12-2022

Developing and Facilitating Temporary Team Mental Models Through an Information-Sharing Recommender System

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Developing and Facilitating Temporary Team Mental Models Through an Information-Sharing Recommender System

A Dissertation
Presented to
the Graduate School of
Clemson University

In Partial Fulfillment
of the Requirements for the Degree
Doctor of Philosophy
Human-Centered Computing

by
Geoff Musick
December 2022

Accepted by:
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Abstract

It is well understood that teams are essential and common in many aspects of life, both work and leisure. Due to the importance of teams, much research attention has focused on how to improve team processes and outcomes. Of particular interest are the cognitive aspects of teamwork including *team mental models* (TMMs). Among many other benefits, TMMs involve team members forming a compatible understanding of the task and team in order to more efficiently make decisions. This understanding is sometimes classified using four TMM domains: equipment (e.g., operating procedures), task (e.g., strategies), team interactions (e.g., interdependencies) and teammates (e.g., tendencies). Of particular interest to this dissertation is accelerating the development of *teammate* TMMs which include members understanding the knowledge, skills, attitudes, preferences, and tendencies of their teammates. An accurate *teammate* TMM allows teams to predict and account for the needs and behaviors of their teammates. Although much research has highlighted how the development of the four TMM domains can be supported, promoting the development of *teammate* TMMs is particularly challenging for a specific type of team: temporary teams.

Temporary teams, in contrast to ongoing teams, involve unknown teammates, novel tasks, short task times (alternatively limited interactions), and members disbanding after completing their task. These teams are increasingly used by organizations as they can be agilely formed with individual members selected to accomplish

a specific task. Such teams are commonly used in contexts such as film production, the military, emergency response, and software development, just to name a few. Importantly, although these teams benefit greatly from *teammate* TMMs due to the efficiencies gained in decision making while working under limited deadlines, the literature is severely limited in understanding how to support temporary teams in this way. As prior research has suggested, an opportunity to accelerate *teammate* TMM development on temporary teams is through the use of technology to selectively share teammate information to support these TMMs. However, this solution poses numerous privacy concerns. This dissertation uses four studies to create a foundational and thorough understanding of how recommender system technology can be used to promote *teammate* TMMs through information sharing while limiting privacy concerns.

Study 1 takes a highly exploratory approach to set a foundation for future dissertation studies. This study investigates what information is perceived to be helpful for promoting *teammate* TMMs on actual temporary teams. Qualitative data suggests that sharing teammate information related to skills/preferences, conflict management styles, and work ethic/reliability is perceived as beneficial to supporting *teammate* TMMs. Also, this data provides a foundational understanding for what should be involved in information-sharing recommendations for promoting *teammate* TMMs. Quantitative results indicate that conflict management data is perceived as more helpful and appropriate to share than personality data.

Study 2 investigates the presentation of these recommendations through the factors of anonymity and explanations. Although explanations did not improve trust or satisfaction in the system, providing recommendations associated with a specific teammate name significantly improved several team measures associated with TMMs for actual temporary teams compared to teams who received anonymous recommendations. This study also sheds light on what temporary team members perceive as the benefits to sharing this information and what they perceive as concerns to their privacy.

Study 3 investigates how the group/team context and individual differences can influence disclosure behavior when using an information-sharing recommender system. Findings suggest that members of teams who are fully assessed as a team are more willing to unconditionally disclose personal information than members who are assessed as an individual or members who are mixed assessed as an individual and a team. The results also show how different individual differences and different information types are associated with disclosure behavior.

Finally, Study 4 investigates how the occurrence and content of explanations can influence disclosure behavior and system perceptions of an information-sharing recommender system. Data from this study highlights how benefit explanations provided during disclosure can increase disclosure and explanations provided during recommendations can influence perceptions of trust competence. Meanwhile, benefit-related explanations can decrease privacy concerns.

The aforementioned studies fill numerous research gaps relating to teamwork literature (i.e., TMMs and temporary teams) and recommender system research. In addition to contributions to these fields, this dissertation results in design recommendations that inform both the design of group recommender systems and the novel technology conceptualized through this dissertation, information-sharing recommender systems.

For Maggie and Quill.

Acknowledgements

My advisor, Nathan McNeese, for being the best advisor anyone could hope for. Thank you for taking a chance on me when you did not have to. Much of how I view research and the scientific method can be attributed to your mentorship and thoughtful remarks. Your consistent nudges for me to push my research and writing *one more step* was foundational in the culmination of this dissertation. I will forever respect your ability to motivate the team to achieve great things while also pushing us to create balance in our lives.

My dissertation committee, Bart Knijnenburg, Guo Freeman, and Marissa Shuffler, for their time, patience with me, and eagerness to help. Dr. Knijnenburg is truly a remarkable researcher, particularly with stats, and this dissertation would not be possible if not for his guidance and persistence in answering my seemingly never-ending questions. Dr. Freeman played a significant role in guiding me through my first major publications. This included training me in thematic analysis as well as providing me with a solid foundation in how to be an academic writer, skills that were essential for producing this dissertation. Dr. Shuffler was of great assistance in bouncing ideas off of early on in the dissertation's conceptualization due to her expertise in team building and training. Further she was always ready to help provide guidance for participant recruitment for teamwork research.

The TRACE Research Group, for not only being a group of exceptional committed researchers, but also being people that are a joy to be around and always willing to lend a hand. At this point the size of TRACE has exceeded that which would be practical to thank everyone by name. But know that each of you made an impact on me as a person and as a researcher.

With that being said, I would be remiss to not acknowledge a few members of TRACE specifically. Chris Flathmann, Rui Zhang, and Beau Schelble were a part of TRACE when I arrived and helped to bring me into the fold. Through the trials of research, imposter syndrome, and setbacks, we each bonded in our own special way. Chris, for blazing a path for many of us and being my "mentor". Rui, for collaborating on so many papers and for always having such thoughtful advice. Beau, for being an amazing sounding board for research ideas and always being eager to take a look at my stats. Finally, though not a part of the above-mentioned PhD cohort, I must give a special acknowledgement to Josh Little. Josh provided the vast majority of development work for the research platform used in this dissertation which made many things possible. Josh has an amazing attention to detail and the talent to make projects come to life in short time.

