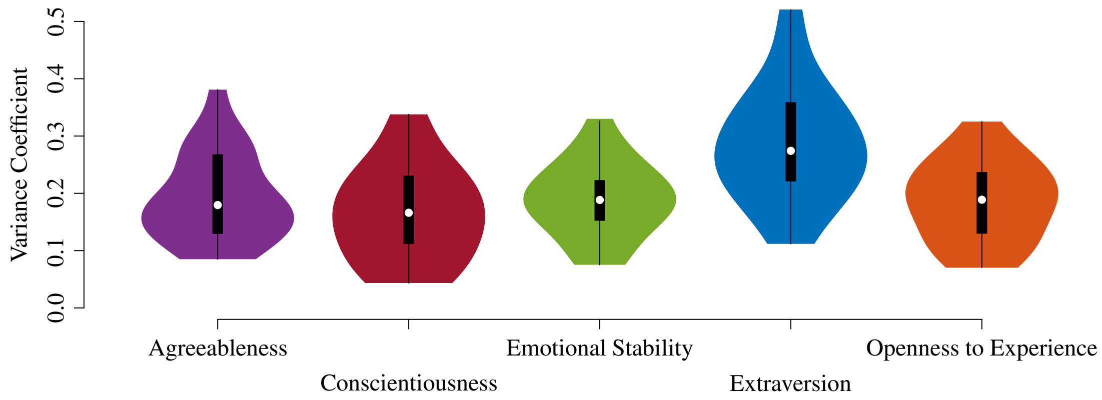


Figure 2.17: Distribution of Variance Coefficient of Big-Five Personality Dimensions. Violin plots of the variance coefficient of agreeableness, conscientiousness, emotional stability, extraversion, and openness to experice with respect to groups.

Hypothesis 1. *High-performing individuals have a high individual participation.*

Hypothesis 2. *High-performing groups have a high balance of participation.*

Using the data collected from the Slaon Fellows, these hypotheses were examined with respect to real-life settings. Understanding the correlation between participation and performance is especially relevant for improving group collaboration.

Dependent Variables

The individual grades of the Sloan Fellows of 2016/17 were used as measure of performance. In the first half of the summer term 2016, in which the study and data collection took place, the Sloan Fellows attended the three courses “Financial Accounting“, “Marketing and Strategy“, as well as “Data, Models, and Decisions“.

“Financial Accounting“ addresses the basic concepts of corporate financial accounting and reporting. The grading in this course is composed of 50% final exam, 30% group assignments, 10% individual quizzes in class, and 10% class participation. “Marketing and Strategy“ is an introductory course to the key concepts and processes of marketing and strategy. It brings all students to the same level of knowledge and prepares them for the electives in the subsequents terms. The grading in this courses consists of 40% final project, which is accomplished in groups, 30% group assignments, and 30% class participation. The last course in the first half of the summer term is “Data, Models, and Decisions“. It introduces students to the basic tools in using

Table 2.5: Dependent Variables for Analysis of Performance. Index i denotes the participant and index j denotes the group of the respective participant.

Variable	**Symbol**	**Resolution**	**Type**
Grade in ”Data, Models, and Decisions”	g_{ij}	Member	Categorical/ordinal
Grade in ”Financial Accounting”	g_{ij}	Member	Categorical/ordinal
Grade in ”Marketing and Strategy”	g_{ij}	Member	Categorical/ordinal

Table 2.6: Conversion From Letter Grading to Numeric Grading.

Letter Grading	**Numeric Grading**
A+	4.33
A	4.00
A-	3.67
B+	3.33
B	3.00
B-	2.67
C+	2.33
C	2.00
C-	1.67
D+	1.33
D	1.00
D-	0.67
F	0.00

data to make informed management decisions. The grading in “Data, Models, and Decision“ is composed of 40% final exam, 30% individual and group assignments, 20% midterm test, and 10% class participation. The distribution of grades can be seen in Figure 2.18. Furthermore, an overview on the dependent variables can be found in Table 2.5.

The students were graded according to the academic letter grading system in the United States [Com17]. The five letters A, B, C, D, and F indicate the performance with A being the best and F (for failed) being the worst grade. Additional + and - symbols are used for awarding and allow for a higher level of detail. The letter grades were converted to numeric grades using Table 2.6. The letters A, B, C, D, and F were mapped onto the numbers 4, 3, 2, 1, and 0, respectively. For + grades, 0.33 was added to the numbers and for - grades, 0.33 was substracted from the numbers. Higher grades indicate higher performance hence.

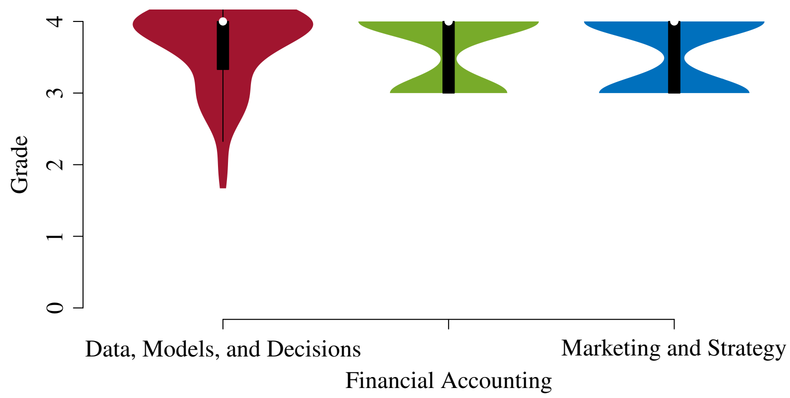


Figure 2.18: Distribution of Grades. Violin plots of the individual grades in the courses of the summer term 2016.

Independent Variables

The measures of participation listed in Table 2.1 and Table 2.3 were used as independent variables, where each measure was fitted in a seperate model. Percentage of turns, percentage of airtime, and length of turns were used on individual level and the normalized HHIs in terms of turns and airtime were used on group level. In order to avoid an omitted-variable bias, the selected LASSO subsets of the prior analyses were used in addition to the respective measure of participation. Omitted variables are correlated with the dependent variable as well as one or more independent variables of a model. They are incorrectly not included in the model and cause the estimates to be biased [Woo15]. Since it was known from the prior analyses that the variables selected by LASSO are correlated with the measures of participation, they were included to the model. Furthermore, all continuous variables were standardized using the z-sore. An overview on the five different sets of independent variables is given in Table 2.7.

Linear Mixed Model

The individual grades of the Sloan Fellows were composed of both individual and group performance. For that reason, they were assumed to be positively correlated within groups. In order to account for the dependence of observations, Linear Mixed Models (LMMs) were applied. They are commonly used to deal with correlated data.

With the ordinary linear regression model introduced in Section 2.4.1, the only assumption that is made about variation is that the residuals follow a normal distribution. All other variables

Table 2.7: Sets of Independent Variables for Analysis of Performance. Index i denotes the participant, index j the group of the participant, and index k the respective independent variabe of the set.

Variable	Symbol	Resolution	Type
Percentage of turns	p_{ij}	Member	Continuous
LASSO subset according to Table 2.2	x_{ik}	Member	Continuous/dummy
Percentage of airtime	p_{ij}	Member	Continuous
LASSO subset according to Table 2.2	x_{ik}	Member	Continuous/dummy
Length of turns	p_{ij}	Member	Continuous
LASSO subset according to Table 2.2	x_{ik}	Member	Continuous/dummy
Normalized HHI of turns	h_j^*	Group	Continuous
LASSO subset according to Table 2.4	x_{jk}	Group	Continuous/dummy
Normalized HHI of airtime	h_j^*	Group	Continuous
LASSO subset according to Table 2.4	x_{jk}	Group	Continuous/dummy

in the model are constant. For that reason, they are also referred to as fixed effects and the model is also known as fixed effects model. In LMMs, one or more variables in the model are additionally assumed to be randomly drawn from a normal distribution. These variables are referred to as random effects and the name of LMMs is originated in the fact that they include a mixture of fixed and random effects [Bro15].

For the purpose of analyzing the correlation between individual grades and individual participation, the model was fitted as defined in Equation 2.15, where g_{ij} is the grade of a student i in group j in a certain course. The fixed effects included in this model are one of the measures of individual participation p_{ij} and the respective LASSO subset of demographic and personality variables x_{ik}. In addition to the overall intercept β_0, a random intercept u_j is modeled for each group j. The random intercepts u_j and the residuals e_{ij} are both assumed to be drawn from a normal distribution, where σ_u^2 is the variance of the random intercepts and σ^2 the variance of the residuals, respectively.

$$\begin{aligned}
g_{ij} &= \beta_0 + \beta_1 p_{ij} + \left(\sum_{k=1}^{p} \beta_{k+1} x_{ik}\right) + u_j + e_{ij} \\
u_j &\sim \mathcal{N}(0, \sigma_u^2) \\
e_{ij} &\sim \mathcal{N}(0, \sigma^2)
\end{aligned} \tag{2.15}$$

In LMMs, each random effect gives rise to a variance component quantifying the variation due to the random effect only. The variance components of the random effects occur in addition to the variance component of the residuals. Therefore, the total variance of observations is defined by the sum of all variance components in the model [Bro15]. As depicted in Equation 2.16 , the total variance in this case is defined by the sum of the variance of the random intercepts as well as the variance of the residuals.

$$\mathrm{var}(g_{ij}) = \mathrm{var}(u_j + e_{ij}) = \sigma_u^2 + \sigma^2 \tag{2.16}$$

Considering the covariance $\mathrm{cov}(g_{ij}, g_{i'j'})$ of any pair of observations in Equation 2.17, the covariance is equal to zero in case of observations from different groups (i.e. $j \neq j'$) and it is unequal to zero in case of observations from the same group (i.e. $j = j'$). Thus, observations from the same group are correlated and have covariance equal the group variance component, whereas observations from different groups are uncorrelated. In this way, LMMs allow to handle dependent observations [Bro15].

$$\mathrm{cov}(g_{ij}, g_{i'j'}) = \mathrm{cov}(u_j + e_{ij}, u_{j'} + e_{i'j'}) = \begin{cases} \sigma_u^2 + \sigma^2 & \text{if } i = i' \\ \sigma_u^2 & \text{if } i \neq i' \text{ and } j = j' \\ 0 & \text{otherwise} \end{cases} \tag{2.17}$$

For the purpose of analyzing the correlation between individual grades and the balance of participation in a group, the model was fitted as defined in Equation 2.18. The model is the same as the one introduced in Equation 2.15, where only different fixed effects were used. The fixed effects used in this model are the normalized HHI h_j^* either in terms of turns of airtime and the respective LASSO subset of the level and diversity indices x_{jk} of the demographic and personality variables addressed in Section 2.4.2.

$$\begin{aligned} g_{ij} &= \beta_0 + \beta_1 h_j^* + \left(\sum_{k=1}^{p} \beta_{k+1} x_{jk} \right) + u_j + e_{ij} \\ u_j &\sim \mathcal{N}(0, \sigma_u^2) \\ e_{ij} &\sim \mathcal{N}(0, \sigma^2) \end{aligned} \tag{2.18}$$

In R, the LMMs were fitted using function `lme` of the `nlme` package [Pin17]. Furthermore, one model was fitted for each combination of a dependent and an independent variable. With individual grades from three different courses as dependent variables (see Table 2.10) and five different sets of independent variables (see Table 2.11), 15 models were fitted in total.

Ordered Logit Model

The dependent variables are ordinal rather than continuous. The letter or numeric grading is made up of the ordered categories listed in Table 2.6. For that reason, applying LMMs has some limitations [Gri14]. Among others, linear regression models assume normally distributed residuals. This assumption is obviously violated in case of ordinal data and compromises the validity and reliability of the previously fitted models. LMMs were fitted for ease of interpretability and because they were often advocated to be a reasonable approach anyway [Hel09]. However, in order to give additional proof of the results, ordered logit models were fitted in addition.

Ordered logit models, also known as ordinal regression models or cumulative link models, are an extension of logistic regression models allowing for more than two categories of the dependent variable. They are by far the most popular approach for dealing with ordinal data [Gri14]. In this work, the ordinal variable for the grade of a student i in group j is denoted as G_{ij}. It can fall into the categories $c = 1, \cdots, C$ where C is the number of different grades. G_{ij} follows a multinomial distribution with parameter $\boldsymbol{\pi}$ where π_{ijc} is the probability of student i in group j having grade c dependent on the independent variables or covariates $\boldsymbol{x}_{ij}$.

$$\pi_{ijc} = P(G_{ij} = c|\boldsymbol{x}_{ij}) \tag{2.19}$$

Instead of modeling the probabilities π_{ijc} of each category c of the ordinal variable, ordered logit models refer to the cumulative probability γ_{ijc} of a certain category c or a lower category. The cumulative probability is again evaluated contingent on the covariates $\boldsymbol{x}_{ij}$ [Chr15a].

$$\gamma_{ijc} = P(G_{ij} \leq c|\boldsymbol{x}_{ij}) = \pi_{ij1} + \cdots + \pi_{ijc} \tag{2.20}$$

The cumulative probabilities are linked using the logit function, which is the logarithm of odds or in other words the logarithm of a certain probability divided by the counter probability. The cumulative logits are defined for all but the last category C because the cumulative probability for the last category sums up to one [Chr15a].

$$\text{logit}(\gamma_{ijc}) = \text{logit}(P(G_{ij} \leq c|\boldsymbol{x}_{ij})) = \log\left(\frac{P(G_{ij} \leq c|\boldsymbol{x}_{ij})}{1 - P(G_{ij} \leq c|\boldsymbol{x}_{ij})}\right) \tag{2.21}$$

The ordered logit model is finally fitted by evaluating $C-1$ equations for the $C-1$ cumulative logits according to Equation 2.22. In this connection, θ_c are so-called threshold coefficients.

They are dependent on the category and can be considered as own intercepts for each category. Therefore, no overall intercept is available. The independent variables $\boldsymbol{x}_{ij}^T$ and the respective coefficients $\boldsymbol{\beta}$ are independent of the categories furthermore [Chr15a].

$$\operatorname{logit}(\gamma_{ijc}) = \theta_c - \boldsymbol{x}_{ij}^T \boldsymbol{\beta} \tag{2.22}$$

In order to examine the correlation between participation and performance, the same independent variables (both fixed and random) were used for the LMMs and the ordered logit models. Therefore, the final models for analyzing the correlation between individual participation and performance as well as between balance of participation and performance were fitted as defined in Equation 2.23 and Equation 2.24, respectively.

$$\begin{aligned} \operatorname{logit}(\gamma_{ijc}) &= \theta_c - \beta_1 p_{ij} - \left(\sum_{k=1}^{p} \beta_{k+1} x_{ik} \right) - u_j \\ u_j &\sim \mathcal{N}(0, \sigma_u^2) \end{aligned} \tag{2.23}$$

$$\begin{aligned} \operatorname{logit}(\gamma_{ijc}) &= \theta_c - \beta_1 h_j^* - \left(\sum_{k=1}^{p} \beta_{k+1} x_{jk} \right) - u_j \\ u_j &\sim \mathcal{N}(0, \sigma_u^2) \end{aligned} \tag{2.24}$$

The ordered logit models were fitted using function `clmm` of the R package `ordinal` [Chr15b]. As with the LMMs, 15 models were fitted in total.

2.4.4 Satisfaction

The satisfaction of groups was shown to be highly impacted by group dynamics [Sha71, Mye00]. In particular, it was assumed that students that actively and highly participate are more satisfied with the experience of the group collaboration and therefore have a higher overall satisfaction. According to these findings and assumptions, the following hypothesis were postulated and examined in this part of the analysis.

Hypothesis 3. *There is a positive relationship between individual participation and the perceived value of the own perspective to the meetings as well as the comfortability in sharing the own perspective to the meetings.*

Table 2.8: Dependent Variables for Analysis of Satisfaction. Index w denotes the week, index i the participant, and index j the group of the respective participant.

Variable	Symbol	Resolution	Type
Satisfaction w.r.t. Q1	s_{wij}	Member and week	Categorical/ordinal
Satisfaction w.r.t. Q2	s_{wij}	Member and week	Categorical/ordinal
Satisfaction w.r.t. Q3	s_{wij}	Member and week	Categorical/ordinal
Satisfaction w.r.t. Q4	s_{wij}	Member and week	Categorical/ordinal

Hypothesis 4. *There is a positive relationship between the balance of particiaption and the satisfaction with the outcome of the meetings as well as the process used in the meetings.*

Dependent Variables

Satisfaction data were obtained using the satisfaction survey introduced in Section 2.1.3. The Sloan Fellows were asked to answer the following four question once a week during the four weeks of data collection:

Q1 How satisfied are you with the outcome of the meeting?

Q2 How satisfied are you with the process used in the meeting?

Q3 How valuable do you think your perspective was to the meeting?

Q4 How comfortable were you in sharing your perspective with the team?

Each question was answered on a seven-point scale ranging from one (extremely satisfied) to seven (extremely dissatisfied). Thus, the number increases as satisfaction decreases. The survey as well as the seven-point scale and its detailed meaning can be found in Appendix B.2. The answers to each of the four questions were used as separate dependent variables for the purpose of analyzing the correlation between participation and satisfaction. The dependent variables are listed in Table 2.8 and their distribution can be found in Figure 2.19.

Independent Variables

As with the analysis of performance, the previously computed measures of participation were separately used as independent variables. For the correlation between individual participation and satisfaction, the percentage of turns, the percentage of airtime, as well as the length of turns were used as independent variables in separate models. For the correlation between balance of

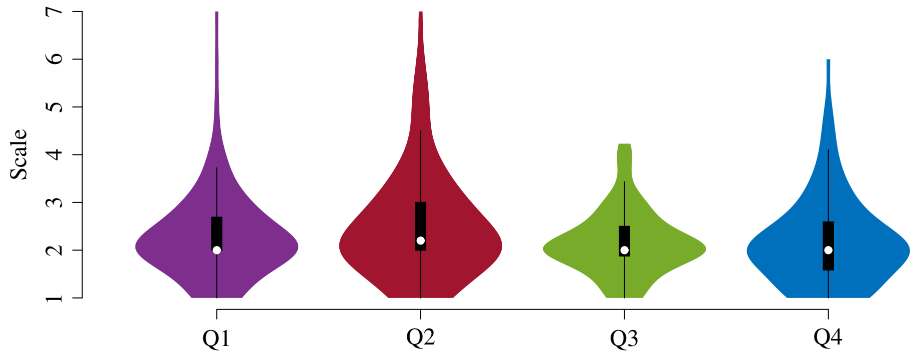


Figure 2.19: Distribution of Satisfaction. Violin plots of individual answers to the four questions of the satisfaction survey about the outcome of the meetings (Q1), the process used in the meetings (Q2), the value of the own perspective (Q3), as well as the comfortability of sharing the own perspective (Q4). The lower the value, the higher the satisfaction.

participation and satisfaction, the normalized HHIs in terms of turns and airtime were considered. In addition to the the measures of participation, the respective selected LASSO subsets from the analyses in Section 2.4.1 and Section 2.4.2 were used as independent variables in order to avoid an omitted-variable bias again. The satisfaction data used as dependent variables were collected once a week. Therefore, the measures of participation used as independent variables were not averaged over all meetings as it was the case in the previous analyses, but over all meetings within a week. Furthermore, dummy variables were used in order to model the four weeks, where week one was used as reference. A detailed overview can be found in Table 2.9.

Linear Mixed Model

One LMM was fitted for each combination of one of the four dependent variables (see Table 2.8) and one of the five sets of independent variables (see Table 2.9). Thus, 20 models were fitted in total. All survey questions about satisfaction referred to meetings, which were accomplished in groups. For that reason, the observations were assumed to be correlated within groups as well. A random effect for groups was chosen in order to account for the within-group correlation. Since the survey questions were answered once a week, several observations were available per student. These observations were additionally correlated within subjects because of the repeated measures. In order to account for the within-subject correlation as well, a nested random effect for subject was added to the models as well. The random effect was nested because students were consistently nested in groups.

Table 2.9: Sets of Independent Variables for Analysis of Satisfaction. Index w denotes the week, index i the participant, index j the group of the respective participant, and index k the independent variable of the respective set.