My friends, for always being supportive and kind. Particularly, Tim, Benton, and Isaiah for your consistent and enduring friendship. You always help me de-stress and help me keep things in perspective. Tate and Steph, for continually motivating me with glimpses of "life after the PhD". Dr. Divine Maloney, for giving the right advice at the right time. Dr. Scott Bledsoe, for your letter of encouragement at halftime - I really needed that. And Dr. Jeff Edmonds, for providing mentorship, being a fellow runner friend, and teaching me early that "a PhD is a marathon and not a sprint."

And last but not least my family.

My in-laws, Laurie, Mike, Jess, Andrew, Bob, (etc., etc., etc. - there are just so many), for being incredible family and always doing anything and everything to support Maggie, Quill, and I no matter where we are and what we are doing.

My sister, Ashley, for always modeling what pursuing your dreams AND living life to the fullest looks like. My parents, Larry and Kathy, for loving me and always being my biggest cheerleaders for the past few decades. The last leg of this dissertation would not have been possible without you moving out to live near us, taking care of Kathy's parents, and consistently taking care of Quill. This dissertation was a team effort and you are proof of that.

And finally Maggie and Quill. Quill, we found out about you halfway through our dissertations. Thank you for providing motivation to finish, giving us a consistent reason to laugh and smile (and sometimes cry) everyday, as well as being a constant reminder of what is important in life. And Maggie. You are the reason why I even started this PhD. Thank you for your example and motivation through this process. Thank you for supporting me at moments that I wanted to quit. The past four years have been full of highs and lows and you have been there for me every step of the way. Thank you for everything and cheers to many more years of adventures.

Let everything happen to you; beauty and terror;

just keep going; no feeling is final.

- Rainer Maria Rilke

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Chapter 1

Introduction

This chapter provides a high-level overview of the dissertation. First, the real-world problems that motivate this dissertation are described. Second, prior research is highlighted which point to the gaps that motivate this research. Third, these research gaps are connected to the specific research questions that they motivate. Finally, a summary of studies is provided including descriptions of each study and how the studies are connected.

1.1 Problem Motivation

This dissertation is motivated by the relationship between a specific type of team, **temporary teams**, and a teamwork construct that is of great importance to teamwork, **team mental models** (TMMs). A description of each of these and how they relate is provided in the following paragraphs.

Teams are ubiquitous in many organizations as they allow individuals to collaborate in order to complete tasks more effectively and achieve goals that would likely hinder the individuals or take much longer if they worked on their own [99]. This has motivated many researchers and organizational leaders to study teamwork so that these teams may achieve increased effectiveness [70]. A significant amount of research has focused on the cognitive aspects of teamwork, especially TMMs [263]. Mental models are organized mental representations of the world that allow individuals to predict what will occur next [324]. The construct of TMMs is used to describe how these knowledge structures are shared and used to promote team functioning [201]. TMMs involve team members forming compatible mental models about the task and team, which facilitate more efficient and effective decision-making [244]. Some researchers use four domains to categorize TMMs including models of the equipment (e.g., operating procedures), task (e.g., strategies), team interactions (e.g., interdependencies), and teammates (e.g., tendencies) [74].

Although studying TMMs is motivating in its own right, the intersection of TMMs with a particular category of teams, temporary teams, is of particular interest. Temporary teams, in contrast to ongoing teams, are characterized by having unknown teammates, novel tasks, short task times (or few interactions between members [41]), and members disbanding after task completion [230]. Based on these classification factors, temporary teams can be seen in a myriad of contexts such as software development [160], film production [233], company projects [362], the military [159], and many more [16]. Temporary teams are an important type of team in that they are increasingly used in organizations due to their dynamic nature and ability to complete novel and specific tasks [362, 233, 86]. This dissertation will particularly focus on temporary project teams which are more stable and interact for longer than action teams [155, 238, 16].

In acknowledging the importance of TMMs to teamwork and of temporary teams to the modern workforce, it should also be noted that temporary teams benefit greatly from having accurate and similar TMMs. As temporary teams only work together for relatively short periods of time or with few interactions, the efficiency of their decision-making is highly important [230]. The ability of TMMs to improve processes such as coordination and communication is of particular interest to temporary teams that might work under stressful, time-sensitive, or unusual situations where time constraints do not allow teams to freely communicate and strategize [54, 238]. As such, prior research has found that TMMs are more strongly predictive of performance in novel environments compared to routine ones [238].

Unfortunately, temporary teams are particularly limited in their ability to develop *teammate* TMMs which contain knowledge of teammates (e.g., their knowledge, skills, attitudes, preferences, tendencies, etc. [244]) since they are working with unknown teammates [86]. This deficit for temporary teams can heavily limit these teams since having inaccurate *teammate* TMMs can have a negative effect on team performance [227] and team communication [238]. But how can *teammate* TMMs be supported on temporary teams? As TMMs take time/interactions to develop [226, 266, 68, 314] and temporary teams are limited by member interactions [134, 351], much attention has focused on how various *other TMM domains* can be developed *prior* to a temporary team tasks beginning. For instance, research has pointed to the importance of training [348] and experience [348, 103] in developing *task* and *equipment* TMMs. Also, cross training can be used to facilitate *team interaction* TMM development [237]. However, less is understood regarding how to specifically support *teammate* TMMs on temporary teams which are mostly developed through teammate interactions and are supported by time and task iterations [368, 249]. Unfortunately, the nature of temporary teams (i.e., unknown teammates, short time period, and disbanding) limits the amount of interactions between teammates [351, 60, 92]; therefore, the *teammate* TMMs on these teams are undersupported.

In summary, this dissertation is motivated by the problem that temporary teams, an important and common type of team, benefit greatly from TMMs yet face challenges to develop them due to unknown teammates and time constraints. This problem especially pertains to *teammate* TMMs which are specific to a particular task and team and take time and interactions to develop. Therefore, we need to better understand how to support *teammate* TMMs on temporary teams. In this dissertation, I explore the use of teammate information sharing as a means to develop these TMMs on temporary teams through the use of recommender system technology.

1.2 Research Motivation

In the problem motivation it was emphasized that temporary teams benefit from, yet are limited by their development of *teammate* TMMs. As described throughout this section, an opportunity to address this deficit is through sharing teammate information. The nature of this sharing would be multi-faceted as many aspects such as models of individual differences/similarities present on a team, models of what different individuals perceive as useful information to receive, and models of what different individuals perceive as appropriate to share would need to be considered. Models of this complexity inherently require technology solutions, especially for the sharing to be scalable. Fortunately, a highly capable modern technology known as recommender systems would provide the affordance to share information between teammates intelligently by integrating multiple models [318].

With this in mind, the research motivation for this dissertation is twofold. First, I will briefly describe the research gaps pertaining to temporary team TMMs in the context of Computer-Supported Cooperative Work (CSCW). CSCW research has long been interested in supporting teamwork with technology including the cognitive aspects of teamwork (e.g., [272]). Second, I will describe the research gaps related to *group* recommender systems, a particular form of a recommender system that is highly relevant to this dissertation.

1.2.1 Temporary Teams, Team Mental Models, and CSCW

As described in the Problem Motivation section (1.1), it is important to support TMMs on temporary teams. Although research has shown how *task*, *equipment*, and *team interaction* TMMs can be supported on temporary teams through experience, training, and cross training (e.g., [348, 103, 237]), less is known regarding how to support *teammate* TMMs with unknown teammates. The field of CSCW has revealed two potential avenues for supporting *teammate* TMMs on temporary teams including: (1) selectively choosing team composition and (2) sharing teammate information.

First, various computer-supported approaches have been used to select team members that might naturally have more similar TMMs including the use of recommender systems [377]. These methods result in teams with more shared work experiences [86], more social connections [133], or similar learning styles [210]. In this way researchers have considered using technology to selectively choose team members who are more similar to promote team outcomes. However, temporary teams often do not have the luxury of selecting members to optimize *teammate* TMMs and are formed based on the skills required and the availability of members [45].

The second approach to support *teammate* TMMs on temporary teams, although not explicitly stated through the lens of TMMs, has involved sharing teammate information with other team members. Initial research has shown that sharing teammate skill information with technology relates to improved performance and teammate satisfaction on temporary virtual teams [409]. Other CSCW research has suggested using technology to share teammate personality and tendency information in addition to teammate skills during team formation [118, 394]. Although this line of inquiry shows promise, little research has investigated what information to share to specifically promote *teammate* TMMs in the temporary team context. Thus, the following research gap still exists:

> *The literature has investigated sharing teammate information to improve teamwork on temporary teams; however, the lens and motivation of promoting teammate TMMs has yet to be explored including what information to share.*

Another factor to consider is privacy when dealing with personal information sharing. *Teammate* TMMs deal with knowledge of teammates. This knowledge is multi-faceted and might contain information about teammate skills (e.g., what they are good at, what they are bad at), preferences, tendencies, and attitudes. Privacy can be defined as controlling personal information [350]. And in the technology context, privacy concern has been defined as concern about losing privacy from sharing personal information to an external agent (e.g., technology) [407, 95, 406] or to group members through the use of technology [274]. Therefore, the concept of sharing personal information (e.g., teammate skills, tendencies, etc.) by technology will likely cause privacy concerns for some and should be considered. For instance, some studies have looked at having team discussions about their personality traits instead of having technology share the information [303, 69]. Alternatively a study looked at sharing anonymized/aggregated results as a means to reduce or minimize privacy concerns [288]. Importantly, the prior studies that have investigated such direct teammate information sharing (e.g., skills information [409] and personality information [394]) have not considered how to share the information to mitigate privacy concerns. More research is required in order to understand the numerous human factors involved in teammate information sharing so that such a system is effective and accepted. Thus, the following research gap still exists:

> *The primary focus on previous tools to share teammate information has been on improving teamwork with little attention paid to privacy concerns and how these can be reduced through the sharing process.*

1.2.2 Group Recommender Systems and Information Sharing

To address the problem motivations previously outlined (i.e., the opportunity to selectively share teammate information to accelerate *teammate* TMMs on temporary teams), a new technology needs to be conceptualized. This technology, an information-sharing recommender system, is inspired by recommender system technology. Recommender systems use algorithms, often artificial intelligence (AI), to suggest items or information that a particular user might be interested in (e.g., music, movies, news) [319, 318]. These systems are typically designed for users who typically do not have the experience or time to sift through an overwhelming number of possibilities [318].

The attributes of recommender systems seem promising for the challenge of sharing teammate information. If the goal of sharing teammate information is to accelerate the development of *teammate* TMMs, team members do not have time to sift through large amounts of data about their teammates, nor do they likely have the expertise to know what information is the most helpful to know. Information-sharing recommender systems could utilize data for each member on a team and selectively share helpful information relevant to teamwork in a teammate-specific manner (i.e., Teammate A would receive information about Teammate B and C; Teammate B would receive information about Teammate A and C; etc.). A full description of this conceptualized technology, including a description of the research platform used in this dissertation can be found in Chapter 3.

Importantly, an information-sharing recommender system is novel and needs to stand on the shoulders of researchers who have worked on similar technologies. In this regard, group recommender systems offer a highly relevant research field to this dissertation. A group recommender system, compared to a typical single-user recommender system, makes recommendations to a group by accounting for preferences of each member (e.g., Recommendation: "This group might be interested in the movie *The Fellowship of the Ring*") [167, 87]. This differs from an information-sharing recommender system which involves recommending pieces of teammate information to individual members on the team (e.g., Recommendation: "Do not bring up fantasy movies around teammate Tim because they will get distracted"). However, the similarities between these two types of recommender system are numerous, particularly involving privacy, which makes group recommender system research a valuable field of research to draw from.