Variable	Symbol	Resolution	Type
Percentage of turns	p_{wij}	Member and week	Continuous
LASSO subset according to Table 2.2	x_{ik}	Member	Continuous/dummy
Week 2	$w2_w$	Week	Dummy
Week 3	$w3_w$	Week	Dummy
Week 4	$w4_w$	Week	Dummy
Percentage of airtime	p_{wij}	Member and week	Continuous
LASSO subset according to Table 2.2	x_{ik}	Member	Continuous/dummy
Week 2	$w2_w$	Week	Dummy
Week 3	$w3_w$	Week	Dummy
Week 4	$w4_w$	Week	Dummy
Length of turns	p_{wij}	Member and week	Continuous
LASSO subset according to Table 2.2	x_{ik}	Member	Continuous/dummy
Week 2	$w2_w$	Week	Dummy
Week 3	$w3_w$	Week	Dummy
Week 4	$w4_w$	Week	Dummy
Normalized HHI of turns	h^*_{wj}	Group and week	Continuous
LASSO subset according to Table 2.4	x_{jk}	Group	Continuous/dummy
Week 2	$w2_w$	Week	Dummy
Week 3	$w3_w$	Week	Dummy
Week 4	$w4_w$	Week	Dummy
Normalized HHI of airtime	h^*_{wj}	Group and week	Continuous
LASSO subset according to Table 2.4	x_{jk}	Group	Continuous/dummy
Week 2	$w2_w$	Week	Dummy
Week 3	$w3_w$	Week	Dummy
Week 4	$w4_w$	Week	Dummy

Equation 2.25 formalizes the model for analyzing the correlation between individual participation and satisfaction, where s_{wij} denotes the answer to one of the survey questions in week w of student i affiliated to group j. The independent variables correspond to the ones from the performance analysis with the only difference that the participation measures p_{wij} are computed separately for each week w. In addition, dummy variables were added for the four weeks. Furthermore, the model has random intercepts u_{ij} and v_j accounting for the within-group correlation and the within-subject correlation, respectively.

$$
\begin{aligned}
s_{wij} &= \beta_0 + \beta_1 p_{wij} + \left(\sum_{k=1}^{p} \beta_{k+1} x_{ik}\right) + \beta_{p+2} w2_w + \beta_{p+3} w3_w + \beta_{p+4} w4_w + u_{ij} + v_i + e_{wij} \\
u_{ij} &\sim \mathcal{N}(0, \sigma_u^2) \\
v_i &\sim \mathcal{N}(0, \sigma_v^2) \\
e_{wij} &\sim \mathcal{N}(0, \sigma^2)
\end{aligned}
\tag{2.25}
$$

The variance of observations is defined by the sum of the variances of the two random effects σ_u^2 and σ_v^2 as well as the variance of residuals σ_2.

$$
\text{var}(s_{wij}) = \text{var}(u_{ij} + v_i + e_{wij}) = \sigma_u^2 + \sigma_v^2 + \sigma^2 \tag{2.26}
$$

Considering the covariance $\text{cov}(s_{wij}, s_{w'i'j'})$ of any pair of observations, the covariance is equal to zero in case of observations that are neither from the same subject nor from the same group (i.e. $i \neq i'$ and $j \neq j'$). Correlation is allowed for observations from the same subject (i.e. $i = i'$) or the same group (i.e. $j = j'$) though. The covariance is equal to the sum of the respective variance components in these cases.

$$
\begin{aligned}
\text{cov}(s_{wij}, s_{w'i'j'}) &= \text{cov}(u_{ij} + v_i + e_{wij}, u_{i'j'} + v_{i'} + e_{w'i'j'}) \\
&= \begin{cases}
\sigma_u^2 + \sigma_v^2 + \sigma^2 & \text{if } i = i' \text{ and } w = w' \\
\sigma_u^2 + \sigma_v^2 & \text{if } i = i' \text{ and } w \neq w' \\
\sigma_u^2 & \text{if } i \neq i' \text{ and } j = j' \\
0 & \text{otherwise}
\end{cases}
\end{aligned}
\tag{2.27}
$$

For the purpose of examining the correlation between balance of participation and satisfaction, Equation 2.28 formalizes the applied model. The normalized HHIs h^*_{wj} in terms of turns or airtime are again evaluated separately for each week.

$$\begin{aligned}
s_{wij} &= \beta_0 + \beta_1 h^*_{wj} + \left(\sum_{k=1}^{p} \beta_{k+1} x_{jk}\right) + \beta_{p+2} w2_w + \beta_{p+3} w3_w + \beta_{p+4} w4_w + u_{ij} + v_i + e_{wij} \\
u_{ij} &\sim \mathcal{N}(0, \sigma_u^2) \\
v_i &\sim \mathcal{N}(0, \sigma_v^2) \\
e_{wij} &\sim \mathcal{N}(0, \sigma^2)
\end{aligned} \tag{2.28}$$

Not all students answered the satisfaction survey every week. Some students even stopped submitting answers after a certain week. This instance of missing data is a common problem in longitudinal studies over a period of time [Ver09]. Fortunately, mixed models automatically handle missing data by means of full maximum likelihood estimation. Rather than disregarding incomplete cases, they use all available data to produce unbiased estimates. The only assumption that has to be made about the data is that the data are missing at random (MAR). MAR is an assumption, in which the probability of missing data on a variable is not allowed to be related to the would-be values of that variable, but on other variables in the model. MAR was shown to be a reasonable assumption in most studies and it is especially considered to be a reasonable assumption in this work [Hes15].

Ordered Logit Model

The dependent variables used in this part of the analysis are again ordinal. The answers to the satisfaction survey can fall in seven ordered categories from one (extremely satisfied) to seven (extremely dissatisfied). Applying LMMs has some limitations hence [Gri14]. Among others, the normality assumption of linear models is violated, and beyond that, the real distance between the categories is in actually not known. For that reason, ordered logit models were fitted in addition. They were used in order to additionally prove the easily interpretable results obtained from the LMMs of the previous step. An introduction to ordered logit models was given in Section 2.4.3. In this part of the analysis, the ordinal variable for the satisfaction in week w of student i affiliated to group j is denoted as S_{wij}. The cumulative probability γ_{wijc} of a certain category c or a lower is further defined by Equation 2.29.

$$\gamma_{wijc} = P(S_{wij} \leq c|\boldsymbol{x}_{wij}) \tag{2.29}$$

For the purpose of analyzing the correlation between individual participation and satisfaction, the ordered logit model was fitted according to Equation 2.30, where the fixed and random effects are the same as with the LMMs of the previous step. Furthermore, Equation 2.31 formalizes the model used for analyzing the correlation between balance of participation and satisfaction.

$$\begin{aligned}\text{logit}(\gamma_{wijc}) &= \theta_c - \beta_1 p_{wij} - \left(\sum_{k=1}^{p} \beta_{k+1} x_{ik}\right) - \beta_{p+2} w2_w - \beta_{p+3} w3_w - \beta_{p+4} w4_w - u_{ij} - v_i \\ u_j &\sim \mathcal{N}(0, \sigma_u^2) \\ v_i &\sim \mathcal{N}(0, \sigma_v^2)\end{aligned} \tag{2.30}$$

$$\begin{aligned}\text{logit}(\gamma_{wijc}) &= \theta_c - \beta_1 h_w j^* - \left(\sum_{k=1}^{p} \beta_{k+1} x_{jk}\right) - \beta_{p+2} w2_w - \beta_{p+3} w3_w - \beta_{p+4} w4_w - u_{ij} - v_i \\ u_j &\sim \mathcal{N}(0, \sigma_u^2) \\ v_i &\sim \mathcal{N}(0, \sigma_v^2)\end{aligned} \tag{2.31}$$

As with the LMMs, 20 models were fitted in total for each combination of dependent and independent variables.

2.4.5 Effect of Real-Time Feedback

In the previous sections, data were modeled in order to understand participation in groups as well as its correlation to performance and satisfaction. In this section, it is further examined whether feedback on conversation dynamics can influence participation and in turn improve performance and satisfaction. The round-table visualization, which was used to give feedback in this study, was often shown to be an effective tool in laboratory settings [Kim08, Kim09]. In this work, these finding were examined in real-life settings. Therefore, the following two hypotheses were postulated and examined.

Table 2.10: Dependent Variables for Analysis of Feedback. Index w denotes the week and index j the group.

Variable	Symbol	Resolution	Type
Normalized HHI of turns	h^*_{wj}	Group and week	Continuous
Normalized HHI of airtime	h^*_{wj}	Group and week	Continuous

Hypothesis 5. *The applied round-table visualization influences the groups to have a higher balance of participation.*

Hypothesis 6. *Continuous use of the round-table visualization trains the students to become more aware of conversation dynamics. Thus, higher balance of participation lasts even after the groups stop using the round-table visualization.*

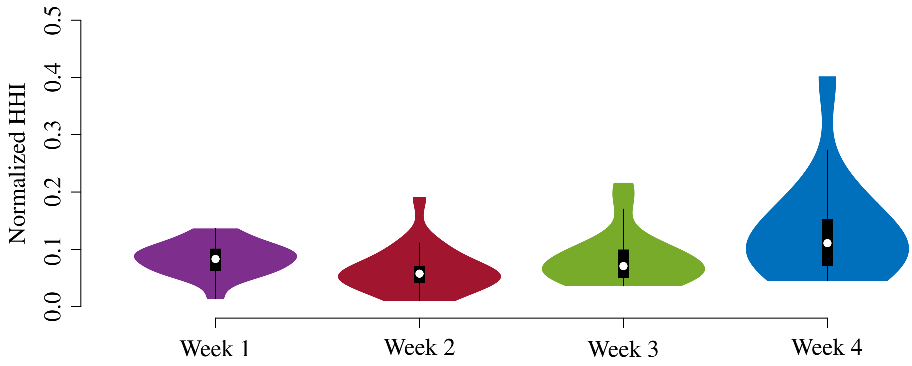
Dependent Variables

Feedback was given by visualizing the conversation dynamics in real-time using the app of the Open Badges system introduced in Section 2.1.2. The participations of a meeting were drawn around a round-table and a ball in the middle of the round-table as well as lines from the participations to the ball represented the balance of participation of all participations and the amount of participation of individual participants, respectively. The moderator of the meeting was responsible for observing the visualization and for encouraging the participants to contribute equally to the conversation in order to hold the ball in the middle.

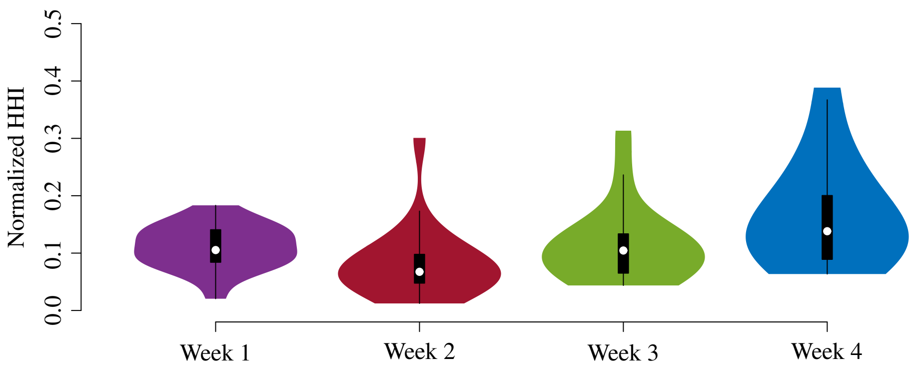
The balance of participation was the variable of interest hence. For the purpose of examining the effect of the visualization on the balance of participation, the normalized HHIs in terms of turns and airtime were computed as introduced in Section 2.4.2 in Equation 2.10 and 2.11. However, they were averaged over all meetings within a week so that data were available per group and week instead of per group only. The dependent variables are listed in Table 2.10 and their distribution can be seen in Figure 2.20.

Independent Variables

In order to be able to examine the effect of feedback, a crossover study design with an ABBA pattern was chosen and the visualization was only enabled in week two and three, and disabled in week one and four. The ABBA pattern was the same for all groups. Three different sets of independent variables were used to model these circumstances.



(a) Turns



(b) Airtime

Figure 2.20: Distribution of Normalized Herfindahl Index over Weeks. Violin plots of normalized HHI over the four weeks of data collection. The visualization of the Open Badges system was enabled in week two and three and disabled in week one and four.

Table 2.11: Sets of Independent Variables for Analyis of Feedback. Index w dentoes the week and index j the group.

Variable	Symbol	Resolution	Type
Visualization	v_w	Week	Dummy
Week 2	$w2_w$	Week	Dummy
Week 3	$w3_w$	Week	Dummy
Week 4	$w4_w$	Week	Dummy
Week 2	$w2_w$	Week	Dummy
Week 3	$w3_w$	Week	Dummy
Week 4	$w4_w$	Week	Dummy
Moderator	m_{wj}	Group and week	Dummy

Only one dummy variable for the information whether the visualization was switched on or off was contained in the first set. It was one for week two and three and zero for week one and four. However, the visualization was expected to have a continuing or learning effect in week four, where it was switched off again. In order to model this hypothesis, the four weeks were modeled separately using dummy variables with week one as reference value. It was known from the participants that not all of the groups used the app with the visualization in all meetings. Some of them did not assign a moderator and therefore, just put the smartphone with the feedback aside and did not observe the visualization. In order to model that circumstance, a third set of independent variables was used that contained the dummy variables for the four weeks and a dummy variable for the compliance in addition. Combined with the weekly satisfaction survey, the Sloan Fellows were asked whether they were a moderator in at least one meeting of the respective week. This information was used as compliance variable. The dummy variable was one if the group had at least one moderator in a week and it was zero if the group did not had a moderator at all. An overview on the three different sets of indepdendent variables can be seen in Table 2.11.

Linear Mixed Model

Due to the repeated measures, multiple observations were available per group. In order to account for the correlated observations, LMMs with a random effect for groups were applied. The random effect as well as the variance and covariance structure of the models are the same as introduced in Section 2.4.3. Furthermore, not all groups collected data in all weeks. Some groups even stopped collecting data after a certain week. However, as addressed in Section 2.4.4, the applied

LMMs automatically deal with missing data under the reasonable assumption of MAR.

For the first set of independent variables, the model is defined in Equation 2.32, where v_w is the dummy variable indicating whether the visualization was switched on or off in week w. The dependent variable h^*_{wj} is the normalized HHI again. The model was both fitted for the normalized HHI in terms of turns and airtime.

$$\begin{aligned} h^*_{wj} &= \beta_0 + \beta_1 v_w + u_j + e_{wj} \\ u_j &\sim \mathcal{N}(0, \sigma_u^2) \\ e_{wj} &\sim \mathcal{N}(0, \sigma^2) \end{aligned} \tag{2.32}$$

For the second set of independent variables, the model is defined in Equation 2.33. The four weeks are modeled by means of three dummy variables $w2_w$, $w3_w$, and $w3_w$ for week two, three and four, again.

$$\begin{aligned} h^*_{wj} &= \beta_0 + \beta_1 w2_w + \beta_2 w3_w + \beta_3 w4_w + u_j + e_{wj} \\ u_j &\sim \mathcal{N}(0, \sigma_u^2) \\ e_{wj} &\sim \mathcal{N}(0, \sigma^2) \end{aligned} \tag{2.33}$$

The model for the third set of independent variable is defined in Equation 2.34. In this model, a dummy variable m_{wj} indicating whether there was a moderator in week w and group j is considered in addition.

$$\begin{aligned} h^*_{wj} &= \beta_0 + \beta_1 w2_w + \beta_2 w3_w + \beta_3 w4_w + \beta_4 m_{wj} + u_j + e_{wj} \\ u_j &\sim \mathcal{N}(0, \sigma_u^2) \\ e_{wj} &\sim \mathcal{N}(0, \sigma^2) \end{aligned} \tag{2.34}$$

2.4.6 Effect of Required Expertise

Balance of participation was often shown to be a major indicator for successful group collaboration [Pen12]. However, this finding was mostly proven in laboratory settings and with tasks that did not require prior expertise of the group members. In real-life settings such as the group meetings of the Sloan Fellows, prior expertise is required though. The administrators of the MIT Sloan School of Management even try to put students with different fields of expertise together

Table 2.12: Dependent Variables for Analysis of Expertise. Index m denotes the meeting and index j the group.

Variable	Symbol	Resolution	Type
Normalized HHI of turns	h^*_{mj}	Group and meeting	Continuous
Normalized HHI of airtime	h^*_{mj}	Group and meeting	Continuous

into the same group so that a broad range of knowledge is covered in each group. For that reason, it is assumed that balance of participation is not beneficial in all circumstances. In meetings with required expertise, unbalanced participation might be preferable if the expert speaks and the other groups members listen and learn from the expert.

In order to start examining this hypothesis, the correlation between the balance of required expertise and the balance of participation in a meeting is analyzed in this section. In meetings with specific required expertise, experts are assumed to speak more in order to teach the other group members and the other group members are assumed to speak less in order to learn from the experts. For that reason, these meetings are assumed to have a lower balance of participation than meetings with no specific expertise required. Therefore, the following hypothesis was postulated and investigated.

Hypothesis 7. *A high imbalance of required expertise in a meeting is correlated with a high imbalance of participation of the group and the other way round.*

Dependent Variables

In order to investigate this hypothesis, the balance of participation was used as dependent variable. It was computed by means of the normalized HHI in terms of turns and airtime as introduced in Section 2.4.2 in Equation 2.10 and 2.11. However, in contrast to Section 2.4.2, the normalized HHI was not averaged over all meetings and one observations was available per meeting. The dependent variables are listed in 2.12.

Independent Variables

For the purpose of examining the correlation between the balance of required expertise and the balance of participation, a measure for the balance of required expertise was needed. In the summer term 2016, in which data were collected, the Slaon Fellows attended the three courses ”Financial Accounting”, ”Marketing and Strategy”, and ”Data, Models and Decisions” In the meetings, they worked together on group assignments for these courses. The three courses required different fields of expertise furthermore. In order to measure the balance of required expertise, the course syllabi were used in a first step in order to derive different weights for the different courses for each meeting. The higher the weighting of a course in a meeting, the more time is assumed to be taken for this course and the more the expert of this course is assumed to speak. The weights were determined based on due dates of group assignments and according to the following four principles:

1. Courses are weighted equally by default.
2. The weight of a course in increased as more assignments are due.
3. The weight of a course is increased as sooner as an assignment is due.
4. The weight of a course is increased as more important the assignment is based on the contribution of the assignment to the overall grade of the course.

In agreement with the four principles, meetings were mapped onto absolute weights for each course using the course syllabi as defined in Equation 2.35. The absolute weight of a course c in a meeting m is denoted as γ_{cm}. It is given a default value of one in order to implement the first principle. In respect of the second principle, it is increased for each assignment a within n days from the meeting, where d_{ma} is the number of days between meeting m and the due date of an assignment a and where N_c is the number of assignments in course c. The third and fourth principle were implemented by means of the remaining equation. For each assignment, the absolute weight of a course is increased as sooner as the assignment is due by means of $\frac{1}{d_{ma}}$ and it is increased as more important the assignment is due by means of g_a, where g_a is the grading of the assignment. The least important group assignment had a sharing of 3.5% of the overall grading and the most important group assignment, the final project in the course "Marketing and Strategy", had a sharing of 40%. Therefore, g_a ranged from 0.035 to 0.4.

$$\gamma_{cm} = 1 + \sum_{\substack{a=1 \\ d_{ma}<n}}^{N_c} \alpha \cdot \frac{1}{d_{ma}} \cdot g_a \tag{2.35}$$

The absolute weight γ_{cm} can be adjusted using the two parameters n and α. Parameter n determines the number of days beginning with the meeting, in which assignments are considered. The higher n, the more assignments are considered for weighting. The parameter α determines how much weight is given to assignments compared against the default value of one. The higher α, the more weight is given to assignments in general. The approach used for measuring the required expertise in a meeting is a rough estimation only. It was used because no data were collected about the topics or fields of expertise of a meeting in advance. In order to still improve reliability of the approach, a wide range of values for the two parameters n and α was used. The values used for parameter n are $n = 1, 2, ..., 7$ and the values used for parameter α are $\alpha = 5, 10, ...50$.

Furthermore, a second and simplified version of the mapping function was considered in addition. It is defined in Equation 2.36. In this equation, the first principle is dismissed and no default value is given to the weights. For that reason, no parameter α determining how much weight is given to the assignments compared against the default value is needed as well. This mapping function provides much more extreme values than the complex mapping function before. In case that there are no assignments within n days from a meeting m for course c, the absolute weight γ_{cm} equals to zero. Again, the values used for parameter n ranged from 1 to 7.

$$\gamma_{cm} = \sum_{\substack{a=1 \\ d_{ma}<n}}^{N_c} \frac{1}{d_{ma}} \cdot g_a \tag{2.36}$$

After computing the absolute weights γ_{cm} for each course c and meeting m, relative weights were computed by means of Equation 2.37. In this connection, γ^*_{cm} are the relative weights and C is the number of courses, i.e. $C = 3$ in this case. Taken together, the relative weight γ^*_{cm} of a course c and a meeting m is computed by dividing the absolute weight of the course and the meeting by the sum of absolute weights of all courses in the meeting.

$$\gamma^*_{cm} = \frac{\gamma_{cm}}{\sum_{i=1}^{C} \gamma_{im}} \tag{2.37}$$

The absolute weights were finally used to compute a measure for the balance of required expertise. The normalized HHI, which was introduced in Section 2.4.2, was computed according to Equation 2.10 and Equation 2.11 using the relative weights of all courses in a certain meeting. The normalized HHI of relative course weight as a measure of balance of required expertise was used as independent variable in the end. It was computed for each meeting.

Linear Mixed Model

In this part of the analysis, one observation was available per meeting, i.e. multiple observations were available per group. In order to account for the correlated observations due to the repeated measures, a LMM was fitted with a random effect for groups. Once again, the random effect, the variance, as well as the covariance structure are the same as in Section 2.4.3. The model

Table 2.13: Set of Independent Variables for Analysis of Expertise. Index m denotes the meeting and index j the group. The normalized HHI of expertise was computed with regard to the complex and the simple mapping function as well as with regard to different values for the paramters α and n.

Variable	**Symbol**	**Resolution**	**Type**
Normalized HHI of expertise	$\hat{h}_{mj}$	Group and meeting	Continuous

is defined in Equation 2.38, where h^*_{mj} is the normalized HHI in terms of turns or airtime of a meeting m and a group j and where $\hat{h}^*_{mk}$ is the normalized HHI in terms of course weights.

$$\begin{aligned} h^*_{mj} &= \beta_0 + \beta_1 \hat{h}^*_{mj} + u_j + e_{mj} \\ u_j &\sim \mathcal{N}(0, \sigma_u^2) \\ e_{mj} &\sim \mathcal{N}(0, \sigma^2) \end{aligned} \tag{2.38}$$

2.5 Evaluation

In order to obtain meaningful results, the fitted models were finally evaluated. In a first step, they were checked for their underlying assumptions as well as other conspicuities. In a second step, a number of measures was computed or extracted from the fitted models in order to be able to quantify and interpret the results. The evaluation was accomplished in R again.

2.5.1 Model Diagnostics

Model diagnostics are indispensable in order to ensure validity and reliability of the results. The used linear and logistic models were checked for their underlying assumptions as well as conspicuous observations. This information was subsequently used to correctly interpret the results and to draw conclusions from the results.

Linear Models

Linear models such as the applied linear regression models, the covariance pattern models, and the linear mixed models underlay the following assumptions [Fox15, Wei05].

1. *Linearity*: The dependent variable of the model has a linear relationship with the independent variables of the model.

2. *Homoscedasticity*: The residuals of the model have constant variance.

3. *Independence*: The residuals of the model are mutually independent.

4. *Normality*: The residuals of the model are normally distributed.

5. *Absence of Multicollinearity*: The independent variables of the model are not or only slightly related to each other.

The assumption of linearity was checked by means of residual plots. Residuals were plotted both against fitted values and independent variables in order to detect assumption violations in the form of curvy or other non-linear patterns. Plotting was accomplished by means of function `plot` of standard `graphics`. For the purpose of checking the assumption of homoscedasticity or constant residual variance, residuals were plotted against fitted values again. Non-constant boundaries of residuals around zero indicated assumption violations in this connection. Meeting the assumption of independence was a question of data collection and modeling in the first place. Violations of the independence assumptions were resolved by using covariance pattern models and linear mixed models. The assumption of normality was checked by means of histogram plots of residuals as well as Q-Q plots. The histogram plots had to be bell-shaped and the Q-Q plots had to approximate a straight line in order to verify the assumption. They were created by means of function `hist` of standard package `graphics` and function `qqnorm` of standard package `stats`, respectively. Finally, the absence of multicollinearity was checked using the variance inflation factor (VIF). The VIF was computed by means of function `vif` of package `car` [Fox16] for linear regression models and an adapted version of the function for covariance pattern models and linear mixed models. It had to be lower or equal to four in order to meet the assumption.

In addition to checking the models for assumption violations, they were checked for outliers and influential observations [Wei05]. Although it is not acceptable to simply delete conspicuous observations, information about outliers and influential observations can help understand the results and additionally reveal irrelevant or incorrect data. In this work, outliers and influential observations were particularly detected by means of Q-Q plots.

Logistic Models

The assumption of concern of ordered logit models is the *proportional odds assumption* [O'C06]. According to this assumption, each independent variable has the same cumulative split of the ordinal dependent variable. In other words, each independent variable has the same effect on each cumulative logit of the ordinal dependent variable. The ordered logit models were checked for the proportional odds assumption by means of the functions `nominal_test` and `scale_test` of the package `ordinal` [Chr15b]. Both functions are only applicable to `clm` models. Therefore, a respective `clm` model without random effects was fitted for each `clmm` model with random effects in order to check the assumption.

There are several alternatives in case of violations of the proportional odds assumption [O'C06]. The first alternative is to fit a series of binary logistic regression models instead of only one ordered logistic regression model. Depending on the number of levels of the ordinal dependent variable, this approach results in a vast amount of models though and was not suited in this work. Another alternative are partial proportional odds models. These models relax the proportional odds assumption and allow for an interaction between certain independent variables and the different cumulative logit comparisons. With the function `clm` of the package `oridnal` [Chr15b], partial proportional odds models can be fitted by defining the respective independent variables as `nominal` or `scale` effects. Partial proportional odds models are only appropriate if the violation of the proportional odds assumption can be ascribed to a small subset of independent variables though. If it is ascribed to a higher number of independent variables, another alternative is to neglect the ordinal nature of the dependent variable and to fit a multinomial or linear model instead. The limitations of these models have to be considered for interpretation though.

2.5.2 Model Measures

After ensuring validity and reliability of the results by applying model diagnostics, a number of measures was computed or extracted from the fitted models in order to quantify and interpret the results. The measures are introduced in the following.

Coefficient

For the intercept and each of the independent variables, the coefficient β_k was estimated [Dra14]. It states the correlation between the respective independent variable and the dependent variable. For dummy variables, the coefficient corresponds to the change in the value of the dependent variable when the value of the independent variable changes from zero to one. For standardized continuous variables, the coefficient corresponds to the change in the value of the dependent variable when the value of the independent variable changes by one standard deviation. In case of ordered logit models, the coefficients refer to the change in the value of the cumulative logits of the dependent variable instead of the dependent variable by itself.

As noted in the prior sections, the linear regression models were fitted using function `lm` from standard package `stats`, the covariance pattern models were fitted using function `gls` from package `nlme` [Pin17], the linear mixed models were fitted using function `lme` from package `nlme` [Pin17] , and the ordered logit models were fitted using function `clm` and `clmm` from package `ordinal` [Chr15b]. Consequently, the coefficients were obtained by means of these functions.

P Value

For the intercept and each of the independent variables, p values were additionally computed in order to get information about the statistical significance of the coefficients [Dra14]. The smaller a p value, the higher the statistical significance of the corresponding coefficient. In this work, three significance levels at 0.01, 0.05, and 0.1 were considered. Once again, the p values were obtained by the stated functions for fitting the models.

Confidence Interval

In addition to p values, confidence intervals were computed in order to get information about the certainty of the estimated coefficients [Dra14]. A confidence interval is a range of values that is likely to contain the real value of the coefficient. In this work, a 95% confidence interval was computed for each of the coefficients. It is related to the significance level at 0.05.

For linear regression models, the confidence intervals were computed using function `confint` of standard package `stats`. For covariance pattern models and linear mixed models, they were computed using function `intervals` of package `nlme` [Pin17], and function `confint` of package `ordinal` [Chr15b] was used for ordered logit models.

Number of Levels

For models with random effects, the number of levels for each random effect was extracted in order to get information about the nature of the random effect.

Intraclass Correlation Coefficient

The Intraclass Correlation Coefficient (ICC) is a measure for evaluating and interpreting random effects [O'C08]. It is defined as the ratio of the variance component of a random effect to the total variance of observations and reports the proportion of the total variance of observations that is accounted for by the random effect. It can also be interpreted as the correlation among observations within the same level of the random effect (e.g, student, group). The ICC of a random effect r is given in Equation 2.39, where σ_r^2 is the variance of the random effect, N the total number of random effects in the model, and σ^2 the variance of residuals.

$$ICC_r = \frac{\sigma_r^2}{(\sum_{i=1}^{N} \sigma_i^2) + \sigma_2} \tag{2.39}$$

For covariance pattern models, the parameter ρ obtained by the function `gls` of package `nlme` [Pin17] corresponds to the ICC. For linear mixed models and ordered logit models, the variance components were extracted by means of function `VarCorr` of package `nlme` [Pin17] and `ordinal` [Chr15b], respectively. Furthermore, in case of ordered logit models, the residuals were assumed to follow a standard logistic distribution and the variance of residuals σ^2 was set to $\pi^2/3$ hence [O'C10].

Number of Observations

The number of observations in the dataset was used as an additional model measure. It was of particular interest for interpreting the p values and confidence intervals.

R Squared

The R^2, also known as coefficient of determination, is the most common measure for assessing the overall model fit [Dra14]. It states the proportion of variance in the dependent variable that is explained by the independent variables. However, R^2 increases as the number of independent variables in the model increases. For that reason, the adjusted R^2 accounting for the number of independent variables is often considered to be superior. For the linear regression models, both measures were obtained from function `lm` of standard package `stats`.

Because of the more complex variance structures, the ordinary R^2 and adjusted R^2 could not be applied to the remaining models. Therefore, pseudo R^2 measures were used. For linear mixed models, Nakagawa and Schielzeth [Nak13, Joh14] derived two easily interpretable and accepted measures of R^2. The first one is called marginal R^2 and describes the proportion of variance explained by the fixed effects alone. The second one is called conditional R^2 and describes the proportion of variance explained by both the fixed and random effects. Both measures were computed using function `sem.model.fits` of package `piecewiseSEM` [Lef15]. For covariance pattern models, the same function was used to derive pseudo R^2 values. However, since these models do not contain random effects, only the marginal R^2 could be computed. Because of the underlying covariance pattern of the models, this value has to be interpreted with caution though.

For ordered logit models, the pseudo R^2 measures of McFadden [McF73] as well as Cox and Snell [Cox89] are most commonly used. They were often recommended for logistic models and are standardly reported by common statistical packages such as SAS and SPSS [All13]. Both measures were computed using function `nagelkerke` of package `rcompanion` [Man17].

Chapter 3

Results

The methods used for analyzing conversation dynamics in meetings of Sloan Fellows were introduced in Chapter 2. Data were collected, processed, cleansed, and modeled, and the fitted models were finally evaluated. The corresponding results are presented in this chapter. Possible assumption violations and conspicuous observations are outlined and the actual results and model measures are reported in detail.

3.1 Individual Participation

The linear regression models meet all assumptions expect the independence assumption because of the correlation of percentage of turns and airtime within groups. Therefore, covariance pattern models were fitted in addition. They meet all assumptions without exception.

The results for percentage of turns are listed in Table 3.1. The variables selected by LASSO are the dummy variables for being female, Asian, and member of a five-member group as well as the continuous variables for the personality traits agreeableness and extraversion. The results for the linear regression model and the covariance pattern model coincide to a large extent. For both models, there is a significant negative effect for being Asian, a significant positive effect for extraversion, and a significant negative effect for being member of a five-member group. For the covariance pattern model, agreeableness is significantly and negatively correlated with percentage of turns as well. The covariance pattern model reports a moderate negative correlation ($|ICC| > 0.2$) within groups. Furthermore, a large amount of variance ($R^2 > 0.25$) is explained by the independent variables for both models.

Table 3.2 shows the results for percentage of airtime. The variables selected by LASSO are the same as before with the dummy variable for ethnicity Middle East in addition. The results

Table 3.1: Results for Percentage of Turns. Results of the linear regression model (LRM) and the covariance pattern model (CPM) for percentage of turns.

	Percentage of turns	
	LRM	CPM
(Intercept)	0.2961***	0.2886***
	[0.2576, 0.3346]	[0.2629, 0.3143]
Female	-0.0268	-0.0188
	[-0.0607, 0.0071]	[-0.0480, 0.0104]
Asia	-0.0710***	-0.0585***
	[-0.1059, -0.0361]	[-0.0907, -0.0262]
Agreeableness	-0.0106	-0.0101*
	[-0.0264, 0.0052]	[-0.0217, 0.0016]
Extraversion	0.0218***	0.0124*
	[0.0056, 0.0379]	[-0.0010, 0.0258]
Five-member group	-0.0565***	-0.0554***
	[-0.0953, -0.0177]	[-0.0776, -0.0333]
N_{group}	–	21
ICC_{group}	–	-0.2084
N	100	100
R^2	0.3122	–
Adjusted R^2	0.2756	–
Marginal R^2	–	0.3296

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
5% confidence interval reported in square brackets

for being Asian, extraversion, and being member of a five-member group are comparable to the results for percentage of turns. Furthermore, being female is significantly and negatively correlated with percentage of turns for both models. Again, there is a moderate negative correlation ($|ICC| > 0.2$) within groups for the covariance pattern model and a large amount of variance ($R^2 > 0.25$) is explained by the independent variables for both models.

The results for length of turns are listed in Table 3.3. The variables selected by LASSO are the dummy variables for being female, Asian, South American, and South Asian as well as the continuous variable for extraversion. The only significant effect for length of turns is the dummy variable for being female. It is negatively correlated with the dependent variable. The independent variables explain a small ($R^2 \leq 0.15$) and medium ($R^2 > 0.15$) amount of variance

Table 3.2: Results for Percentage of Airtime. Results of the linear regression model (LRM) and the covariance pattern model (CPM) for percentage of airtime.

	Percentage of airtime	
	LRM	CPM
(Intercept)	0.3056***	0.2922***
	[0.2617, 0.3495]	[0.2636, 0.3208]
Female	-0.0477**	-0.0287*
	[-0.0863, -0.0090]	[-0.0612, 0.0039]
Asia	-0.0817***	-0.0615***
	[-0.1217, -0.0416]	[-0.0976, -0.0255]
Middle East	-0.0668	-0.0381
	[-0.1715, 0.0379]	[-0.1205, 0.0442]
Agreeableness	-0.0103	-0.0087
	[-0.0284, 0.0077]	[-0.0223, 0.0049]
Extraversion	0.0249***	0.0148*
	[0.0065, 0.0433]	[-0.0002, 0.0297]
Five-member group	-0.0537**	-0.0536***
	[-0.0981, -0.0093]	[-0.0783, -0.0289]
N_{group}	–	21
ICC_{group}	–	-0.2152
N	100	100
R^2	0.3159	–
Adjusted R^2	0.2717	–
Marginal R^2	–	0.3210

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
5% confidence interval reported in square brackets

for the covariance pattern model and the linear regression model, respectively. The extended models used for examining interaction terms of main effects do not reveal significant effects of the interaction terms. Their results can be found in Appendix C.1.

3.2 Balance of Participation

The linear regression models for the normalized HHI of turns and airtime do not violate any of the underlying assumptions. The results for both models can be found in Table 3.4. The

Table 3.3: Results for Length of Turns. Results of the linear regression model (LRM) and the covariance pattern model (CPM) for length of turns in seconds.

	Length of turns	
	LRM	CPM
(Intercept)	5.5459***	5.5641***
	[5.2078, 5.8839]	[5.2050, 5.9230]
Female	-0.6475***	-0.6197***
	[-1.0561, -0.2388]	[-0.9833, -0.2559]
Asia	-0.2389	-0.2799
	[-0.6976, 0.2197]	[-0.6824, 0.1225]
South America	0.3619	0.3126
	[-0.1687, 0.8925]	[-0.1493, 0.7745]
South Asia	0.4529	0.3417
	[-0.2375, 1.1433]	[-0.2736, 0.9570]
Extraversion	0.1535	0.1423
	[-0.0427, 0.3497]	[-0.0329, 0.3176]
N_{group}	–	21
ICC_{group}	–	0.2553
N	100	100
R^2	0.1734	–
Adjusted R^2	0.1295	–
Marginal R^2	–	0.1380

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
5% confidence interval reported in square brackets

variables selected by LASSO are the same for both models. Only the two level indices median conscientiousness and median openness to experiences were selected. Both variables are negatively correlated with the normalized HHI of turns and airtime, i.e. positively correlated with the balance of participation in terms of turns and airtime. Median openness to experiences has a significant effect for both the normalized HHI of turns and airtime, where median conscientiousness has a significant effect for the normalized HHI of airtime only. The independent variables explain a large amount of variance ($R^2 > 0.25$) for the normalized HHI of turns and a very large amount of variance ($R^2 > 0.35$) for the normalized HHI of airtime. Again, the extended models used for examining interaction terms do not reveal significant effects of the interaction terms. Their results can be found in Appendix C.2.

Table 3.4: Results for Normalized HHI of Turns and Airtime. Results of the linear regression model (LRM) for the normalized HHI of turns and airtime.

	Normalized HHI of turns	Normalized HHI of airtime
	LRM	LRM
(Intercept)	0.0833***	0.1088***
	[0.0710, 0.0955]	[-0.0312, 0.0006]
Median conscientiousness	-0.0083	-0.0153*
	[-0.0214, 0.0048]	[-0.0312, 0.0006]
Median openness to experiences	-0.0118*	-0.0151*
	[-0.0248, 0.0013]	[-0.0311, 0.0007]
N	21	21
R^2	0.2911	0.3866
Adjusted R^2	0.2124	0.3185

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
5% confidence interval reported in square brackets

3.3 Performance

For the purpose of examining the correlation between percentage of turns, percentage of airtime, length of turns, normalized HHI of turns, and normalized HHI of airtime as well as the grades in the courses ”Data, Models, and Decision”, ”Financial Accounting”, and ”Marketing and Strategy”, 30 different models were fitted in total. The results for percentage of turns and percentage of airtime as well as for the normalized HHI of turns and the normalized HHI of airtime are similar. Therefore, the results for percentage of turns and the normalized HHI of turns are presented in this section, and the results for percentage of airtime and the normalized HHI of airtime can be found in Appendix C.3. Furthermore, no significant effects are revealed for length of turns. For that reason, these results can be found in Appendix C.3 as well.

The linear mixed models do not meet all of the underlying assumptions. Because of the ordinal nature of the dependent variables, they violate the normality assumption. Ordered logit models were used in order to resolve the assumption violation.

Table 3.5 lists the results for all courses and percentage of turns. Regarding course ”Data, Models, and Decisions”, the tests used for checking for the proportional odds assumption of the ordered logit model did not produce meaningful results. Therefore, no certainty can be given that the ordered logit model meets the proportional odds assumption. The results for both the linear mixed model and the ordered logit model report a significant positive effect for percentage of turns. Furthermore, the correlation within groups is infinitesimally small and a small ($R^2 \leq 0.15$) to medium ($R^2 > 0.15$) amount of variance is explained by the independent variables. Regarding course "Financial Accounting", the ordered logit model meets the proportional odds assumption. Again, the results report a positive correlation between percentage of turns and the grade in "Financial Accounting". The correlation within groups is infinitesimally small and a large amount of variance ($R^2 > 0.25$) is explained by the independent variables. With regard to course "Marketing and Strategy", the ordered logit model does not meet the proportional odds assumption. The tests used for checking for the assumption indicated that almost all independent variables contribute to the assumption violation. Therefore, *no* partial proportional odds model was fitted. In terms of the results, there is no significant effect for percentage of turns for the linear mixed model but a significant positive effect for the ordered logit model. Furthermore, the linear mixed model and the ordered logit model report a high ($|ICC| > 0.4$) and very high ($|ICC| > 0.6$) correlation within groups, respectively. The independent variables explain a small amount of variance ($R^2 \leq 0.15$) for the linear mixed model and a medium amount of variance ($R^2 > 0.15$) for the ordered logit model.