Group recommender systems must use individual preferences to generate group recommendations [167]. Importantly, these recommender systems must also provide explanations for recommendations that are unwanted by some members (e.g., Situation: "Chris is not interested in watching *The Fellowship of the Ring* and does not understand why the system is recommending that movie"). As explanations in group recommendations might divulge individual preferences (e.g., Explanation: "Tate and Maggie *REALLY* like movies inspired by Tolkien books"), the explanations provided might create privacy concerns for group members [240, 279, 277]. Therefore, a parallel can be drawn between a recommender system that shares teammate information to support *teammate* TMMs and a group recommender system that provides explanations to help groups reach a consensus. Both systems involve the potential of sharing information to other members in the group, potentially creating privacy concerns.

This body of research has pointed to important findings such as crafting explanations that exclude personal information that users do not want to share [277] and considering both efficacy and privacy when presenting explanations [239, 279]. Other research has investigated how various factors relate to member information disclosure in group recommender systems including individual differences (e.g., personality and conflict management styles), the context of the group, and the sensitivity of the information [278, 274, 278, 306].

Although these findings are important, less is understood regarding how they relate to such a different context (i.e., teammate information sharing). A teammate information-sharing recommender system involves notable differences including: (1) they share personal information *as the recommendation* rather than sharing member preferences as part of the explanation and (2) they specifically involve the teaming context which contains important motivational differences from a group [129]. These distinctions require a thorough investigation to create preliminary guidelines so that researchers and designers can understand how to explain the recommendations and how certain factors such as personal differences, information type, and group type influence disclosure. As users feel more comfortable sharing more information, more helpful information can be shared (information-sharing recommender systems) and better explanations can be provided (group recommender systems). Thus, the following two research gaps exist:

The concept of sharing personal information as the recommendation in recommender systems is novel and requires preliminary understanding and *guidelines to promote efficacy while reducing privacy concerns.*

Prior recommender system research has only investigated leisure group contexts with the specific teamwork context yet to be examined and how it might influence privacy concerns and disclosure.

1.3 Research Questions and Gaps

This dissertation addresses numerous dissertation-wide and study-specific research questions that all fall under the umbrella goal of **understanding how a teammate information-sharing recommender system can be designed to promote *teammate* TMMs while limiting privacy concerns**. Table 1.1, outlines the overall research questions that motivate and guide this dissertation as well as this umbrella research question, RQ0.

RQ#	Research Question
RQ0	How can a teammate information-sharing recommender system be designed to promote *teammate* TMMs while limiting privacy concerns?
RQ1	What teammate information should be used/shared to promote teammate TMMs while limiting privacy concerns on temporary teams?
RQ2	How can teammate information recommendations be presented to promote *teammate* TMMs on temporary teams and positive system perceptions?
RQ3	How does a temporary teaming environment mediate disclosure behavior and privacy concerns in an information-sharing recommender system?
RQ4	How do other factors (e.g., individual differences, explanations) influence disclosure behavior and privacy concerns?

Table 1.1: Research Questions

Each of these research questions is built on an existing research gap or gaps. Table 1.2 outlines how the research questions of this dissertation relate to specific research gaps. Note that RQ0 is not included in this table as it is associated with all of the stated research gaps and encompasses all research questions.

Research Gap	Research Questions
The literature has investigated sharing teammate information to improve teamwork on temporary teams; however, the lens and motivation of promoting teammate TMMs has yet to be explored including what information to share.	RQ1, RQ2
The primary focus on previous tools to share teammate information has been on improving teamwork with little attention paid to privacy concerns and how these can be reduced through the sharing process.	RQ1, RQ2, RQ4
The concept of sharing personal information as the recommendation in recommender systems is novel and requires preliminary understanding and guidelines to promote efficacy while reducing privacy concerns.	All RQs
Prior recommender system research has only investigated groups with the specific teamwork context yet to be examined and how it might influence privacy concerns.	RQ3

Table 1.2: Research Gaps Being Closed By Research Questions

1.4 Summary of Studies

This dissertation utilizes four research studies to address the mentioned research gaps and research questions. Each of these studies are described in detail in their respective chapters. Further, a summary of each study is provided in the following subsections. At a high level, Table 1.3 outlines which studies contribute to each research question that this dissertation addresses.

Study #	Short Study Title	Research Questions Addressed
1	Information Sharing to Promote *Teammate* TMMs	RQ1, RQ2, RQ4
2	Anonymity and Explanations	RQ2, RQ3
3	Disclosure in Group/Team Contexts	RQ1, RQ3, RQ4
4	When and What to Explain	RQ2, RQ4

Table 1.3: Studies that Address Each Research Question

As this dissertation contains four studies, it has the opportunity to address each of the dissertation-level research questions from multiple angles. Although this is summarized in Table 1.3, Figure 1.1 provides a helpful visualization for how the different aspects of the dissertation, the research questions, and the studies are connected. This visualization has research questions organized by color (i.e., RQ1 - green, RQ2 - red, RQ3 - purple, RQ4 - blue) and has each study connected to various avenues of inquiry. For instance, information utilized (RQ1) is approached by Study 1 and Study 3 through different angles such as promoting *teammate* TMMs and benefit/privacy respectively.