Table 3.6 shows the results for all courses and the normalized HHI of turns. Regarding course "Data, Models, and Decisions", the tests used for checking for the proportional odds assumption of the ordered logit model did again not produce meaningful results. Furthermore, there are no significant effects for both the linear mixed model and the ordered logit model and only a small amount of variance ($R^2 \leq 0.15$) is explained by the independent variables. With regard to course "Financial Accounting", the ordered logit model meets the proportional odds assumption. For both models, there is a significant positive correlation between the normalized HHI of turns and the grade in course "Financial Accounting", i.e. a significant negative correlation between the balance of participation and the grade in course "Financial Accounting". The correlation within groups is again infinitesimally small. Due to the small within-group correlation and associated computational issues, the ordered logit model had to be fitted without random effects. The independent variables explain a small amount of variance ($R^2 \leq 0.15$) for both models. Regarding course "Marketing and Strategy", the ordered logit model again violates the proportional odds assumption. However, *no* partial proportional odds model was fitted for the same reason as before. There are no significant effects for both models furthermore. The correlation within groups is reported to be high ($|ICC| > 0.4$) for the linear mixed model and very high ($|ICC| > 0.6$) for the ordered logit model. Besides, a small amount of variance ($R^2 \leq 0.15$) is explained by the independent variables.

Table 3.5: Results for all Courses and Percentage of Turns. Results of the linear mixed model (LMM) and the ordered logit model (OLM) for all courses and percentage of turns.

	Data, Models, and Decisions		Financial Accounting		Marketing and Strategy	
	LMM	OLM	LMM	OLM	LMM	OLM
(Intercept)	3.6275***	–	3.5903***	–	3.4872***	–
	[3.3521, 3.9029]	–	[3.3662, 3.8144]	–	[3.1205, 3.8538]	–
Percentage of turns	0.2033***	0.7630***	0.2755***	1.8319***	0.0667	0.8231*
	[0.0793, 0.3273]	[0.3013, 1.2247]	[0.1746, 0.3764]	[0.8608, 2.8030]	[-0.0147, 0.1481]	[-0.1405, 1.7866]
Female	-0.3265***	-1.1202***	-0.1566*	-1.0642*	0.1325*	1.9016*
	[-0.5541, -0.0990]	[-1.9314, -0.3089]	[-0.3417, 0.0286]	[-2.2740, 0.1455]	[-0.0234, 0.2883]	[-0.0957, 3.8989]
Asia	0.4240***	1.4011***	0.3130***	1.9363***	-0.1365	-0.8366
	[0.1738, 0.6743]	[0.4729, 2.3293]	[0.1093, 0.5166]	[0.5334, 3.3391]	[-0.3042, 0.0311]	[-2.5562, 0.8831]
Agreeableness	-0.0410	-0.0176	0.0042	-0.0217	0.0634*	0.7051*
	[-0.1466, 0.0645]	[-0.4059, 0.3707]	[-0.0817, 0.0900]	[-0.5426, 0.4993]	[-0.0122, 0.1391]	[-0.1243, 1.5346]
Extraversion	-0.0176	-0.0477	-0.0773	-0.4648	0.0403	0.5781
	[-0.1286, 0.0933]	[-0.4556, 0.3601]	[-0.1676, 0.0129]	[-1.0941, 0.1645]	[-0.0369, 0.1175]	[-0.2816, 1.4378]
Five-member group	-0.0157	-0.1479	-0.0563	-0.5971	0.0710	1.0574
	[-0.2975, 0.2660]	[-1.1109, 0.8151]	[-0.2856, 0.1730]	[-1.9785, 0.7843]	[-0.3543, 0.4964]	[-2.7495, 4.8643]
N_{group}	21	21	21	21	21	21
ICC_{group}	8.1422e-10	9.2703e-10	4.3819e-09	0.0078	0.5413	0.7589
N	100	100	100	100	100	100
Marginal R^2	0.2457	–	0.3103	–	0.0863	–
Conditional R^2	0.2457	–	0.3103	–	0.5808	–
Mc Fadden R^2	–	0.0752	–	0.2982	–	0.1599
Cox and Snell R^2	–	0.2252	–	0.3307	–	0.1622

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$, 5% confidence interval reported in square brackets

Table 3.6: Results for all Courses and Normalized HHI of Turns. Results of the linear mixed model (LMM) and the ordered logit model (OLM) for all courses and the normalized HHI of turns.

	Data, Models, and Decisions		Financial Accounting		Marketing and Strategy	
	LMM	OLM	LMM	OLM	LMM	OLM
(Intercept)	3.6536***	–	3.6000***	–	3.5387***	–
	[3.5381, 3.7691]	–	[3.5024, 3.6976]	–	[3.3600, 3.7175]	–
Normalized HHI of turns	0.0095	0.0661	0.1030*	0.4374*	0.1607	1.3225
	[-0.1295, 0.1486]	[-0.3465, 0.4788]	[-0.0146, 0.2205]	[-0.0517, 0.9652]	[-0.0351, 0.3564]	[-0.3542, 2.9991]
Median conscientiousness	-0.0320	-0.0203	0.0706	0.2978	0.1073	0.9385
	[-0.1650, 0.1009]	[-0.4032, 0.3626]	[-0.0417, 0.1830]	[-0.1425, 0.7671]	[-0.0969, 0.3115]	[-0.4668, 2.3439]
Median openness to experiences	-0.0626	-0.1559	0.0269	0.1143	-0.0170	-0.2247
	[-0.2036, 0.0783]	[-0.5638, 0.2520]	[-0.0923, 0.1460]	[-0.3561, 0.5845]	[-0.2334, 0.1994]	[-1.5538, 1.1043]
N_{group}	21	21	21	–	21	21
ICC_{group}	1.6411e-09	8.9238e-10	8.5214e-10	–	0.5437	0.6523
N	100	100	100	100	100	100
Marginal R^2	0.0201	–	0.0366	–	0.0905	–
Conditional R^2	0.0201	–	0.0366	–	0.5850	–
Mc Fadden R^2	–	0.0037	–	0.0282	–	0.0424
Cox and Snell R^2	–	0.0125	–	0.0372	–	0.0458

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$, 5% confidence interval reported in square brackets

3.4 Satisfaction

For the purpose of examining the correlation between percentage of turns, percentage of airtime, length of turns, normalized HHI of turns, and normalized HHI of airtime as well as the questions Q1, Q2, Q3, and Q4 of the satisfaction survey, 40 different models were fitted in total. The results are similar for percentage of turns and percentage of airtime as well as for the normalized HHI of turns and the normalized HHI of airtime. Furthermore, no significant effects are revealed for length of turns. For that reason, the results for percentage of turns and the normalized HHI of turns are presented in this section and the remaining results can be found in Appendix C.4.

Because of the ordinal nature of the dependent variables, the linear mixed models violate the normality assumption. As described in Section 2.4.4, ordered logit models were used in order to resolve the assumption violation.

Table 3.7 lists the results for the satisfaction with the outcome of the meetings (Q1) and the process used in the meetings (Q2) as well as percentage of turns. Regarding question Q1, the ordered logit model violates the proportional odds assumption. However, the tests indicated that most of the independent variables contribute to the assumption violation and *no* partial proportional odds model was additionally fitted hence. Both the linear mixed model and the ordered logit model do not reveal a significant effect for percentage of turns. However, week 3 is significantly and positively correlated with the question Q1, i.e. significantly and negatively correlated with the satisfaction with the outcome of the meetings. The amount of variance explained by the independent variables is small ($R^2 < 0.15$) for both models. Regarding question Q2, the ordered logit model meets the proportional odds assumption. Percentage of turns is again not significantly correlated with the dependent variable. However, there is a significant and negative effect for week 4, i.e. week 4 is significantly and positively correlated with the satisfaction with the process used in the meetings. Only a small amount of variance ($R^2 \leq 0.15$) is explained by the independent variables for both models.

The results for the perceived value of the own perspective to the meetings (Q3) and the comfortability in sharing the own perspective to the meetings (Q4) as well as percentage of turns are shown in Table 3.8. Regarding question Q3, the ordered logit model meets the proportional odds assumption. Furthermore, there is a significant negative effect for percentage of airtime, i.e. percentage of airtime is significantly and positively correlated with the perceived value of the own perspective to the meetings. In both models, only a small amount of variance ($R^2 \leq 0.15$) is explained by the random effects. With regard to question Q4, the proportional odds assumption is not met for the ordered logit model. However, *no* partial proportional odds model was fitted for the same reason as before. Both models report a significant negative effect for percentage of

Table 3.7: Results for Q1 and Q2 and Percentage of Turns. Results of the linear mixed model (LMM) and the ordered logit model (OLM) for the satisfaction with the outcome of the meetings (Q1) and the process used in the meetings (Q2) as well as percentage of turns.

	Q1		Q2	
	LMM	OLM	LMM	OLM
(Intercept)	2.0228***	–	2.3099***	–
	[1.4500, 2.5957]	–	[1.6307, 2.9892]	–
Percentage of turns	-0.0566	-0.1491	-0.0748	-0.2305
	[-0.2117, 0.0985]	[-0.5320, 0.2339]	[-0.2548, 0.1051]	[-0.6347, 0.1737]
Female	0.0412	-0.0272	0.1049	0.1257
	[-0.2926, 0.3749]	[-0.9079, 0.8534]	[-0.3403, 0.5500]	[-0.8829, 1.1342]
Asia	0.0728	0.5143	0.0105	0.3010
	[-0.2895, 0.4351]	[-0.4242, 1.4527]	[-0.4633, 0.4843]	[-0.7625, 1.3644]
Agreeableness	-0.0322	-0.1277	-0.0939	-0.3213
	[-0.1963, 0.1318]	[-0.5645, 0.3091]	[-0.3133, 0.1256]	[-0.8199, 0.1773]
Extraversion	-0.0508	-0.0390	0.0156	0.0649
	[-0.2135, 0.1118]	[-0.4593, 0.3814]	[-0.1991, 0.2303]	[-0.4226, 0.5523]
Five-member group	0.2745	0.4999	0.3131	0.5038
	[-0.3528, 0.9019]	[-0.8015, 1.8013]	[-0.4303, 1.0565]	[-0.9725, 1.9802]
Week 2	-0.1231	-0.1853	-0.2656*	-0.3950
	[-0.4182, 0.1720]	[-0.8368, 0.4662]	[-0.5612, 0.0301]	[-1.0411, 0.2511]
Week 3	0.4443***	0.8359**	0.1827	0.4141
	[0.1341, 0.7546]	[0.1375, 1.5342]	[-0.1274, 0.4928]	[-0.2649, 1.0930]
Week 4	-0.1900	-0.6537	-0.3501*	-0.8923*
	[-0.5395, 0.1595]	[-1.4483, 0.1409]	[-0.7006, 0.0004]	[-1.6809, -0.1037]
N_{group}	21	21	21	21
ICC_{group}	0.1687	0.1238	0.1467	0.1251
N_{member}	99	99	99	99
ICC_{member}	0.1489	0.3374	0.3525	0.4393
N	279	279	279	279
Marginal R^2	0.0584	–	0.0443	–
Conditional R^2	0.3575	–	0.5213	–
Mc Fadden R^2	–	0.0257	–	0.0204
Cox and Snell R^2	–	0.0601	–	0.0528

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
5% confidence interval reported in square brackets

Table 3.8: Results for Q3 and Q4 and Percentage of Turns. Results of the linear mixed model (LMM) and the ordered logit model (OLM) for the considered value of the own perspective to the meetings (Q3) and the comfortability in sharing the own perspective in the meetings (Q4) as well as percentage of turns.

	Q3		Q4	
	LMM	OLM	LMM	OLM
(Intercept)	2.1051***	–	2.0559***	–
	[1.7454, 2.4648]	–	[1.5320, 2.5792]	–
Percentage of turns	-0.1924***	-0.7375***	-0.2464***	-0.8191***
	[-0.3041, -0.0807]	[-1.1638, -0.3112]	[-0.3950, -0.0977]	[-1.2284, -0.4097]
Female	-0.1067	-0.4343	-0.1517	-0.7642*
	[-0.3731, 0.1598]	[-1.3655, 0.4968]	[-0.5011, 0.1978]	[-1.6499, 0.1215]
Asia	0.0474	0.2419	-0.0431	-0.0868
	[-0.2388, 0.3339]	[-0.7508, 1.2346]	[-0.4178, 0.3316]	[-1.0149, 0.8413]
Agreeableness	-0.0466	-0.1466	-0.0852	-0.2236
	[-0.1761, 0.0830]	[-0.6062, 0.3130]	[-0.2567, 0.0864]	[-0.6615, 0.2142]
Extraversion	-0.0096	0.0048	-0.0276	-0.1218
	[-0.1379, 0.1188]	[-0.4441, 0.4538]	[-0.1965, 0.1414]	[-0.5445, 0.3009]
Five-member group	0.1157	0.5648	0.1399	0.6301
	[-0.2624, 0.4938]	[-0.7006, 1.8303]	[-0.4264, 0.7061]	[-0.6240, 1.8842]
Week 2	-0.1099	-0.2839	-0.0381	0.0281
	[-0.2966, 0.0768]	[-0.9535, 0.3857]	[-0.2920, 0.2158]	[-0.6064, 0.6625]
Week 3	0.0268	0.0094	0.1862	0.2153
	[-0.1692, 0.2228]	[-0.7033, 0.7221]	[-0.0804, 0.4528]	[-0.4791, 0.9097]
Week 4	-0.1570	-0.5748	0.0099	-0.1651
	[-0.3779, 0.0640]	[-1.3866, 0.2370]	[-0.2909, 0.3107]	[-0.9468, 0.6165]
N_{group}	21	21	21	21
ICC_{group}	0.0664	0.0791	0.1235	0.0974
N_{member}	99	99	99	99
ICC_{member}	0.3554	0.4007	0.3013	0.3511
N	279	279	279	279
Marginal R^2	0.0796	–	0.0641	–
Conditional R^2	0.4678	–	0.4616	–
Mc Fadden R^2	–	0.0352	–	0.0341
Cox and Snell R^2	–	0.0700	–	0.0790

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
5% confidence interval reported in square brackets

turns, i.e. a significant positive correlation between percentage of turns and the comfortability in sharing the own perspective to the meetings. Furthermore, a small amount of variance ($R^2 \leq 0.15$) is explained by the independent variables for both models.

The results for questions Q1 and Q2 and the normalized HHI of turns are listed in Table 3.9, an the results for questions Q3 And Q4 and the normalized HHI of turns are listed in Table 3.10. As with percentage of turns, the proportional odds assumption of the ordered logit models is not met for questions Q1 and Q4, and it is met for questions Q2 and Q3. None of the models reports a significant effect for the normalized HHI of turns and only a small amount of variance ($R^2 \leq 0.15$) is explained by the dependent variables for all models.

3.5 Effect of Real-Time Feedback

The diagnostic plots used to check the models for assumption violations as well as outliers and influential observations revealed a conspicuous observation for all models fitted for the analysis of feedback. Figure 3.1 exemplarily shows a residual plot for one of the models with the conspicuous observation in the right upper corner. This observation has a high influence on the model results. Although it is valid and cannot simply be removed from the dataset, results are both shown for the dataset with and without the observation in order to be able assess the influence of the observation. Moreover, the diagnostic plots manifested that the all of the used models meet all of the underlying assumptions.

Table 3.11 shows the results for the normalized HHI of turns and the first set of independent variables with a single dummy variable for the visualization. The results for the normalized HHI of airtime are similar and can be found in Appendix C.5. The table shows that there is a significant negative effect for the visualization, i.e. that the visualization is significantly and positively correlated with the balance of participation. Furthermore, only a small amount of variance ($R^2 \leq 0.15$) is explained by the independent variable of the first set.

Table 3.12 shows the results for the normalized HHI of turns and the second set of independent variables with three dummy variables for week two, three and four. Again, the results for the normalized HHI of airtime are similar and can be found in Appendix C.5. For the dataset with the influential observation, there is a significant and positive effect for the fourth week only. For the dataset without the influential observations, there is a significant and negative effect for the second week in addition. The amount of variance explained by the independent variables of the second set is medium ($R^2 > 0.15$) for the dataset with and small ($R^2 \leq 0.15$) for the dataset without the influential observation.

Table 3.9: Results for Q1 and Q2 and Normalized HHI of Turns. Results of the linear mixed model (LMM) and the ordered logit model (OLM) for the satisfaction with the outcome of the meetings (Q1) and the process used in the meetings (Q2) as well as normalized HHI of turns.

	Q1		Q2	
	LMM	OLM	LMM	OLM
(Intercept)	2.2514***	–	2.5747***	–
	[1.9693, 2.5336]	–	[2.2424, 2.9070]	–
Normalized HHI of turns	-0.0147	-0.1021	-0.0463	-0.1567
	[-0.1677, 0.1383]	[-0.4524, 0.2482]	[-0.2036, 0.1110]	[-0.5040, 0.1906]
Median conscientiousness	0.0345	0.1688	0.0565	
	[-0.2279, 0.2970]	[-0.3724, 0.7101]	[-0.2738, 0.3867]	[-0.4332, 0.8204]
Median openness to experiences	0.2420*	0.3641	0.1360	0.1908
	[-0.0125, 0.4966]	[-0.1646, 0.8928]	[-0.1830, 0.4549]	[-0.4138, 0.7954]
Week 2	-0.1150	-0.2002	-0.2832*	-0.4618
	[-0.4178, 0.1878]	[-0.8736, 0.4733]	[-0.5882, 0.0219]	[-1.1299, 0.2064]
Week 3	0.4321***	0.8095**	0.1719	0.3830
	[0.1233, 0.7410]	[0.1119, 1.5071]	[-0.1380, 0.4818]	[-0.2944, 1.0604]
Week 4	-0.1574	-0.5494	-0.3082*	-0.7791*
	[-0.5215, 0.2066]	[-1.3800, 0.2813]	[-0.6757, 0.0593]	[-1.5986, 0.0404]
N_{group}	21	21	21	21
ICC_{group}	0.1378	0.0799	0.1474	0.0927
N_{member}	99	99	99	99
ICC_{member}	0.1495	0.3831	0.3416	0.4738
N	279	279	279	279
Marginal R^2	0.0975	–	0.0451	–
Conditional R^2	0.3567	–	0.5120	–
Mc Fadden R^2	–	0.0256	–	0.0178
Cox and Snell R^2	–	0.0600	–	0.0463

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
5% confidence interval reported in square brackets

Table 3.10: Results for Q3 and Q4 and Normalized HHI of Turns. Results of the linear mixed model (LMM) and the ordered logit model (OLM) for the considered value of the own perspective to the meetings (Q3) and the comfortability in sharing the own perspective in the meetings (Q4) as well as normalized HHI of turns.

	Q3		Q4	
	LMM	OLM	LMM	OLM
(Intercept)	2.1740***	–	2.0954***	–
	[2.0012, 2.3468]	–	[1.8488, 2.3420]	–
Normalized HHI of turns	-0.0712	-0.2518	-0.0456	-0.1383
	[-0.1688, 0.0264]	[-0.6033, 0.0998]	[-0.1787, 0.0876]	[-0.4856, 0.2090]
Median conscientiousness	0.0166	0.0010	-0.0027	0.0567
	[-0.1398, 0.1730]	[-0.4954, 0.4974]	[-0.2329, 0.2275]	[-0.4201, 0.5336]
Median openness to experiences	0.0925	0.4089*	0.1726	0.3978*
	[-0.0596, 0.2446]	[-0.0766, 0.8944]	[-0.0507, 0.3960]	[-0.0681, 0.8637]
Week 2	-0.1438	-0.4063	-0.0619	-0.0481
	[-0.3379, 0.0504]	[-1.0960, 0.2834]	[-0.3245, 0.2007]	[-0.7052, 0.6089]
Week 3	0.0003	-0.0949	0.1545	0.1280
	[-0.1972, 0.1977]	[-0.8031, 0.6132]	[-0.1125, 0.4215]	[-0.5611, 0.8171]
Week 4	-0.1023	-0.3725	0.0496	-0.0388
	[-0.3354, 0.1308]	[-1.2118, 0.4668]	[-0.2660, 0.3653]	[-0.8509, 0.7733]
N_{group}	21	21	21	21
ICC_{group}	0.0290	0.0091	0.0666	0.0081
N_{member}	99	99	99	99
ICC_{member}	0.3969	0.4914	0.3603	0.4743
N	279	279	279	279
Marginal R^2	0.0374	–	0.0361	–
Conditional R^2	0.4473	–	0.4476	–
Mc Fadden R^2	–	0.0145	–	0.0073
Cox and Snell R^2	–	0.0295	–	0.0174

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
5% confidence interval reported in square brackets

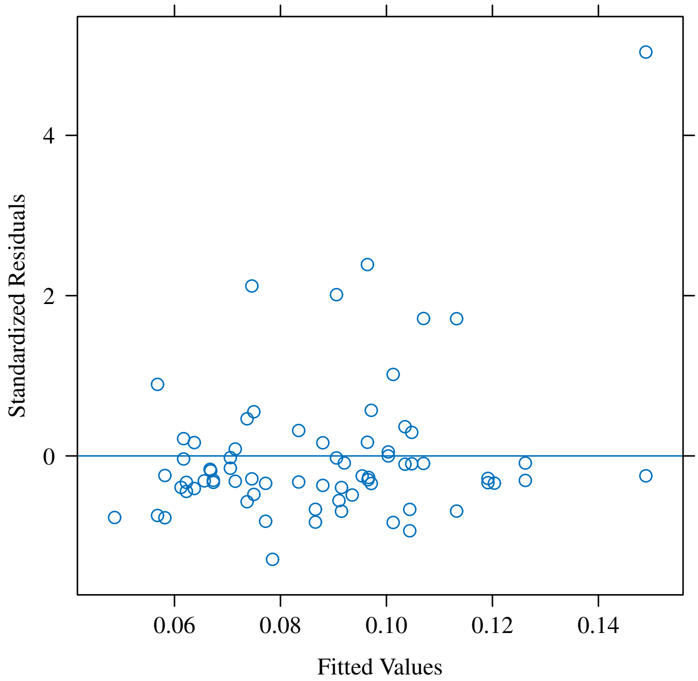


Figure 3.1: Residual Plot Influential Observation. The residual plot for the normalized HHI of turns and the first set of independent variables reveals an influential observation in the right upper corner.

The results for the normalized HHI of turns and the third set of variables are listed in Table 3.13. The similar results for the normalized HHI of airtime can be seen in Appendix C.5. Although the third set comprises an additional dummy variable for the moderator, the results are hardly different to the results for the second set of variables.

3.6 Effect of Required Expertise

Two different mapping functions were used in order to estimate the required expertise in the meetings. The more complex mapping function has two parameters. Parameter n determines the number of days in which assignments are considered and parameter α determines the weighting of the assignments. Different values $n = 1, 2, ..., 7$ and $\alpha = 5, 10, ..., 50$ were considered for both parameters and one model was fitted for each combination of parameter values. Figure 3.2 shows the coefficient of the normalized HHI of expertise for all of these models. The coefficient is positive for all combinations of parameter values meaning that there is a positive correlation

Table 3.11: Results for Normalized HHI of Turns and First Set of Independent Variables. Results of linear mixed model (LMM) with and without outlier for normalized HHI of turns as well as first set of independent variables.

	Normalized HHI of turns	
	LMM with outlier	LMM without outlier
(Intercept)	0.1018***	0.0934***
	[0.0814, 0.1221]	[0.0778, 0.1091]
Visualization	-0.0298**	-0.0212**
	[-0.0538, -0.0057]	[-0.0398, -0.0027]
N_{group}	21	21
ICC_{group}	0.1837	0.1755
N	71	70
Marginal R^2	0.0679	0.0601
Conditional R^2	0.2391	0.2251

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
5% confidence interval reported in square brackets

Table 3.12: Results for Normalized HHI of Turns and Second Set of Independent Variables. Results of linear mixed model (LMM) with and without outlier for normalized HHI of turns as well as second set of independent variables.

	Normalized HHI of turns	
	LMM with outlier	LMM without outlier
(Intercept)	0.0843***	0.0843***
	[0.0611, 0.1076]	[0.0663, 0.1024]
Week 2	-0.0212	-0.0211*
	[-0.0517, 0.0094]	[-0.0450, 0.0028]
Week 3	-0.0024	-0.0023
	[-0.0334, 0.0287]	[-0.0265, 0.0220]
Week 4	0.0471***	0.0260*
	[0.0126, 0.0816]	[-0.0017, 0.0537]
N_{group}	21	21
ICC_{group}	0.1893	0.1738
N	71	70
Marginal R^2	0.1585	0.1236
Conditional R^2	0.3178	0.2759

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
5% confidence interval reported in square brackets

Table 3.13: Results for Normalized HHI of Turns and Third Set of Independent Variables. Results of linear mixed model (LMM) with and without outlier for normalized HHI of turns as well as third set of independent variables.

	Normalized HHI of turns	
	LMM with outlier	LMM without outlier
(Intercept)	0.0688***	0.0762***
	[0.0290, 0.1087]	[0.0450, 0.1074]
Week 2	-0.0219	-0.0215*
	[-0.0528, 0.0089]	[-0.0457, 0.0026]
Week 3	-0.0001	-0.0011
	[-0.0317, 0.0315]	[-0.0258, 0.0237]
Week 4	0.0507***	0.0280*
	[0.0153, 0.0862]	[-0.0006, 0.0567]
Moderator	0.0171	0.0090
	[-0.0186, 0.0529]	[-0.0191, 0.0371]
N_{group}	21	21
ICC_{group}	0.1721	0.1627
N	71	70
Marginal R^2	0.1682	0.1272
Conditional R^2	0.3114	0.2692

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
5% confidence interval reported in square brackets

between the balance of expertise and the balance of participation. Figure 3.3 shows the corresponding p values. The results are significant at the 0.1 level for all combinations of parameter values expect the combinations with $n = 1$. The significance increases as the values of both parameters increase.

The more simple mapping function has one parameter only. It only considers courses with assignment within n days and copes without parameter α hence. Again, the values $n = 1, 2, ..., 7$ were considered for the parameter and one model was fitted for each parameter value. For all of these models, the coefficient of the normalized HHI of expertise can be seen in Figure 3.4. The coefficients are consistently positive but smaller compared to the coefficients of the more complex mapping function. The corresponding p values are shown in Figure 3.5. It can be seen that only the coefficients for parameter values $n = 2$ and $n = 3$ are significant at level 0.1 and 0.05, respectively.

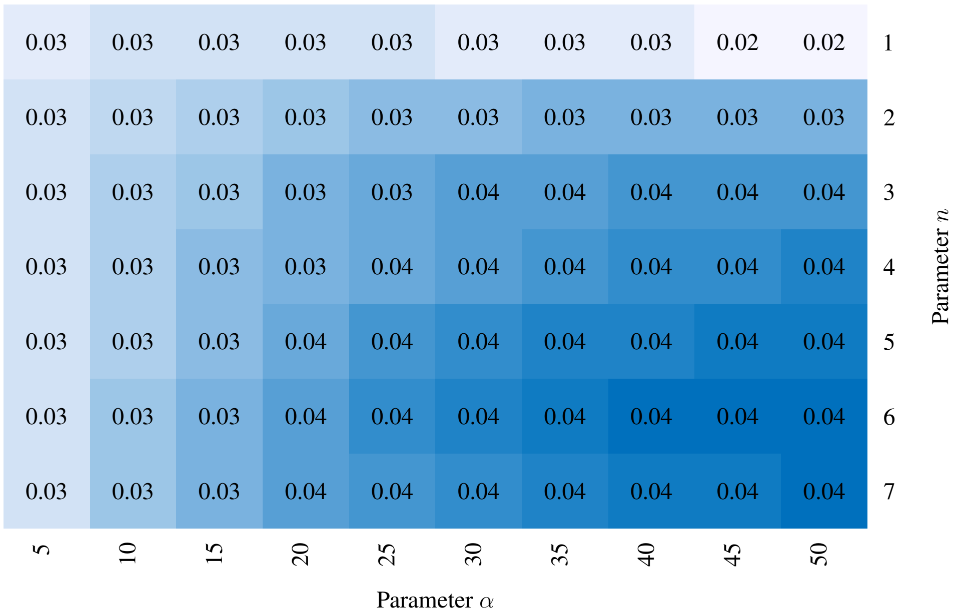


Figure 3.2: Coefficients for Complex Mapping Function. Parameter α determines the weighting of assignments, parameter n the number of days in which assignments are considered. The coefficients are consistently positive.

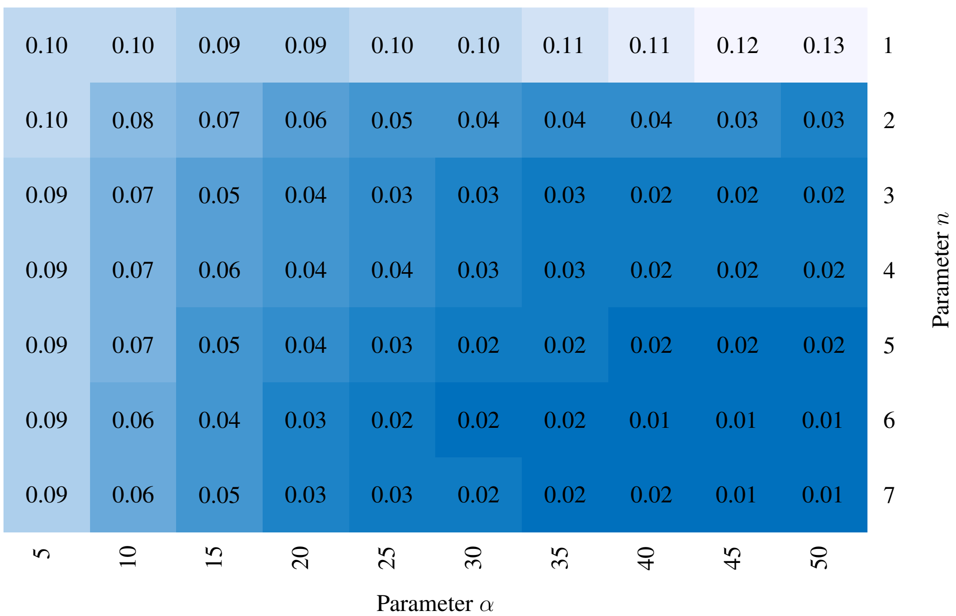


Figure 3.3: P Values for Complex Mapping Function. Parameter α determines the weighting of assignments, parameter n the number of days in which assignments are considered. The results are significant for all combinations of parameter values expect of $n = 1$.

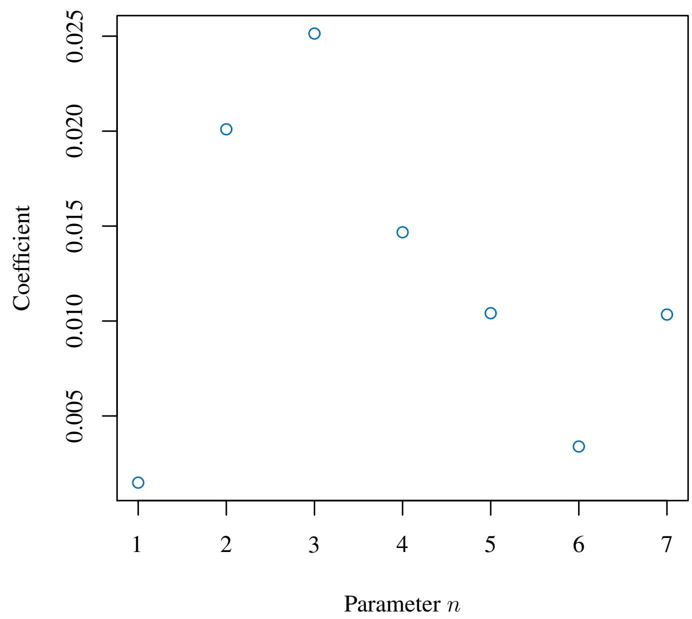


Figure 3.4: Coefficients for Simple Mapping Function. Parameter n determines the number of days in which assignments are considered. The coefficients are consistently positive.

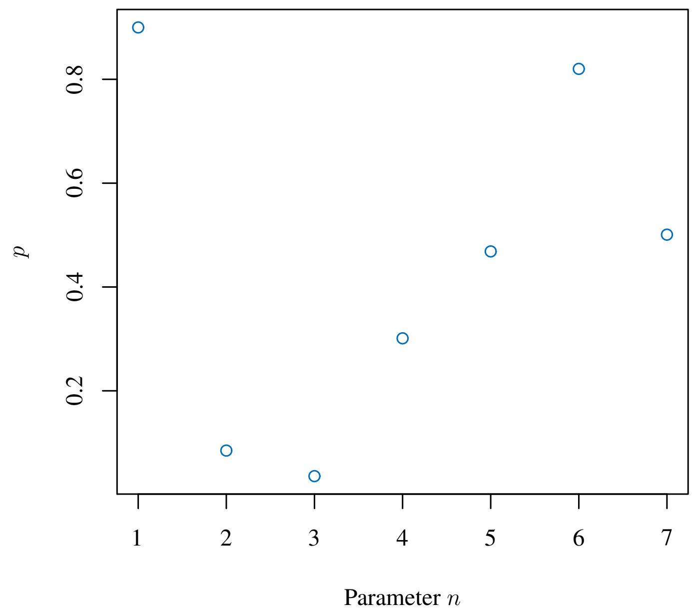


Figure 3.5: P Values for Simple Mapping Function. Parameter n determines the number of days in which assignments are considered. Only the results for $n = 2$ and $n = 3$ are significant with $p = 0.08$ and $p = 0.03$, respectively.

Chapter 4

Discussion

In order to get new insights into group collaboration, meetings of Sloan Fellows are analyzed in this work. They are particularly analyzed with regard to participation and its relationship to performance and satisfaction. Furthermore, the effect of real-time feedback on participation and in turn performance and satisfaction is examined. The applied methods from collecting data to processing, cleansing, modeling, and evaluating data were introduced in Chapter 2. The corresponding results were presented in Chapter 3. In this chapter, both the methods and results are discussed and conclusions are drawn from the results.

4.1 Dataset

A large amount of data was collected in the study. In total, data were available from 100 Sloan Fellows assigned to 21 study groups. Furthermore, data were collected over a long period of time of four weeks. The number of meetings amounted to 233 and their total duration summed up to 344.11 hours. Due to the admission criteria of the MIT Sloan Fellows program, solely outstanding mid-career professional participated in the study. They were *not* evenly distributed regarding gender and ethnicity. About one third of the participants were female and the remaining two thirds were male. The distribution of ethnicities can be found in Figure 2.11.

The Open Badges system as well as three different surveys were used for data collection. The system was easy to use and the custom hardware badges were unobtrusive. They did not interfere the behavior of the participants. The tools employed in the study allowed for collecting a wide range of different types of data. Volume data were obtained from the Open Badges System and demographic, personality, as well as satisfaction data were obtained from the surveys. Performance data were additionally supplied in the form of individual grades.

In contrast to most studies in literature [Kim08, Kim09, Pen12], data were collected in real-life settings, i.e. out-of-class meetings of Sloan Fellows. No constraints were given on the meetings. The participants were free in how often they met, how long they met, and how they organized their meetings. The naturalistic study allowed for capturing genuine behavior of the participants as well as for validating prior findings from laboratory studies in the real world. However, it also entailed some limitations. The assignment of students to study groups was given by the MIT Sloan School of Management. Furthermore, a control/trial study was not possible due to constraints of the MIT Sloan Fellow program. During the data collection, some issues came up that were not able to control for. For example, some groups split up in subgroups and worked on different assignment. They only presented their results in the joint group meetings. Other groups reported that they did not assign a moderator or use the app at all. Besides, the curriculum of the Sloan Fellows program covered trainings on coaching and team building. These trainings were assumed to slightly affect groups dynamics as well. Both the benefits and limitations of the naturalistic study have to be considered for interpreting the results.

The collected data were subsequently processed in order to detect voice activity and to extract measures of participation. The VAD algorithm was not evaluated. However, it has demonstrated success in a wide range of prior projects. In order to ensure robustness and to avoid false positives, the VAD algorithm assumed that only one participant was speaking at any time. Furthermore, only simple measures of participation referring to turns or airtime were used in the study. No more complex measures were used in order to keep the models simple and robust in terms of potential inaccuracy of the VAD algorithm. However, both the assumption of non-overlapping speech and the only extraction of simple measures of participation limited the further analysis. For that reason, a potential direction of this work is to refine the VAD algorithm and additionally use more complex measures of participation.

4.2 Individual Participation

In order to deeply understand participation, factors affecting the amount and manner of individual participation were analyzed first. Because of the negative correlation of percentage of participation within groups, the applied linear regression models violate the independence assumption. They were applied in order to get a first tendency of factors affecting individual participation. However, the independence assumption is often considered to be the most important assumption. Additional covariance pattern models were applied in order to resolve the assumption violation. They ensure reliability and allow for validating the results of the linear regression models.

The results for percentage of turns can be found in Table 3.1. The variables selected by LASSO are the dummy variables for being female, Asian, and member of a five-member group as well as the continuous variables for the personality traits agreeableness and extraversion. For that reason, these variables are most descriptive for percentage of turns. The dummy variable for being member of a five-member group was used in order to account for different percentages due to different numbers of members. According to expectations, it is significantly ($p < 0.01$) and negatively correlated with percentage of turns. The results of the covariance pattern model state that the percentage of turns of members of five-member groups is 5.54% less than the one of members of four-member groups. The results further reveal a significant ($p < 0.01$) and negative effect for being Asian. According to the covariance pattern model, the percentage of turns of Asians is 5.85% less than the one of Europeans and thus, being Asian has the largest effect size among all variables in the model. The further significant effects of the covariance pattern model are the two personality traits agreeableness and extraversion. Both effects are significant at level 0.1 though. For that reason, it is assumed that being Asian has a stronger effect on percentage of turns than agreeableness and extraversion. Besides, the covariance pattern model reports a moderate negative correlation ($|ICC| > 0.2$) within groups. Due to the obvious correlation of percentage of participation within groups, this finding was expected and confirms the need of additionally applying the covariance pattern model. Both for the linear regression model and the covariance pattern model, a large amount of variance ($R^2 > 0.25$) is explained by the independent variables, which is indicative for the strong effects of the independent variables.

The results for percentge of airtime can be found in Table 3.2. The same variables were selected by LASSO as for percentage of turns with the dummy variable for ethnicity Middle East in addition. The similarity of the sets of independent variables is ascribed to the similarity of percentage of turns and airtime. As expected and as before, being member of a five-member group is significantly ($p < 0.01$) and negatively correlated with the dependent variable. The results for begin Asian and extraversion are comparable as well and ascribed to the similarity of the dependent variables again. According to the covariance pattern model, the percentage of airtime of Asians is 6.15% less than the one of Europeans and one standard deviation increase of extraversion implies a 1.48% increase of percentage of airtime. Agreeableness has a significant effect neither for the linear regression model nor for the covariance pattern model. Being female is significantly ($p < 0.1$) and negatively correlated with percentage of airtime though. According the covariance pattern model, the percentage of airtime of women is 2.87% less than one of men. Regarding the correlation of percentage of airtime within groups, the expectations are again met and there is moderate negative correlation ($|ICC| > 0.2$). Furthermore, a large amount of variance ($R^2 > 0.25$) is explained by the independent variables indicating the strength of the revealed factors affecting percentage of airtime.

The results for length of turns can be found in Table 3.3. The variables selected by LASSO are the dummy variables for being female, Asian, South American, South Asian, as well as the continuous variables for the personality trait extraversion. These variables are most descriptive for length of turns. The only significant ($p < 0.01$) effect in the model is the dummy variable for being female. The covariance pattern model states that turns of women are 0.6197 seconds shorter than turns of men. Furthermore, there is moderate positive correlation ($|ICC| > 0.2$) of length of turns within groups. This finding was rather unexpected and might be traced back to the fact that different groups organized their meetings differently. For example, some groups met in order to jointly work on assignments, whereas other groups separately worked on assignments in advance and met in order to present their results only. The independent variables in the model only explain a small amount of variance of length of turns ($R^2 \leq 0.15$). This might also be due to the fact that only one of the variables has a significant effect.

Taken together, there are three fundamental factors affecting individual participation. First, *Asians* have less turns and therefore speak less. This factor was shown to have a considerable effect size as well as significance at level 0.01. Second, *extroverts* have more turns and therefore speak more. This factor was shown to have a rather small effect size as well as significance at level 0.1 only. Third and last, *women* have shorter turns but roughly speak for the same amount. This factor was shown to have considerable effect size and significance at level 0.01 again.