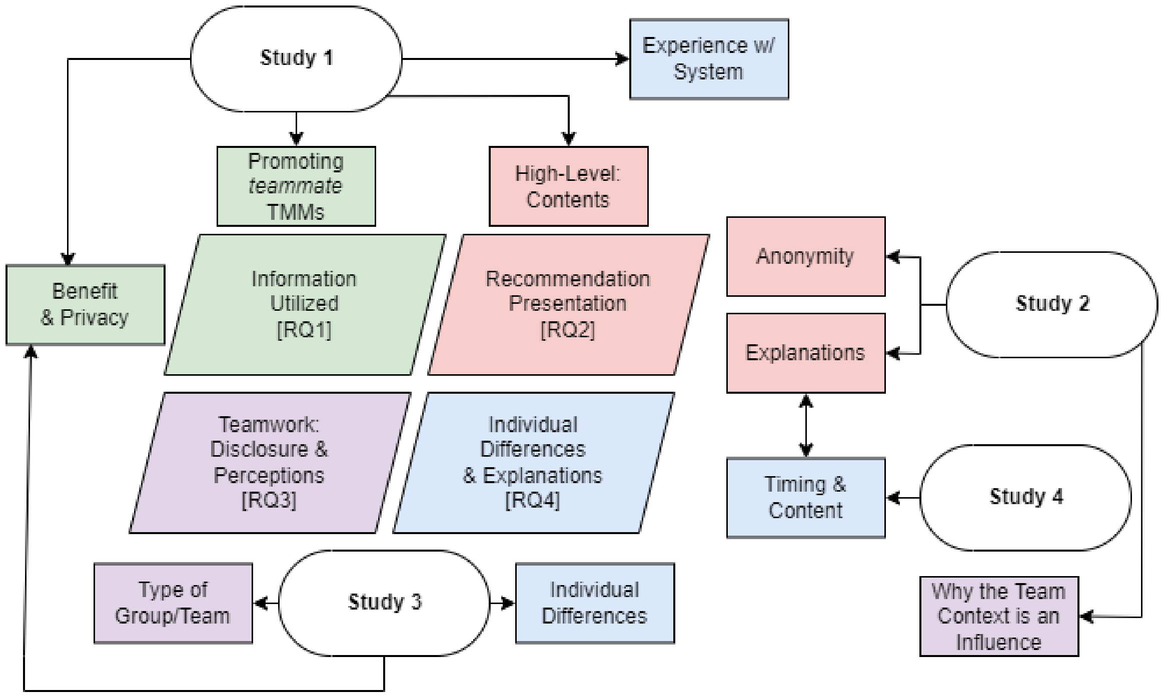


Figure 1.1: Study-RQ Connections

1.4.1 Study 1: Information Sharing to Promote *Teammate* TMMs

As Study 1 is the first study of this dissertation and the first study to explore information-sharing to promote *teammate* TMMs on temporary teams, it was important to take an exploratory approach. The highly exploratory nature of this study allowed for this first study to set the groundwork and motivation for future dissertation studies as well as an understanding for how the research platform should be designed.

This study utilizes actual temporary teams working on a semester-long undergraduate project. Qualitative data was collected to understand what information is important to share to promote *teammate* TMMs on temporary teams and how technology can improve the sharing of such information. Additionally, this preliminary study explores the use of two popular personal assessments, personality and conflict management styles, and how these assessments are perceived by temporary teams in terms of accuracy and the helpfulness/appropriateness of sharing such information.

The results from this study set a solid foundation for the dissertation. First, findings indicate that temporary teams are particularly interested in teammate information related to task skills/preferences, conflict management styles, and work ethic / reliability (RQ1). Second, thematic analysis revealed important insights into how sharing teammate information can be improved with technology including providing actionable insights as well as limiting the number of recommendations provided (RQ2). Third, quantitative results indicate that experience receiving teammate information improves perceptions regarding helpfulness and appropriateness (RQ4). Participants also found sharing conflict management information to be more helpful and appropriate (RQ1).

1.4.2 Study 2: Effects of Anonymity and Explanations on Team Outcomes and System Perceptions

The second study of the dissertation focuses on how recommendation presentation factors such as anonymity and explanations can influence user perceptions of the system as well as team outcomes. This study involved actual student teams working on semester-long projects. Each team received recommendations pertaining to each of their teammates with some teams receiving (a) anonymized information, (b) identified information, or (c) identified information with explanation provided. Repeated measures in the form of surveys were taken throughout the course of the project. Additionally, interviews were conducted at the conclusion of the project to understand how team members perceived the balance between privacy concerns and the benefits of using the system.

The quantitative data from this study resulted in important findings including: (1) identifying teammate recommendations is important to improve team outcomes (RQ2); (2) there was no evidence that anonymizing recommendations improves privacy perceptions (RQ2); and (3) participants were most satisfied with the system when the recommendations were identified with no explanations provided (RQ2). Additionally, thematic analysis revealed numerous insights regarding why they found the system to be beneficial to their *teammate* TMMs and why they did or did perceive there to be privacy concerns (RQ2, RQ3).

1.4.3 Study 3: Disclosure in Group/Team Contexts

Prior literature points to challenges in users providing personal information to group recommender systems. Since higher disclosure results in potentially better recommendations (e.g., more information to inform the algorithm), study two involves considering the group context as an important factor for personal information disclosure. Specifically, Study 3 compares groups versus teams and how this context distinction affects information disclosure. This distinction is further delineated by varying how the teams are assessed (i.e., 100% individually assessed, assessed 50% individual and 50% as a team, and 100% team assessed). While investigating how these contexts influence disclosure, individual differences are measured and analyzed to understand how such differences might influence information disclosure. Additionally, this study looks at personality and conflict management style assessments at an item level, 35 in total, to determine what information users are more/less willing to share, and which of these items they perceive as more/less helpful to receive.

The results of this study revealed insights pertaining to how group context, individual differences, and information type relate to disclosure behavior and system perceptions in an information-sharing recommender system. First, analysis revealed that there was no significant effect of group context on system perceptions (RQ3). However, there was a significant effect of group context on unconditional disclosure as individuals whose grades were fully dependent on the team's success were more likely to disclose information in the categories of emotionality and extraversion compared to participants in the other two conditions (RQ3). Second, this study revealed that the individual difference of personality-openness has a significant positive effect on disclosure behavior in the categories of emotionality and extraversion (RQ4). Third, this study showed how information type is related to disclosure (RQ1). Participants were significantly more likely to disclose information in the categories of Agreeableness, Conscientiousness, and Extroversion compared to the category of Emotionality. Furthermore, sensitive items are significantly associated with a decrease in disclosure in the category of Extraversion.