The first finding is in agreement with literature. Levi [Lev15] reported about cultural differences in the participation of individuals within groups. In addition to the cultural reasoning by itself, he remarked that individuals often limit their participation when they observe negative stereotypes related to their cultural identity. Sato [Sat82] investigated the relationship between ethnicity and patterns of students' classroom participation at university. The author figured out that Asians take significantly less turns than non-Asians. Jones [Jon99] as well as Liu et al. [Liu10] quoted the language as main barrier for even participation among different cultures and argued that non-native students often have difficulties in participating actively in group discussions. This reasoning is also supported by the remark of a participant of this study. He mentioned that *"[...][his] Japanese team member had limitations in discussing in English [...]"*.

The personality trait extraversion is often described with the characteristics dominance, assertiveness, sociability, affiliation, talkativeness, and activeness [Kic97, Dri06]. Evidently, some of these characteristics such as dominance and talkativeness are directly and positively related to the degree of participation. The second finding that extroverts have more turns and speak more is additionally supported by literature. For example, Pentland [Pen10] reported the same. He figured out that speaking time is positively correlated with extraversion and in particular dominance. Lepri et al. [Lep12] have shown that speaking time is an effective indicator of extraversion furthermore. They detected the personality trait solely by speaking time and social gaze.

Regarding the relationship between gender and the participation within groups, different opinions are available in literature. Onnela et al. [Onn14] have shown that women are more talkative in collaborative tasks than men. In contrast to this, Pentland [Pen10] reported that the amount of participation of women and men is nearly the same whereas the pattern of participation is different. In agreement with the present study, he figured out that women have shorter turns compared to men. Women are assumed to condense their arguments more. The finding of shorter turns is supported by Ridgeway [Rid92] as well. However, the author additionally stated that women participate less in general. Karpowitz et al. [Kar12] came to the same result. They have shown that in most circumstances, women's participation is under 75% of that of men. The reason for the varying results in literature might be traced back to the varying circumstances of the studies. For example, Karpowitz et al. additionally remarked that the participation of women is highly dependent on the gender composition of groups. The lower the number of women in a group, the less the women participate and the bigger the gender gap. The gender composition of the groups in this study can be seen in Figure 2.15. Since there were less female than male participants, women were underrepresented. The groups involved either no or at least two women though.

4.3 Balance of Participation

The linear regression models used to uncover factors affecting balance of participation meet all of their underlying assumptions. Therefore, validity and reliability of their results are assured. The results can be found in Table 3.4. The same variables were selected by LASSO for the normalized HHI of turns and airtime. This can be ascribed to the similarity of the two variables. Out of 24 level and diversity indices, LASSO selected median conscientiousness and median openness to experiences. They are most descriptive for balance of participation. Median conscientiousness has a significant and negative effect for the normalized HHI of airtime. Per standard deviation increase of median conscientiousness, the normalized HHI of turns decreases by 0.0153. For a better understanding of the value, Figure 2.13 exemplifies values of the normalized HHI. A decrease of the normalized HHI corresponds to an increase of the balance of participation furthermore. Median openness to experiences has a significant and negative effect for both the normalized HHI of turns and airtime with a comparable effect size. Both median conscientiousness and median openness to experiences are only significant at level 0.1. Due to the small number of observations, it is hard to get significant results and reasonable to accept results at significance level 0.1 though. The two independent variables explain a large ($R^2 > 0.25$) to very large ($R^2 > 0.35$) amount of variance for both models. This can be ascribed to the small number of observations as well as the strength of the effects.

To conclude, there are two factors affecting balance of participation. First, the higher the *level of conscientiousness* within a group, the higher the balance of participation. Second, the higher the *level of openness to experiences* within a group, the higher the balance of participation. Both factors have a considerable effect size and are significant at the reasonable level 0.1.

A lot of research has been done on group composition with respect to the Big-Five personality dimensions. Conscientiousness and openness to experiences were the most often used personality dimensions for describing group composition [Hal05]. In contrast to this study, group composition was mostly examined with reference to performance [Hal05]. In this study, it is examined with reference to evenness of participation, which is considered to be a key indicator for performance though. In agreement with this study, Neuman et al. [Mat08] figured out that the level of conscientiousness and openness to experiences is positively correlated with performance (among others). Although Kichuck and Wiesner [Kic97] postulated the same effect for conscientiousness, they reported that the diversity of conscientiousness is negatively related to performance instead (among others). They did not reveal a significant effect for openness to experiences at all. Furthermore, the authors remarked that the optimal group composition with respect to the Big-Five personality dimensions depends on the circumstances and the task of group collaboration. In the present study, the students were required to autonomously organize meetings and work on assignments together. They had to be self-initiated as well as self-responsible. The personality trait conscientiousness is associated with the degree to which an individual is dependent, responsible, purposeful, organized, and mindful to details. The higher the level of conscientiousness in a group, the higher the need for achievement and the higher the desire for effective group collaboration. This might be the reason for the positive correlation between the level of conscientiousness and the balance of participation. The MIT Sloan Fellows are diverse in terms of ethnicity, personality, and background. In order to achieve effective group collaboration and even participation among group members, it is crucial that the group members negotiate cultural and other barriers. The personality trait openness to experiences is associated with the degree to which an individual is imaginative, adventurous, creative, and open-minded. These characteristics help group members to get together and negotiate potential barriers. This might be the reason for the positive effect of the level of openness to experiences.

4.4 Performance

In order to understand and improve performance in group collaboration, the relationship between participation and the grades in the courses ”Data, Models, and Decisions”, ”Financial Accounting”, and ”Marketing and Strategy” was analyzed. It was postulated that highly performing individuals have a high individual participation (Hypothesis 1) and that highly performing groups have a high balance of participation (Hypothesis 2). The distribution of grades is visualized in Figure 2.18. For the courses ”Financial Accounting” and ”Marketing and Strategy”, there is hardly any variance among the students and the students obtained A and B grades only. This made it more difficult to obtain meaningful results.

Linear mixed models were applied in order to obtain easily interpretable results. Because of the ordinal nature of the grades, they do not meet all of the underlying assumptions. However, they were commonly used and often shown to be a reasonable approach anyway [Kol07, Hel09]. In this work, they were considered to be especially reasonable because the distances between the ordered categories of the numeric grades have a meaning and because the linear mixed models were only used for analysis and not for prediction. In order to confirm the results of the linear mixed models and in order to still improve validity and reliability, ordered logit models were fitted in addition and the results of both models were compared. For some of the ordered logit models, the proportional odds assumption is not met. This is not surprising since the proportional odds assumption is known to nearly always result in rejection, particularly when the number of independent variables is large, when some of the independent variables are continuous, or when there is a large number of observations [O'C06]. However, the proportional odds assumption is crucial anyway and the linear mixed models are considered to be more meaningful in case of violations of the assumption.

The results for percentage of turns and the grades in all courses can be seen in Table 3.5. For the courses ”Data, Models, and Decisions” and ”Financial Accounting”, there is a significant ($p < 0.01$) positive effect for percentage of turns for both the linear mixed models and the ordered logit models. The effect size is considerable. According to the linear mixed models, one standard deviation increase of percentage of turns is related to a 0.2033 and 0.2755 improvement of the numeric grade in ”Data, Models, and Decisions” and ”Financial Accounting”, respectively. The within-group correlation of the grades is infinitesimally small meaning that there is no correlation at all. Furthermore, the amount of variance explained by the independent variables is larger for the grades in ”Financial Accounting” ($R^2 > 0.25$) than for the grades in ”Data, Models, and Decision” ($R^2 \leq 0.15$ and $R^2 > 0.15$). One reason for this might be the fact that there is less variance for the grades in ”Financial Accounting” than for the grades in ”Data, Models, and

Decisions" as well. For the course "Marketing and Strategy", there is no significant effect for percentage of turns for the linear mixed models and there is a significant ($p < 0.1$) positive effect for the ordered logit model. However, the ordered logit model does not meet the proportional odds assumption and the results of the linear mixed model are considered to be more meaningful hence. In contrast to the other courses, there is a high ($|ICC| > 0.4$) to very high ($|ICC| > 0.6$) correlation of grades within groups. This can be traced back to the grading in the course. In "Marketing and Strategy", the grade is composed of 40% final project and 30% assignments, which are both accomplished in groups and graded per group. This might also be the reason why there is no correlation between percentage of turns and the grades in this course. Since there are no strong effects, the variance explained by the independent variables is small ($R^2 \leq 0.15$) to medium ($R^2 > 0.15$) for the linear mixed model and the ordered logit model, respectively.

Taken together, depending on the grading, there is a positive correlation between individual participation and performance. This finding proves the postulated Hypothesis 1. However, no information is available on the direction of the correlation. It might either be that high participation (i.e. high motivation, high effort) leads to high performance or that high performance (i.e., high expertise) leads to high participation. Only few research has been done on the correlation between the participation of individuals in groups and their performance. Some studies analyzed the correlation between participation and performance at work though [Wag94]. They revealed a positive effect as well.

The results for the normalized HHI of turns and the grades in all courses are listed in Table 3.6. For the courses "Data, Models, and Decisions" and "Marketing and Strategy", there is no significant effect for the normalized HHI of turns. For the course "Financial Accounting", there is a significant ($p < 0.1$) positive effect for both the linear mixed model and the ordered logit model. According to the linear mixed model, the grade in the course is improved by 0.1030 per standard deviation increase of the normalized HHI of turns. In other words, the higher the balance of participation, the worse the grade. Furthermore, the variance explained by the independent variables is small ($R^2 \leq 0.15$), which additionally substantiates the finding that there is no (strong) correlation between balance of participation and performance. For that reason, Hypothesis 2 is clearly and unexpectedly refuted.

This outcome was particularly unexpected because even participation was shown to be a key indicator for performance by Woolley et al. [Woo10]. However, there are certain differences between the quoted and the present study that might explain the different results. First, Woolley et al. examined the joint group performance whereas the individual performance of group members was examined in this study. Second, performance was measures based on the immediate outcome of group discussions in the quoted study whereas it was measures based on both the immediate outcomes of groups discussions (i.e., group assignments) as well as other deliverables (i.e., exams, class participation) in this study. Third, Woolley et al. performed a laboratory study whereas a naturalistic study was chosen in this work. Due to the real-world settings, the participants organized the meetings by themselves and they were not requested to accomplish a predefined task. Tasks in laboratory settings typically do not require prior expertise of the participants. The opposite is true for the meetings of Sloan Fellows. For that reason, it is assumed that even participation is not beneficial in all circumstances. For example, if there is a specific expertise required in a meeting, it might be more beneficial if the expert speaks and the other members listen and learn from the experts. This assumption is further discussed in Section 4.7. Furthermore, it might be dependent of the specific type of meeting whether even participation is beneficial or not. For example, it might be beneficial in brainstorming meetings where a large amount of different ideas is needed, but it might be less beneficial in meetings where results of individual group members are presented and carried together.

4.5 Satisfaction

For the purpose of understanding and improving satisfaction in group collaboration, the relationship between performance and the satisfaction with the outcome of the meetings, the process used in the meetings, the perceived value of the own perspective, as well as the comfortability in sharing the own perspective was analyzed. It was postulated that there is a positive relationship between the participation of individuals and their perceived value of the own perspective as well as their comfortability in sharing the own perspective (Hypothesis 3). In addition, it was assumed that even participation is related to a high satisfaction with the outcome of the meetings and the process used in the meetings (Hypothesis 4). The distribution of satisfaction in this study is illustrated in Figure 2.19. It can be seen that there is a high satisfaction in general.

Since satisfaction was measured on a seven-point scale, it has an ordinal nature and the linear mixed models do not meet all of the underlying assumptions hence. As discussed in Section 4.4, they are considered to be a reasonable approach anyway, particularly because of the large number of categories of satisfaction and because the linear mixed models are used for analysis and not for prediction. The proportional odds assumption of the ordered logit models is considered to be more crucial. For that reason, linear mixed models are assumed to be more meaningful in case of violations of the proportional odds assumption.

The results for percentage of turns and the satisfaction with the outcome of the meetings and the process used in the meetings can be found in Table 3.7. There is no significant effect for percentage of turns. For the satisfaction with the outcome of the meetings, there is a significant ($p < 0.01$) effect for the third week though. Satisfaction is considerably decreased for the third week. This finding is ascribed to the circumstances of the program. In the third week, the work load was higher compared to the other weeks and the Sloan Fellows were probably more under pressure to perform. They had to submit regular assignments, they had to do a midterm test in the course "Data, Models, and Decisions", and they additionally had to finish the final project in "Marketing and Strategy". For the satisfaction with the process used in the meetings, the linear mixed model reveals significant effects ($p < 0.1$) for both the second and the fourth week. However, the ordered logit model fulfilling the proportional odds assumption only confirms the significant effect for the fourth week. Satisfaction is shown to be higher in the fourth week. This finding might also be ascribed to program circumstances, although no information is available on strong distinctions in this week. The results further reveal that the correlation of satisfaction within the participants is higher than the correlation of satisfaction within groups. The amount of variance explained by the independent variables is small ($R^2 \leq 0.15$) for all models indicating that there are no strong effects.

The results for percentage of turns and the perceived value of the own perspective to the meetings as well as the comfortability in sharing the own perspective to the meetings can be found in Table 3.8. For both the linear mixed models and the ordered logit models, there is a significant ($p < 0.01$) effect for percentage of turns. The higher the percentage of turns, the higher the perceived value of the own perspective as well as the comfortability of sharing the own perspective. For that reason, Hypothesis 3 is proven. Comparing this finding to literature, there is conformity. Satisfaction in group collaboration has been shown to be highly impacted by group dynamics [Sha71, Mye00]. Furthermore, Yang and Baek [Yan] investigated how groups dynamics affect overall satisfaction in workshops. They figured out that active participation is positively correlated with the overall satisfaction. Anderson and Martin [And95] came to the same result. They analyzed the satisfaction of employees in organizations and additionally revealed that satisfaction is high when group members feel included and when they believe their opinion is valued.

The results for the normalized HHI of turns and the satisfaction with the outcome of the meetings and the process used in the meetings are listed in Table 3.9. There is no significant effect for the normalized HHI of turns. As before, satisfaction with the outcome of the meetings is significantly ($p < 0.01$) lower in the third week and satisfaction with the process used in the meetings is significantly ($p < 0.1$) higher in the fourth week. Summarizing the results, Hypothesis 4 is refuted. Even participation is not related to a high satisfaction with the outcome of the meetings or the process used in the meetings. The reasoning might be the same as for the refutation of Hypothesis 2 discussed in Section 4.4. It is assumed that even participation is not beneficial in all circumstances and that it therefore does not result in higher satisfaction with the outcome of the meetings or the process used in the meetings. Although this finding is unexpected, there is a similar result reported in literature. Kim et al. [Kim08] developed the Meeting Mediator which is a real-time portable system detecting social interactions and providing feedback to enhance group collaboration (similar to the Open Badges System used in this work). They applied the Meeting Mediator in group tasks and analyzed the group dynamics. Although the system led to more even participation, it did not lead to more satisfaction.

The results for the normalized HHI of turns and the perceived value of the own perspective to the meetings and the comfortability in sharing the own perspective to meetings are shown in Table 3.10. There is no significant effect for the normalized HHI of turns and there is only a slight correlation within groups. In addition, only a small amount of variance ($R^2 \leq 0.15$) is explained by the independent variables. These results are not surprising since no correlation was expected between the balance of participation and the satisfaction with respect to the own perspective of the individuals.

4.6 Effect of Real-Time Feedback

After examining participation and its relationship to performance and satisfaction, it was further analyzed whether real-time feedback on conversation dynamics can influence participation and in turn improve performance and satisfaction. Therefore, the round-table visualization was switched on and off in certain weeks of the data collection. It was postulated that the visualization influences the groups to have a higher balance of participation (Hypothesis 5) and that the higher balance of participation even lasts after the groups stop using the visualization because of a training effect (Hypothesis 6).

Figure 2.20 shows the distribution of the normalized HHI of turns and airtime over all weeks of the data collection. The figure shows that on average there is a more balanced participation in week two and three where the visualization was switched on. However, the dispersed distributions in the figure also indicate the difficulty of obtaining significant regression results. The results for the normalized HHI of turns and the first set of independent variables with a single dummy variable for the visualization can be found in Table 3.11. The results reveal that the visualization is significantly ($p < 0.05$) correlated with a higher balance of participation. This finding supports Hypothesis 5. The variance explained by the visualization variable is small ($R^2 < 0.15$) though indicating that the effect of the variable is small as well. The results for the normalized HHI of turns and the second set of independent variables with dummy variables for the weeks of the data collection can be found in Table 3.12. There is no significant effect for week two and three where the visualization was switched on. This finding does not support Hypothesis 5. When omitting the influential observation depicted in Figure 3.1, week two is significantly ($p < 0.1$) correlated with a higher balance of participation. Although it is not valid to simply remove the influential observation, the results of the dataset without the influential observation help better understanding the effect of the real-time feedback. For both datasets, there is significantly ($p < 0.1$) less balance of participation in week four where the groups stop using the visualization. This finding is contrary to Hypothesis 6. The results for the normalized HHI of turns and the third set of independent variables containing a compliance variable in addition is shown in Table 3.13. The compliance variable almost makes no difference regarding the results.

Taken together, no clear conclusion can be give on Hypothesis 5. In laboratory settings, the round-table visualization was often shown to effectively encourage balance of participation [Kim08, Kim09]. In the naturalistic setting of this work, at least an average effect was observable. However, the results of this work contradict Hypothesis 6 postulating that there is a training effect of the visualization. The are several possible reasons for the unclear and contradicting results. Due to the naturalistic setting of the study, it was not possible to avoid confounding factors. The Sloan Fellows attended additional events on team building and coaching that might have influenced their conversation dynamics as well. Furthermore, not all of the groups used the round-table visualization. Some of them remarked that they put the smartphones aside and did not observe the real-time feedback. The compliance variable used in the third set of independent variables might have not sufficiently described this fact. Another possible reason related to the assumption mentioned in Section 4.4 is that balance of participation is not beneficial in all circumstances, especially in real-life settings such as the meetings of the Sloan Fellows. Under this assumption, the visualization encouraging balance of participation does not optimally support the groups. For that reason, the Sloan Fellows might have not listen to the feedback. This assumption is further discussed in Section 4.7.

To conclude, it was shown that on average there was more balanced participation in weeks where the real-time feedback was enabled. However, more data is required in order to draw a clear conclusion. For further studies, it is especially recommended to use randomization in order to account for confounding factors and to obtain more meaningful results.

4.7 Effect of Required Expertise

Balance of participation was often shown to be a major indicator for successful group collaboration. However, this finding was mostly proven in laboratory settings with tasks that do not require prior expertise of the participants [Kim08, Kim09]. In naturalistic settings such as the group meetings of the Sloan Fellows, prior expertise is required though. Therefore, it is assumed that even participation is not beneficial in all circumstances. In meetings with required expertise, unbalanced participation might be preferable if the expert speaks and the other group members listen and learn from the expert. In order to start examining this novel hypothesis, the correlation between the balance of required expertise and the balance of participation in a meeting was analyzed. It was postulated that a high imbalance of required expertise in a meeting is correlated with a high imbalance of participation of the group and the other way round (Hypothesis 7).

No data were collected on the required expertise in meetings. For that reason, the data were estimated based on group assignments of the different courses of the Sloan Fellows. Of course, the estimated data are not accurate. In order to still have meaningful results, two different functions (a more complex and a more simple one) were used to estimate the data and a wide range of different parameters was used for each of the functions.

The more complex function gives default weight to each of the courses of the Sloan Fellows and increases the weight based on upcoming assignments. Two parameters determine the number of days in which assignments are considered as well as the weighting of the assignments compared to the default weight. Figure 3.2 shows the respective coefficients for a wide range of different combinations of parameter values. The coefficients are throughout positive meaning that there is a positive correlation between the balance of required expertise and the balance of participation. This finding is in conformity with the postulated hypothesis. Figure 3.3 shows the corresponding significance values. The results are significant at the 0.1 level for all combinations of parameter values expect the combinations in which only assignments within one day are considered. The significance increases as the the number of days in which assignments are considered increases and as the weighting of the assignments increases. This finding again supports Hypothesis 7.

The more simple function only considers courses of the Sloan Fellows that have an assignment due within a certain number of days. For that reason, the function copes without the default weights as well as the parameter determining the weighting of the assignments compared to the default weights. Figure 3.4 shows the respective coefficients. The coefficients are again consistently positive but smaller compared to the coefficients of the more complex function. The corresponding significance values are shown in Figure 3.5. The results are only significant if assignments are considered within two or three days. The results of the more simple function are less robust hence. This can be ascribed to the outputs of the function. The more simple function produces much more extreme values than the more complex one. If there is no assignment due within a certain number of days, the respective course is not considered at all. The parameter values with significant results make sense though. The Sloan Fellows likely focus most on the assignments that are due within two or three days – depending on the effort of the assignment.

Taken together, the results support the assumption that even participation might not be beneficial in all circumstances, especially in meetings with required expertise. However, the results only give a first tendency. No data were collected on the required expertise in meetings and the data were roughly estimated hence. It has to be emphasized that the results have to be treated with caution for that reason. In order to prove the results, a further study would be required in which respective data are collected from the beginning. Because of the novelty of the hypothesis and the lack of research, the results cannot be compared to literature. Because of the additional relevance of the hypothesis, it would be promising to extend the study by mapping participants to their field of expertise and to further deepen the analysis.

Chapter 5

Conclusion

Group collbaoration is the key to success in most realms of work and life. For that reason, it is becoming increasingly important these days. In order to improve group collaboration, it is crucial to understand the underlying group dynamics. They have been shown to be a key factor affecting performance and satisfaction of groups. The main purpose of this study was to deeply understand group dynamics in real-life settings. Therefore, unstructured out-of-class meetings of the Sloan Fellows program – an immersive MBA program for mid-career managers – were analyzed. They were particularly analyzed with respect to factors affecting participation and the relationship between participation and performance as well as satisfaction. Furthermore, it was investigated whether real-time feedback on conversation dynamics can improve participation and in turn performance and satisfaction.

The study was conducted using Open Badges. Open Badges is a portable real-time system for collecting and monitoring social interaction data from people engaged in real-life settings. It consists of custom hardware badges collecting non-linguistic audio data and a smartphone with a mobile application providing real-time feedback by visualizing the conversation dynamics. In addition to non-linguistic audio data, demographic, personality, performance, and satisfaction data were collected using surveys and the individual grades of the Sloan Fellows. In order to study the effect of real-time feedback, the visualization was switched on and off in certain weeks of the data collection. After processing and cleansing the collected data, data were available of 100 Sloan Fellows in 21 study groups. The number of meetings in the four weeks of data collection amounted to 233 and the total duration of the meetings summed up to 344 hours. In contrast to most studies in literature, the dataset contains a large amount of genuine data that were collected in real-life settings over a long period of time. For the purpose of investigating group dynamics based on these data, advanced regression analysis was applied.

With regard to factors affecting participation, gender, age, ethnicity, the Big Five personality traits, and professional experience were considered. Three statistically significant factors were revealed for the amount and manner of participation of individual group members. First, Asians have less turns and therefore speak less. Second, extroverts have more turns and therefore speak more and third, women have shorter turns but roughly speak for the same amount. Two statistically significant factors were further revealed for the evenness of participation among all group members. Both groups with a higher level of openness to experience and a higher level of conscientiousness have more balanced participation. These findings are particularly valuable in order to optimally compose groups.

With regard to the relationship between participation and performance, it was postulated that both individuals with a high amount of participation and groups with a high balance of participation have a high performance. It was proven that there is a statistically significant positive correlation between the amount of participation of individuals and the performance. However, no information is available on the direction of the correlation. It might either be that high participation (i.e., high effort) leads to high performance or that high performance (i.e., high expertise) leads to high participation. No clear correlation was observable between the balance of participation of groups and the performance. Due to prior findings from laboratory studies in literature, this result was unexpected. It is ascribed to the real-life settings of the study. In particular, it is assumed that even participation is not beneficial in all circumstances. For example, in meetings with required expertise it might be preferable if the expert speaks and the other group members listen and learn from the expert.

With regard to the relationship between participation and satisfaction, it was postulated that both individuals with a high amount of participation and groups with a high balance of participation have a high satisfaction. It was proven that there is a statistically significant correlation between the amount of participation of individuals and the perceived valued of the own perspective to the meetings as well as the comfortability in sharing the own perspective in the meetings. However, against expectations no correlation was observable between the balance of participation of groups and the satisfaction. This finding is again ascribed to the real-life settings of the study and the assumption that even participation might not beneficial in all circumstances.

With regard to the effect of real-time feedback on participation and in turn performance and satisfaction, it was postulated that the visualization promotes even participation and that the effect will continue even after the groups stop using the visualization. It was shown that on average there was more balanced participation when the visualization was switched on. However, no statistically significant results were obtained. Furthermore, no training effect of the visualization was observable. For that reason, more data is required in order to draw a clear conclusion. For further studies, it is highly recommended to used randomization in order to account for confounding factors and to obtain more meaningful results.

Due to the unexpected results regarding the relationship between the balance of participation of groups and the performance as well as the satisfaction, it is assumed that even participation is not beneficial in all circumstances and that especially in real-life settings, where prior expertise is required, it might be preferable if the expert speaks and the other group members listen and learn from the expert. In order to start examining this novel hypothesis, it was postulated that a high imbalance of required expertise in a meeting is related to a high imbalance of participation of the group and the other way round. The obtained results support the hypothesis. However, no data were collected about the required expertise in the meetings and the data were estimated hence. For that reason, the results have to be treated with caution. In order to prove the results, a further study is required in which respective data are collected from the beginning.

The study uncovered insightful patterns of social interactions and provided a deeper understanding of group dynamics in real-life settings. Additional study is required in order to clarify some of the borderline significant results. In particular, the analysis of the effect of real-time feedback on participation and performance as well as satisfaction has to be continued. For further studies, it is highly recommended to use randomization in order to account for confounding factors due to the real-life settings and in order to obtain more meaningful results. Furthermore, the novel hypothesis that even participation is not beneficial in all circumstances has to be analyzed in more detail. A continuing study is required in which data about the required expertise in meetings are collected from the beginning. Because of the novelty and the relevance of the hypothesis, it is also promising to extend the study mapping group members to their field of expertise and to further deepen the analysis. Depending on the results of the study, the visualization of the real-time feedback can be adapted in order to provide appropriate advice and be more optimally supportive. The applied voice activity detection algorithm had some limitations. Due to the algorithm, overlapping speech segments were not allowed and only simple features of participation were considered. Another possible future direction of this work is to refine the algorithm and to allow for more complex features of participation. In particular, it would be interesting to include features of dominance that are often based on overlapping speech segments. The data of this study were collected over a long period of time of four weeks. Due to the longitudinal study, another promising direction of this study is to analyze temporal changes of group dynamics. The temporal changes of dominance within the groups would be of particular interest.

Appendix A

Patents

A.1 US 9443521 (B1)

Title	*Methods for Automatically Analyzing Conversational Turn-Taking Patterns*
Publication Number	US 9443521 (B1)
Publication Date	September 13, 2016
Inventor(s)	Daniel Olguin Olguin, Tuomas Jaanu, Maegen Demko
Assignee(s)	Sociometric Solutions, Inc.
Abstract	Presented are a system and methods for automatically extracting, analyzing and visualizing conversational turn-taking patterns during co-located and remote social interactions. The visualization tool measures group conversation dynamics based on wirelessly or otherwise obtained electronic sensor data corresponding to each participant. The group conversation dynamics that are determined (or detected) include, per participant, turn duration, turn-taking speed, number of turns, number of overlapping turns, number of successful interruptions and number of unsuccessful interruptions. Also calculated are participant mirroring statistics, activity statistics, consistency statistics, influence statistics and social network statistics. The visualizations may be output with user configurable parameters.

A.2 US 20140278455 (A1)

Title	*Providing Feedback Pertaining to Communication Style*
Publication Number	US 20140278455 (A1)
Publication Date	September 18, 2014
Inventor(s)	Nirupama Chandrasekaran, Mary P. Czerwinski, Andrea L. Hartzler, Rupa A. Patel, Wanda M. Pratt, Asta J. Roseway
Assignee(s)	Microsoft Corporation
Abstract	An approach is described herein for providing feedback to the participants of a communication session. The approach entails automatically collecting cue information that characterizes, at least in part, the communication behavior that is exhibited during the communication session. The approach then generates signal information based on the cue information. In one case, the signal information conveys the empathy that is exhibited during the communication session. In one case, the signal information may have an affiliation dimension and a control dimension. Any participant can use the signal information during and/or after the communication session to gain awareness of his or her communication style, and to potentially modify his or behavior in response thereto.

A.3 US 20170154637 (A1)

Title	*Communication Pattern Monitoring and Behavioral Cues*
Publication Number	US 20170154637 (A1)
Publication Date	June 1, 2017
Inventor(s)	Jean Chu, Susan L. Diamond, Oiza V. Dorgu, William Fang, Peter B. Hom, Jenny S. Li, Jeremy Tio, Jing-Na Yua
Assignee(s)	International Business Machines Corporation
Abstract	Embodiments include method, systems and computer program products for monitoring communication patterns and performing behavioral cues. Aspects include determining a relationship model for a conversation, wherein the relationship model includes one or more speech behavior rules. Aspects also include receiving and analyzing an audio of the conversation and based on a determination that one or more of the speech behavior rules are being violated, generating a passive alert to a participant in the conversation that has violated one of the speech behavior rules to prompt a change a behavior of the participant. Based on a determination that the behavior of the participant has not improved in a time period since the passive alert, aspects include performing an active intervention in the conversation.

Appendix B

Surveys

B.1 Demographic Survey

1. First name: ______________________
2. Last name: ______________________
3. Study group: ______________________
4. Email address: ______________________
5. Sex: ______________________
6. Age: ______________________
7. Region of primary citizenship: ______________________
8. First citizenship: ______________________
9. Second citizenship: ______________________
10. Country of job: ______________________
11. Number of years of experience: ______________________
12. Organization or activity industry: ______________________
13. Most recent graduate deegree: ______________________
14. Most recent undergraduate degree: ______________________
15. First school major: ______________________
16. Second school major: ______________________

B.2 Satisfaction Survey

Q1 How satisfied are you with the outcome of the meeting?

(1) Extremely satisfied
(2) Moderately satisfied
(3) Slightly satisfied
(4) Neither satisfied nor dissatisfied
(5) Slightly dissatisfied
(6) Moderately dissatisfied
(7) Extremely dissatisfied

Q2 How satisfied are you with the process used in the meeting?

(1) Extremely satisfied
(2) Moderately satisfied
(3) Slightly satisfied
(4) Neither satisfied nor dissatisfied
(5) Slightly dissatisfied
(6) Moderately dissatisfied
(7) Extremely dissatisfied

Q3 How valuable do you think your perspective was to the meeting?

(1) Extremely valuable
(2) Moderately valuable
(3) Slightly valuable
(4) Neither valuable nor unvaluable
(5) Slightly unvaluable
(6) Moderately unvaluable
(7) Extremely unvaluable

Q4 How comfortable were you in sharing your perspective with the team?

(1) Extremely comfortable

(2) Moderately comfortable

(3) Slightly comfortable

(4) Neither comfortable nor uncomfortable

(5) Slightly uncomfortable

(6) Moderately uncomfortable

(7) Extremely uncomfortable

Appendix C

Regression Tables

C.1 Individual Participation

Table C.1: Results for Individual Participation With Interaction Terms. Results of the covariance pattern model (CPM) with interaction terms for main effects for percentage of turns and airtime. No interaction term was added for length of turns since there was only one main effect.

	Percentage of turns	Percentage of airtime
	CPM	CPM
(Intercept)	0.2894***	0.2946***
	[0.2629, 0.3158]	[0.2652, 0.3239]
Female	-0.0183	-0.0260
	[-0.0485, 0.0119]	[-0.0600, 0.0080]
Asia	-0.0561***	-0.0600***
	[-0.0906, -0.0217]	[-0.0986, -0.0215]
Middle East	–	-0.0503
	–	[-0.1370, 0.0365]
Agreeableness	-0.0108*	-0.0096
	[-0.0231, 0.0016]	[-0.0239, 0.0046]
Extraversion	0.0161**	0.0192**
	[0.0015, 0.0306]	[0.0033, 0.0352]
Five-member group	-0.0546***	-0.0533***
	[-0.0774, -0.0319]	[-0.0790, -0.0276]
Female $*$ Asia	–	0.0058
	–	[-0.0096, 0.0212]
Female $*$ extraversion	–	0.0045
	–	[-0.0088, 0.0178]
Asia $*$ agreeableness	0.0044	–
	[-0.0081, 0.0170]	–
Asia $*$ extraversion	0.0114	0.0115
	[-0.0035, 0.0263]	[-0.0050, 0.0280]
Agreeableness $*$ extraversion	-0.0003	–
	[-0.0128, 0.0121]	–
N_{group}	21	21
ICC_{group}	-0.2030	-0.2071
N	100	100
Marginal R^2	0.3350	0.3375

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
5% confidence interval reported in square brackets

C.2 Balance of Participation

Table C.2: Results for Balance of Participation With Interaction Terms. Results of the linear regression model (LRM) with interaction terms for the normalized HHI of airtime. No interaction terms were added for the normalized HHI of terms since there was only one main effect.

	Normalized HHI of airtime
	LRM
(Intercept)	0.1084***
	[0.0924, 0.1244]
Median conscientiousness	-0.0150*
	[-0.0318, 0.0018]
Median openness to experiences	-0.0149*
	[-0.0316, 0.0017]
Median conscientiousness $*$ Median openness to experiences	0.0014
	[-0.0147, 0.0175]
N	21
R^2	0.3878
Adjusted R^2	0.2797

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
5% confidence interval reported in square brackets

C.3 Performance

Table C.3: Results for all Courses and Percentage of Airtime. Results of the linear mixed model (LMM) and the ordered logit model (OLM) for all courses and percentage of airtime.

	Data, Models, and Decisions		Financial Accounting		Marketing and Strategy	
	LMM	OLM	LMM	OLM	LMM	OLM
(Intercept)	3.6362***	–	3.5948***	–	3.4798***	–
	[3.3583, 3.9141]	–	[3.3683, 3.8213]	–	[3.1162, 3.8434]	–
Percentage of airtime	0.1965***	0.7550***	0.2692***	1.8559***	0.0723*	–
	[0.0711, 0.3220]	[0.3009, 1.2288]	[0.1670, 0.3715]	[1.0800, 2.7952]	[-0.0097, 0.1543]	–
Female	-0.2962**	-0.9801**	-0.1131	-0.7056	0.1503*	–
	[-0.5301, -0.0622]	[-1.8091, -0.1647]	[-0.3038, 0.0776]	[-1.8180, 0.3946]	[-0.0098, 0.3103]	–
Asia	0.4169***	1.3779***	0.3183***	2.0284***	-0.1261	–
	[0.1622, 0.6715]	[0.4527, 2.3357]	[0.1107, 0.5258]	[0.74379, 3.4783]	[-0.2962, 0.04395]	–
Middle East	0.0486	-0.0190	0.3468	2.0949	0.1541	–
	[-0.5711, 0.6683]	[-1.9648, 2.0551]	[-0.1582, 0.8520]	[-0.6084, 5.4327]	[-0.2737, 0.5819]	–
Agreeableness	-0.0439	-0.0347	-0.0035	-0.0948	0.0636*	–
	[-0.1505, 0.0628]	[-0.4213, 0.3574]	[-0.0905, 0.0833]	[-0.6143, 0.4170]	[-0.0123, 0.1395]	–
Extraversion	-0.0159	-0.0412	-0.0771*	-0.4623	0.0402	–
	[-0.1280, 0.0961]	[-0.4505, 0.3640]	[-0.1684, 0.0143]	[-1.0732, 0.0916]	[-0.0372, 0.1175]	–
Five-member group	-0.0372	-0.2091	-0.0939	-0.8589	0.0633	–
	[-0.3190, 0.2445]	[-1.1863, 0.7462]	[-0.3236, 0.1357]	[-2.3554, 0.4748]	[-0.3570, 0.4835]	–
N_{group}	21	–	21	–	21	–
ICC_{group}	8.2938e-10	–	1.6481e-09	–	0.5320	–
N	100	100	100	100	100	–
Marginal R^2	0.2385	–	0.3009	–	0.0923	–
Conditional R^2	0.2385	–	0.3009	–	0.5752	–
Mc Fadden R^2	–	0.0750	–	0.2981	–	–
Cox and Snell R^2	–	0.2245	–	0.3306	–	–

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$, 5% confidence interval reported in square brackets

Table C.4: Results for all Courses and Length of Turns. Results of the linear mixed model (LMM) and the ordered logit model (OLM) for all courses and length of turns in seconds.

	Data, Models, and Decisions		Financial Accounting		Marketing and Strategy	
	LMM	OLM	LMM	OLM	LMM	OLM
(Intercept)	3.2965***	–	3.3438***	–	3.1229***	–
	[2.6041, 3.9890]	–	[2.7271, 3.9607]	–	[2.5791, 3.6666]	–
Length of Turns	0.0720	0.2753	0.0602	0.2738	0.0729	0.8432
	[-0.0476, 0.1917]	[-0.1348, 0.6883]	[-0.0463, 0.1669]	[-0.1935, 0.7411]	[-0.0181, 0.1639]	[-0.1832, 1.8697]
Female	-0.3354***	-1.0917**	-0.2105*	-0.8850*	0.1583*	1.7286*
	[-0.5865, -0.0844]	[-1.9589, -0.2425]	[-0.4342, 0.0131]	[-1.8237, 0.0536]	[-0.0075, 0.3241]	[-0.1217, 3.5789]
Asia	0.2611*	0.6572	0.0804	0.3764	-0.1162	-1.0507
	[-0.0084, 0.5307]	[-0.2502, 1.5700]	[-0.1597, 0.3206]	[-0.6850, 1.4378]	[-0.2902, 0.0577]	[-2.7335, 0.6321]
South America	-0.0742	-0.3452	-0.1178	-0.5207	0.0204	0.0127
	[-0.3873, 0.2389]	[-1.4276, 0.7357]	[-0.3968, 0.1610]	[-1.7114, 0.6699]	[-0.1781, 0.2190]	[-2.1315, 2.1570]
South Asia	0.0115	-0.5488	-0.0875	-0.3904	0.1179	1.0225
	[-0.3956, 0.4186]	[-1.8158, 0.7147]	[-0.4502, 0.2751]	[-1.9351, 1.1544]	[-0.1478, 0.3836]	[-1.6954, 3.7404]
Extraversion	0.0165	0.0967	-0.0237	-0.1057	0.0426	0.5364
	[-0.0996, 0.1327]	[-0.3021, 0.4931]	[-0.1272, 0.0797]	[-0.5491, 0.3377]	[-0.0339, 0.1190]	[-0.2262, 1.2991]
N_{group}	21	–	21	21	21	–
ICC_{group}	8.9647e-10	–	3.3571e-09	1.1646e-09	0.5160	0.7332
N	100	100	100	100	100	100
Marginal R^2	0.1575	–	0.0847	–	0.0851	–
Conditional R^2	0.1575	–	0.0847	–	0.5572	–
Mc Fadden R^2	–	0.0462	–	0.0678	–	0.1439
Cox and Snell R^2	–	0.1150	–	0.0873	–	0.1472

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$, 5% confidence interval reported in square brackets

Table C.5: Results for all Courses and Normalized HHI of Airtime. Results of the linear mixed model (LMM) and the ordered logit model (OLM) for all courses and normalized HHI of airtime.

	Data, Models, and Decisions		Financial Accounting		Marketing and Strategy	
	LMM	OLM	LMM	OLM	LMM	OLM
(Intercept)	3.6536***	–	3.6000***	–	3.5381***	–
	[3.5381, 3.7691]	–	[3.5022, 3.6977]	–	[3.3636, 3.7126]	–
Normalized HHI of airtime	-0.0219	-0.0194	0.1060*	0.4500	0.1435	1.2118
	[-0.1710, 0.1272]	[-0.4558, 0.4242]	[-0.0203, 0.2322]	[-0.0738, 1.0182]	[-0.0636, 0.3506]	[-0.4183, 2.8420]
Median conscientiousness	-0.0426	-0.0459	0.0817	0.3473	0.1176	0.9823
	[-0.1819, 0.0968]	[-0.4503, 0.3580]	[-0.0362, 0.1998]	[-0.1160, 0.8387]	[-0.0906, 0.3258]	[-0.4003, 2.3648]
Median openness to experiences	-0.0759	-0.1921	0.0289	0.1228	-0.0232	-0.2021
	[-0.2193, 0.0675]	[-0.6145, 0.2222]	[-0.0925, 0.1503]	[-0.3556, 0.6035]	[-0.2377, 0.1914]	[-1.5301, 1.1259]
N_{group}	21	–	21	–	21	21
ICC_{group}	1.5253e-09	–	8.7482e-10	–	0.5232	0.6174
N	100	100	100	100	100	100
Marginal R^2	0.0208	–	0.0343	–	0.0749	–
Conditional R^2	0.0208	–	0.0343	–	0.5589	–
Mc Fadden R^2	–	0.0034	–	0.0264	–	0.0364
Cox and Snell R^2	–	0.0116	–	0.0349	–	0.0395

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$, 5% confidence interval reported in square brackets

C.4 Satisfaction

Table C.6: Results for Q1 and Q2 and Percentage of Airtime. Results of the linear mixed model (LMM) and the ordered logit model (OLM) for the satisfaction with the outcome of the meetings (Q1) and the process used in the meetings (Q2) as well as percentage of airtime.