1.4.4 Study 4: When and What to Explain

Counter to prior literature (e.g., [371, 374]), Study 2 results did not show an increase in trust or satisfaction with the system. To better understand these results, Study 4 follows up and explores two factors related to explanation: (1) content and (2) timing/occurrence. Although typical recommender systems provide explanations when recommendations occur [371] and involve algorithmic content so that users know how the system reached a decision [369], the type of recommender system involved in this dissertation (i.e., information-sharing) is novel and requires exploration of alternatives. A promising alternate time for explanations would be during disclosure decisions as this could reduce privacy concerns. Likewise, the content of explanations could involve descriptions of disclosure benefit which might increase disclosure. Thus, the experimental design for Study 4 manipulates these as three variables with content (algorithmic rational or disclosure benefit), occurrence during disclosure (yes or no), and occurrence during recommendations (yes or no).

Study 4 resulted in findings in two categories: disclosure and system perceptions. All of the findings in this study simultaneously relate to RQ2 (presentation) and RQ4(explanations). For **disclosure**, results indicated that providing benefit explanations during disclosure had a near-significant positive effect on disclosure. For **system perceptions**, a Structural Equation Model (SEM) was created to reveal numerous findings. For instance, providing benefit-related explanations had a significant negative effect on privacy concern which partially mediated the relationship between benefit explanations and perceived helpfulness and system satisfaction. Additional findings such as interaction effects between occurrence and content and relationships between individual differences and other perceptions are fully described in Chapter 7.

1.4.5 Inter-Study Motivations

As described in Section 1.3, each of these studies is rooted in dissertation-level research questions that are motivated by gaps in the literature. In addition to these motivations, findings from studies in this dissertation motivated the direction of later studies as well as foundations for research design. This can be visualized in Figure 1.2.

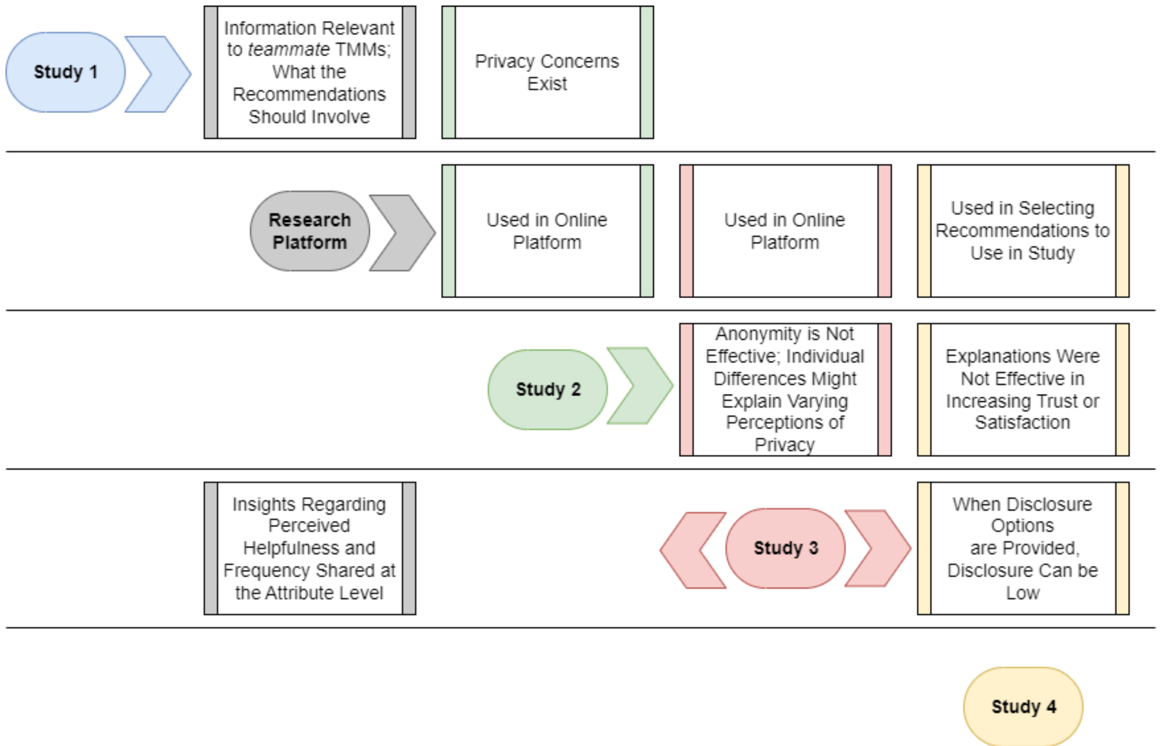


Figure 1.2: Inter-Study Motivations

It is important to note that this figure does not summarize all of the findings from these studies. Rather, it highlights how specific findings motivated other studies or aspects of the dissertation. In Study 1, preliminary findings regarding what information temporary teams find relevant to supporting *teammate* TMMs as well as what the recommendations should involve informed the initial design of the research platform. This research platform is described in full in Chapter 3. Study 1 findings confirmed that privacy concerns exist which motivated Study 2 to explore anonymity as a means to alleviate privacy concerns.

Study 2 revealed that anonymity was ineffective at reducing privacy concerns and qualitative findings suggested that individual differences might explain varying perceptions of privacy. These findings motivated Study 3 to investigate alternative ways to protect user privacy (i.e., disclosure settings) as well as individual differences that might be associated with privacy concerns. Further, in Study 2 it was found that the explanations used were not effective in increasing trust or satisfaction. These findings motivated Study 4 to investigate different content and timing for explanations. In Study 3 participants were provided the option to disclose or not disclose their information. This option resulted in many participants choosing to disclose very little about themselves. This finding motivated Study 4 to investigate other ways to encourage disclosure through communicating disclosure benefits (i.e., explanations during disclosure). Additionally, Study 3 provided findings regarding what information participants were more likely to share and more likely to perceive as helpful at an item level. This produced a disclosure-helpfulness matrix that assisted in selecting which attributes to use in the experimental design of Study 4.

As described above, Study 1 greatly contributed to the design of the online research platform. The online research platform (see Chapter 3) was used in Studies 2 and 3. Meanwhile, aspects of the research platform were used in the research design for Study 4.

1.5 Conclusion

As temporary teams are becoming heavily utilized in the modern workforce, it is important to understand how to support these teams, particularly through the acceleration of their *teammate* TMMs during team formation. Although prior studies have suggested the use of technology to support these teams through information sharing, *this dissertation is the first to explicitly study what information to share and how to share such information to promote teammate TMMs while limiting privacy concerns.* Through the use of four studies, each study provides a valuable and novel contribution toward the design of an information-sharing recommender system. Once again, Figure 1.1 provides an insightful overview of the contributions of each of the studies.

Study 1 contributes to teamwork literature by providing a high-level understanding of what information to share to promote *teammate* TMMs on temporary teams as well as what the recommendations should look like. Study 1 also contributes to recommender system research by providing a foundational and preliminary understanding of what recommendations should contain in an information-sharing recommender system.

Study 2 is the first study to explore how the presentation (i.e., anonymity and explanations) of an information-sharing recommender system influences team outcomes and system perceptions. Thus, these findings contribute to recommender system research with an understanding of what presentation elements are important to system perceptions and team outcomes. Additionally, this study contributes to teamwork literature by providing an understanding of why temporary team members perceive sharing teammate information to be beneficial.

Study 3 is one of the first studies to explicitly compare groups to teams and how that relates to disclosure behavior in recommender systems. This context was previously unexplored in group recommender system research; therefore, this study contributes to an understanding of how the team context influences disclosure. Further, this study contributes to both teamwork and recommender system research by providing empirical evidence of what individual differences influence disclosure behavior, what types of information are perceived as more helpful, and what information team members are less likely to disclose.

Finally, Study 4 is one of the first studies to investigate how explanations can be provided at different times and with different content to influence system perceptions and disclosure in a recommender system. These findings contribute to group recommender system research which seeks to understand how explanations can be better presented and how explanation content and timing/occurrence can influence disclosure behavior.

The contributions of these four studies provide a novel and essential understanding of how various aspects of information-sharing recommender systems relate to the efficacy and perception of the system. These contributions culminate in valuable design recommendations for practitioners as well as a significant foundation for future researchers interested in promoting *teammate* TMMs on temporary teams and/or studying information-sharing recommender systems.

Chapter 2

Background and Related Work

Due to the interdisciplinary nature of this dissertation, I draw upon three different fields of research including teamwork, CSCW, and recommender systems. This chapter is organized into four sections: (1) Teamwork and Temporary Teams, (2) Team Cognition and Team Mental Models, (3) Collaborative Technology and its Role in Teaming, and (4) Group Recommender Systems and Information Sharing.

The first section establishes background for the context of this dissertation, teamwork and temporary teams. A high-level overview of teamwork and the various aspects of teamwork that have been investigated to understand team effectiveness is provided. Next, this section contains a detailed description of temporary teams. Temporary teams are an important and commonly utilized type of team [362] that contain unique challenges (i.e., unknown teammates, short time period, and team disbandment) [86]. These challenges are revisited in subsequent sections through the lens of TMMs and how technology can help them overcome such challenges.

In the second section, an overview of team cognition is presented before focusing in on the important sub-construct of TMMs. For TMMs, I describe prior research pertaining to what TMMs contain and how they are measured. This body of research emphasizes TMM importance through relevant research on how TMMs relate to team performance and team processes [90]. Next, the ways in which TMMs are developed and supported are detailed including factors such as leadership, planning, experience, and training [238, 368]. Most important to this dissertation is how these TMMs are supported on temporary teams. These teams can potentially benefit the most from TMMs [238, 74], yet the nature of temporary teams (e.g., unknown teammates and time constraints) contain barriers to TMM development [368]. Thus, this section ends with an overview of the challenges associated with developing each of the four sub-domains of TMMs (i.e., equipment, task, team interaction, and teammate) and how each one can be supported on temporary teams. This overview points to many challenges in supporting *teammate* TMMs with sharing teammate information as one of the only ways to accelerate its development. However, more research is required to understand what information to share and how to share it.

The third section outlines the interdisciplinary field of CSCW and its contributions to computer-supported teamwork. Within this section, descriptions are provided for how various technology design solutions have supported cognitive aspects of teamwork including awareness, team cognition, and TMMs. As an extension to the previous section (2.2), this section reviews the literature involving CSCW systems that have aimed to improve TMMs as well as trust on temporary teams. However, few studies have provided insights into computer-supported teammate information sharing [409, 394]. In line with the TMM literature review, this review of the CSCW literature suggests that more research is required to understand *what* teammate information to share and *how* to share it to promote efficacy and reduce privacy concerns.

Finally, the fourth section provides an in-depth look at group recommender system explanations. This section begins by describing what group recommender systems are and how they compare to information-sharing recommender systems. Although there are differences between the technologies, there are many overlaps, and thus numerous insights can be gained. A review of prior research points to important literature gaps including: (1) group recommender system research has focused on sharing member preferences when explanations are required rather than member personal information as the recommendation itself [109, 279, 240]; and (2) a lack of group recommender system research that focuses on the teamwork context [278, 275, 306, 277]. These research gaps highlight the need for revisiting group recommender concepts in the information-sharing recommender context such as how to present explanations and how factors such as individual differences, information type, and group type might influence disclosure behavior in this novel context.