	Q1		Q2	
	LMM	OLM	LMM	OLM
(Intercept)	2.0159***	–	2.2980***	–
	[1.4413, 2.5905]	–	[1.6170, 2.9791]	–
Percentage of airtime	-0.0494	-0.1286	-0.0605	-0.1970
	[-0.2073, 0.1084]	[-0.5158, 0.2586]	[-0.2435, 0.1226]	[-0.6051, 0.2112]
Female	0.0352	-0.0367	0.1000	0.1093
	[-0.3064, 0.3769]	[-0.9275, 0.8541]	[-0.3525, 0.5526]	[-0.9043, 1.1230]
Asia	0.0796	0.5453	0.0231	0.3377
	[-0.2911, 0.4503]	[-0.4074, 1.4980]	[-0.4595, 0.5056]	[-0.7368, 1.4121]
Middle East	0.0558	0.2951	0.0489	0.2368
	[-0.8377, 0.9493]	[-2.0460, 2.6361]	[-1.1468, 1.2446]	[-2.5016, 2.9752]
Agreeableness	-0.0300	-0.1279	-0.0914	-0.3171
	[-0.1952, 0.1352]	[-0.5647, 0.3089]	[-0.3119, 0.1291]	[-0.8138, 0.1796]
Extraversion	-0.0520	-0.0423	0.0130	0.0608
	[-0.2159, 0.1120]	[-0.4628, 0.3781]	[-0.2030, 0.2289]	[-0.4247, 0.5463]
Five-member group	0.2808	0.5101	0.3241	0.5259
	[-0.3466, 0.9082]	[-0.7936, 1.8138]	[-0.4192, 1.0674]	[-0.9474, 1.9992]
Week 2	-0.1236	-0.1888	-0.2670*	-0.4002
	[-0.4187, 0.1715]	[-0.8398, 0.4622]	[-0.5629, 0.0290]	[-1.0457, 0.2452]
Week 3	0.4435***	0.8317**	0.1809	0.4085
	[0.1332, 0.7539]	[0.1339, 1.5294]	[-0.1297, 0.4914]	[-0.2696, 1.0865]
Week 4	-0.1893	-0.6536	-0.3503*	-0.8908**
	[-0.5390, 0.1604]	[-1.4484, 0.1413]	[-0.7014, 0.0007]	[-1.6791, -0.1025]
N_{group}	21	21	21	21
ICC_{group}	0.1673	0.1259	0.1452	0.1270
N_{member}	99	99	99	99
ICC_{member}	0.1539	0.3355	0.3554	0.4347
N	279	279	279	279
Marginal R^2	0.0577	–	0.0433	–
Conditional R^2	0.3603	–	0.5222	–
Mc Fadden R^2	–	0.0257	–	0.0200
Cox and Snell R^2	–	0.0599	–	0.0518

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
5% confidence interval reported in square brackets

Table C.7: Results for Q3 and Q4 and Percentage of Airtime. Results of the linear mixed model (LMM) and the ordered logit model (OLM) for the considered value of the own perspective to the meetings (Q3) and the comfortability in sharing the own perspective in the meetings (Q4) as well as percentage of airtime.

	Q3		Q4	
	LMM	OLM	LMM	OLM
(Intercept)	2.1036***	–	2.0797***	–
	[1.7472, 2.4599]	–	[1.5622, 2.5973]	–
Percentage of airtime	-0.1905***	-0.7158***	-0.2783***	-0.8954***
	[-0.3044, -0.0766]	[-1.1424, -0.2892]	[-0.4283, -0.1284]	[-1.3074, -0.4833]
Female	-0.1364	-0.5425	-0.2084	-0.9204**
	[-0.4080, 0.1353]	[-1.4820, 0.3970]	[-0.5582, 0.1415]	[-1.8010, -0.0398]
Asia	0.0400	0.2078	-0.0820	-0.1794
	[-0.2524, 0.3324]	[-0.8001, 1.2158]	[-0.4581, 0.2937]	[-1.1019, 0.7431]
Middle East	-0.1082	-0.6657	-0.2400	-0.6162
	[-0.8230, 0.6066]	[-3.1637, 1.8323]	[-1.1604, 0.6804]	[-2.8713, 1.6390]
Agreeableness	-0.0386	-0.1151	-0.0779	-0.2048
	[-0.1690, 0.0918]	[-0.5757, 0.3454]	[-0.2474, 0.0915]	[-0.6339, 0.2242]
Extraversion	-0.0084	0.0092	-0.0215	-0.1045
	[-0.1378, 0.1210]	[-0.4393, 0.4577]	[-0.1886, 0.1456]	[-0.5184, 0.3094]
Five-member group	0.1387	0.6578	0.1591	0.6801
	[-0.2328, 0.5101]	[-0.5669, 1.8825]	[-0.3977, 0.7160]	[-0.5410, 1.9013]
Week 2	-0.1135	-0.3010	-0.0418	0.0059
	[-0.3006, 0.0736]	[-0.9692, 0.3673]	[-0.2961, 0.2124]	[-0.6270, 0.6387]
Week 3	0.0258	0.0113	0.1885	0.2172
	[-0.1706, 0.2223]	[-0.7001, 0.7228]	[-0.0786, 0.4555]	[-0.4753, 0.9097]
Week 4	-0.1596	-0.5867	0.0052	-0.1889
	[-0.3810, 0.0618]	[-1.3964, 0.2231]	[-0.2961, 0.3064]	[-0.9707, 0.5930]
N_{group}	21	21	21	21
ICC_{group}	0.0570	0.0654	0.1209	0.0942
N_{member}	99	99	99	99
ICC_{member}	0.3641	0.4064	0.2926	0.3365
N	279	279	279	279
Marginal R^2	0.0769	–	0.0739	–
Conditional R^2	0.4656	–	0.4569	–
Mc Fadden R^2	–	0.0337	–	0.0381
Cox and Snell R^2	–	0.0673	–	0.0879

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
5% confidence interval reported in square brackets

Table C.8: Results for Q1 and Q2 and Length of Turns. Results of the linear mixed model (LMM) and the ordered logit model (OLM) for the satisfaction with the outcome of the meetings (Q1) and the process used in the meetings (Q2) as well as length of turns in seconds.

	Q1		Q2	
	LMM	OLM	LMM	OLM
(Intercept)	1.7905***	–	2.2613***	–
	[1.0037, 2.5773]	–	[1.3783, 3.14428]	–
Length of Turns	0.0778	0.1916	0.0658	0.1476
	[-0.0440, 0.1995]	[-0.0953, 0.4785]	[-0.0677, 0.1994]	[-0.1436, 0.4387]
Female	0.1162	0.1852	0.1745	0.3498
	[-0.2320, 0.4643]	[-0.7263, 1.0968]	[-0.2833, 0.6322]	[-0.6921, 1.3917]
Asia	0.1183	0.6700	-0.0524	0.3056
	[-0.2669, 0.5035]	[-0.3462, 1.6862]	[-0.5608, 0.4561]	[-0.8513, 1.4625]
South America	-0.0707	-0.1531	-0.3201	-0.5205
	[-0.5045, 0.3631]	[-1.3061, 0.9999]	[-0.8970, 0.2568]	[-1.8490, 0.8080]
South Asia	-0.0380	0.4520	-0.0994	0.5146
	[-0.6322, 0.5561]	[-1.0973, 2.0012]	[-0.8753, 0.6766]	[-1.2609, 2.2902]
Extraversion	-0.0668	-0.0960	-0.0119	-0.0310
	[-0.2312, 0.0975]	[-0.5238, 0.3319]	[-0.2287, 0.2049]	[-0.5327, 0.4706]
Week 2	-0.1286	-0.2048	-0.2708*	-0.4274
	[-0.4226, 0.1655]	[-0.8574, 0.4477]	[-0.5661, 0.0244]	[-1.0751, 0.2204]
Week 3	0.4075**	0.7524**	0.1477	0.3279
	[0.0954, 0.7196]	[0.0488, 1.4559]	[-0.1653, 0.4607]	[-0.3578, 1.0136]
Week 4	-0.1265	-0.5104	-0.3006	-0.7925*
	[-0.4900, 0.2370]	[-1.3346, 0.3138]	[-0.6666, 0.0654]	[-1.6092, 0.0242]
N_{group}	21	21	21	21
ICC_{group}	0.1453	0.0895	0.1260	0.0888
N_{member}	99	99	99	99
ICC_{member}	0.1692	0.3696	0.3711	0.4735
N	279	279	279	279
Marginal R^2	0.0523	–	0.0354	–
Conditional R^2	0.3503	–	0.5149	–
Mc Fadden R^2	–	0.0266	–	0.0186
Cox and Snell R^2	–	0.0621	–	0.0482

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
5% confidence interval reported in square brackets

Table C.9: Results for Q3 and Q4 and Length of Turns. Results of the linear mixed model (LMM) and the ordered logit model (OLM) for the considered value of the own perspective to the meetings (Q3) and the comfortability in sharing the own perspective in the meetings (Q4) as well as length of turns in seconds.

	Q3		Q4	
	LMM	OLM	LMM	OLM
(Intercept)	2.1173***	–	2.3990***	–
	[1.5782, 2.6565]	–	[1.6593, 3.1386]	–
Length of Turns	-0.0057	-0.0053	-0.0682	-0.1474
	[-0.0893, 0.0779]	[-0.3077, 0.2970]	[-0.1818, 0.0452]	[-0.4465, 0.1518]
Female	-0.0167	-0.0731	-0.0877	-0.4763
	[-0.2931, 0.2597]	[-1.0247, 0.8785]	[-0.4594, 0.2840]	[-1.4128, 0.4602]
Asia	0.2147	0.9327*	0.1660	0.5856
	[-0.0941, 0.5234]	[-0.1280, 1.9934]	[-0.2473, 0.5793]	[-0.4348, 1.6061]
South America	-0.0289	0.1024	0.1905	0.3112
	[-0.3797, 0.3219]	[-1.0981, 1.3030]	[-0.2780, 0.6591]	[-0.8662, 1.4885]
South Asia	0.4270*	1.5967*	0.1867	0.8419
	[-0.0409, 0.8948]	[-0.0155, 3.2089]	[-0.4438, 0.8172]	[-0.6974, 2.3812]
Extraversion	-0.0498	-0.1430	-0.0533	-0.2236
	[-0.1807, 0.0810]	[-0.5915, 0.3056]	[-0.2293, 0.1226]	[-0.6642, 0.2170]
Week 2	-0.1230	-0.3455	-0.0445	-0.0033
	[-0.3135, 0.0675]	[-1.0083, 0.3173]	[-0.3009, 0.2119]	[-0.6344, 0.6279]
Week 3	0.0069	-0.0822	0.1843	0.1989
	[-0.1950, 0.2089]	[-0.7972, 0.6328]	[-0.0876, 0.4562]	[-0.4957, 0.8935]
Week 4	-0.1719	-0.5950	-0.0523	-0.2740
	[-0.4079, 0.0641]	[-1.4319, 0.2419]	[-0.3700, 0.2654]	[-1.0881, 0.5401]
N_{group}	21	21	21	21
ICC_{group}	0.0321	0.0507	0.0969	0.0779
N_{member}	99	99	99	99
ICC_{member}	0.3733	0.4200	0.3376	0.3946
N	279	279	279	279
Marginal R^2	0.0454	–	0.0230	–
Conditional R^2	0.4324	–	0.4474	–
Mc Fadden R^2	–	0.0164	–	0.0091
Cox and Snell R^2	–	0.0333	–	0.0218

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
5% confidence interval reported in square brackets

Table C.10: Results for Q1 and Q2 and Normalized HHI of Airtime. Results of the linear mixed model (LMM) and the ordered logit model (OLM) for the satisfaction with the outcome of the meetings (Q1) and the process used in the meetings (Q2) as well as normalized HHI of airtime.

	Q1		Q2	
	LMM	OLM	LMM	OLM
(Intercept)	2.2514***	–	2.5760***	–
	[1.9696, 2.5333]	–	[2.2421, 2.9098]	–
Normalized HHI of airtime	0.0158	0.0288	-0.0767	-0.1596
	[-0.1396, 0.1712]	[-0.3251, 0.3827]	[-0.2359, 0.0824]	[-0.5118, 0.1926]
Median conscientiousness	0.0400	0.1896	0.0504	0.1927
	[-0.2222, 0.3022]	[-0.3491, 0.7283]	[-0.2825, 0.3832]	[-0.4402, 0.8257]
Median openness to experiences	0.2479*	0.3866	0.1278	0.1850
	[-0.0071, 0.5028]	[-0.1413, 0.9145]	[-0.1941, 0.4497]	[-0.4266, 0.7966]
Week 2	-0.0989	-0.1351	-0.3062*	-0.4836
	[-0.4069, 0.2090]	[-0.8181, 0.5479]	[-0.6156, 0.0033]	[-1.1654, 0.1982]
Week 3	0.4311***	0.8039**	0.1751	0.3885
	[0.1219, 0.7402]	[0.1071, 1.5006]	[-0.1340, 0.4842]	[-0.2893, 1.0664]
Week 4	-0.1783	-0.6406	-0.2898	-0.7804*
	[-0.5413, 0.1847]	[-1.4734, 0.1921]	[-0.6547, 0.0754]	[-1.5997, 0.0389]
N_{group}	21	21	21	21
ICC_{group}	0.1372	0.0791	0.1503	0.0956
N_{member}	99	99	99	99
ICC_{member}	0.1482	0.3802	0.3432	0.4744
N	279	279	279	279
Marginal R^2	0.0978	–	0.0463	–
Conditional R^2	0.3553	–	0.5171	–
Mc Fadden R^2	–	0.0252	–	0.0178
Cox and Snell R^2	–	0.0589	–	0.0463

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
5% confidence interval reported in square brackets

Table C.11: Results for Q3 and Q4 and Normalized HHI of Airtime. Results of the linear mixed model (LMM) and the ordered logit model (OLM) for the considered value of the own perspective to the meetings (Q3) and the comfortability in sharing the own perspective in the meetings (Q4) as well as normalized HHI of airtime.

	Q3		Q4	
	LMM	OLM	LMM	OLM
(Intercept)	2.1751***	–	2.0963***	–
	[2.0024, 2.3477]	–	[1.8493, 2.3433]	–
Normalized HHI of airtime	-0.0255	-0.0762	-0.0351	-0.1496
	[-0.1252, 0.0742]	[-0.4289, 0.2766]	[-0.1705, 0.1001]	[-0.5017, 0.2026]
Median conscientiousness	0.0243	0.0306	-0.0012	0.0544
	[-0.1314, 0.1799]	[-0.4593, 0.5205]	[-0.2320, 0.2297]	[-0.4239, 0.5327]
Median openness to experiences	0.0991	0.4318*	0.1730	0.3910
	[-0.0528, 0.2511]	[-0.0497, 0.9132]	[-0.0516, 0.3976]	[-0.0778, 0.8596]
Week 2	-0.1242	-0.3260	-0.0607	-0.0688
	[-0.3227, 0.0743]	[-1.0236, 0.3716]	[-0.3277, 0.2064]	[-0.7366, 0.5990]
Week 3	-0.0002	-0.1009	0.1554	0.1311
	[-0.1989, 0.1986]	[-0.8065, 0.6046]	[-0.1118, 0.4226]	[-0.5582, 0.8204]
Week 4	-0.1356	-0.4973	0.0413	-0.0364
	[-0.3695, 0.0983]	[-1.3334, 0.3387]	[-0.2736, 0.3561]	[-0.8470, 0.7743]
N_{group}	21	21	21	21
ICC_{group}	0.0279	0.0093	0.0676	0.0092
N_{member}	99	99	99	99
ICC_{member}	0.3901	0.4805	0.3593	0.4734
N	279	279	279	279
Marginal R^2	0.0325	–	0.0356	–
Conditional R^2	0.4369	–	0.4473	–
Mc Fadden R^2	–	0.0113	–	0.0074
Cox and Snell R^2	–	0.0231	–	0.0177

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
5% confidence interval reported in square brackets

C.5 Effect of Real-Time Feedback

Table C.12: Results for Normalized HHI of Airtime and First Set of Independent Variables. Results of linear mixed model (LMM) with and without outlier for normalized HHI of airtime as well as first set of independent variables.

	Normalized HHI of airtime	
	LMM with outlier	LMM without outlier
(Intercept)	0.1320***	0.1249***
	[0.1074, 0.1566]	[0.1027, 0.1470]
Visualization	-0.0361**	-0.0287**
	[-0.0663, -0.0059]	[-0.0563, -0.0010]
N_{group}	21	21
ICC_{group}	0.1380	0.1195
N	71	71
Marginal R^2	0.0664	0.0529
Conditional R^2	0.1953	0.1660

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
5% confidence interval reported in square brackets

Table C.13: Results for Normalized HHI of Airtime and Second Set of Independent Variables. Results of linear mixed model (LMM) with and without outlier for normalized HHI of airtime as well as second set of independent variables.

	Normalized HHI of airtime	
	LMM with outlier	LMM without outlier
(Intercept)	0.1116***	0.1116***
	[0.0831, 0.1401]	[0.0856, 0.1376]
Week 2	-0.0304	-0.0303*
	[-0.0689, 0.0080]	[-0.0658, 0.0052]
Week 3	0.0006	0.0008
	[-0.0385, 0.0397]	[-0.0352, 0.0369]
Week 4	0.0548**	0.0375*
	[0.0115, 0.0982]	[-0.0035, 0.0785]
N_{group}	21	21
ICC_{group}	0.1403	0.1178
N	71	71
Marginal R^2	0.1604	0.1242
Conditional R^2	0.2782	0.2274

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
5% confidence interval reported in square brackets

Table C.14: Results for Normalized HHI of Airtime and Third Set of Independent Variables. Results of linear mixed model (LMM) with and without outlier for normalized HHI of airtime as well as third set of independent variables.

	Normalized HHI of airtime	
	LMM with outlier	LMM without outlier
(Intercept)	0.0905***	0.0966***
	[0.0413, 0.1396]	[0.0515, 0.1417]
Week 2	-0.0314	-0.0310*
	[-0.0703, 0.0074]	[-0.0669, 0.0048]
Week 3	0.0037	0.0030
	[-0.0361, 0.0435]	[-0.0337, 0.0397]
Week 4	0.0599***	0.0414*
	[0.0153, 0.1044]	[-0.0009, 0.0837]
Moderator	0.0234	0.0166
	[-0.0209, 0.0677]	[-0.0242, 0.0574]
N_{group}	21	21
ICC_{group}	0.1219	0.1058
N	71	71
Marginal R^2	0.1726	0.1311
Conditional R^2	0.2734	0.2231

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
5% confidence interval reported in square brackets

Appendix D

Curriculum

Personal Details

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Education

Since 2015	Friedrich-Alexander University Erlangen-Nürnberg, Germany M.S. Computer Science Current Grade: 1.1
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Experience

2016 – 2017	Massachusetts Institute of Technology, Cambridge, USA Research Stay at Human Dynamics Lab for Master Thesis Scholarship: DAAD Fit Weltweit
2015 – 2016	Friedrich-Alexander University Erlangen-Nürnberg, Germany Student Assistant at Pattern Recognition Lab
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Publications

2015 K. Full, H. Leutheuser, J. Schlessman, R. Armitage and B. M. Eskofier, ”Comparative study on classifying gait with a single trunk-mounted inertial-magnetic measurement unit,” *Wearable and Implantable Body Sensor Networks (BSN), 2015 IEEE 12th International Conference on*, Cambridge, MA, 2015, pp. 1-6.

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