2.1 Teamwork and Temporary Teams

2.1.1 Teamwork and Team Effectiveness

Teamwork is an important area of research interest due to: (a) the ubiquity of teams in the modern workforce, (b) the potential of teams to achieve goals that would elude or be more challenging for the respective individuals, and (c) understanding team dynamics promotes the possibility of enhancing positive team outcomes [99, 58, 82, 291]. Although definitions for teams vary slightly in the teamwork literature, many utilize Salas et al.'s (1992) definition that a team is "a distinguishable set of two or more people who interact dynamically, interdependently, and adaptively toward a common and valued goal/object/mission, who have each been assigned specific roles or functions to perform, and who have a limited life span of membership" [329]. Put more simply, teams can be defined as two or more members with task interdependence and shared goals [101].

As expected, an abundance of teamwork research has focused on team effectiveness (e.g., how well teams meet their objectives) [331, 242]. A thorough review by Mathieue and colleagues involved looking at frameworks such as Input-Process-Outcome (IPO), Input-Mediator-Outcome (IMO), and IMOI (representing a cyclical IMO framework) to predict team effectiveness based on various factors [242]. Some research has focused on *inputs* such as training, leadership, and composition (e.g., ability and personality) in their ability to influence team effectiveness directly [23] or indirectly by affecting team mediating processes [161]. However, more research has focused on *processes* and/or *emergent states* and their effect on team outcomes [214, 236]. First, team effectiveness has been shown to be connected to *processes* such as team coordination and communication [224, 366], backup behaviors [304], conflict management [88, 170, 311], and feedback [124]. Second, emergent states (i.e., "cognitive, motivational, and affective states" [236]) such as team confidence [178], climate [280, 185, 89, 71], cohesion [25], trust [198, 218], and team cognition [90] influence team effectiveness.

Although all of these processes and emergent states are important to team effectiveness, team cognition (and more specifically the construct of team mental models) is of particular interest to this dissertation. Thus, the subsequent section, Section 2.2 will include more detailed descriptions of TMMs, their importance, and how they are developed.

2.1.2 Temporary Teams

This dissertation focuses on a specific category of teams known as temporary teams, particularly temporary project teams. Temporary project teams are an important teamwork research context in that: (1) they are an increasingly utilized form of teams in organizations [362, 233]; and (2) they contain different structure, processes, and outcomes from ongoing teams [332, 242, 326, 359]. This form of teamwork is growing in popularity due to their dynamic nature which supports intentional combinations of team members to meet the needs of specific tasks [86, 362, 73].

Although there is some ambiguity as to whether some teams should be considered *temporary* or *ongoing*, most of the literature supports categorizing teams as temporary if they meet four criteria [230, 8, 86]. These criteria involve one pre-task criteria (member diversity), two task criteria (time of task and task type), and one post-task criteria (members disbanding) [230]. First, temporary teams involve *member diversity* where members provide different skills and are often unfamiliar with one another [230]. As described by Dalal et al. (2017), temporary teams "spend little time together before they must begin working on their designated task" (p. 563) [86]. Second, temporary teams work together for a *short period of time* [134, 351, 60, 92]. Third, temporary teams are typically formed to work on *specific and complex tasks* [146, 281, 284]. And fourth, the team typically *disbands* after the task is completed [151, 16, 163, 251]. It is important to note that the second characterization, time, is relative and can cause issues for categorization (e.g., a team might exist for a long period of time with few interactions). For this reason, Bradley et al. (2003) classified teams based on the "intensity and duration" (p. 358) of member interactions instead of the length of the team's existence [41]. Further, these authors noted that ongoing teams typically have two elements that temporary teams lack: (1) they have established norms at the task's onset (i.e., they have a history of interactions); and (2) they have an expectation of future task interactions (i.e., not expecting disbandment) [41].

To better understand what temporary teams are, it is useful to look at what types of teams have been included in this categorization. Prior literature has pointed to four generic types of teams including functional, management, project, and ad hoc teams [150, 234, 308]. According to Saunders and Ahuja (2006), functional and management teams are considered ongoing while project and ad hoc teams are typically considered temporary teams [332]. In addition to project and ad hoc teams, terms such as short-term teams [41, 100], action teams, flash teams [86], and task forces [145] have been used to represent temporary teams. These temporary teams are also assembled for a myriad of purposes [16] including medical trauma teams [200], emergency response [115], military teams [159], film production [233], software development [160], Olympic teams [86], and learning teams [100].

As described above, temporary teams are prevalent and important. However, there are inherent challenges to teamwork based on the nature of these teams (e.g., unknown teammates, short time period, disbanding). First, these teams have the challenge of working with new teammates in contexts that are often new and dynamic. Tannenbaum et al. (2012) note the importance of these teams accelerating their team readiness since their projects are often launched quickly with little time to prepare (i.e., understanding their team and task) [362]. Second, the short time period that temporary team members exist limits their ability to establish norms, processes, teammate understanding, and expectations required to coordinate effectively which affects the team's performance [73, 161, 28]. This time pressure often requires teams to focus more on task completion and less on interpersonal interactions [332, 191]. Third, the aspect of disbanding these teams after they complete their task creates challenges. Ongoing teams have the benefit of performance cycles which allows for the refinement of mental models and processes for future tasks [236, 213, 242]. Disbandment also removes the "shadow of the future" [39] or anticipating interacting with teammates again [332]. This feature, along with the time pressure described previously, contributes to fewer interactions that are interpersonal and non-task related [39, 332]. These challenges for temporary teams will be revisited in Subsection 2.2.4.2 through the lens of understanding how TMMs can be developed and supported on these teams.

2.2 Team Cognition and Team Mental Models

2.2.1 Team Cognition

Of particular relevance to this dissertation is team cognition. The field of social psychology has increasingly gained interest in cognition at the collective level (i.e., group, team) in recent decades [368]. Team cognition is defined as a "cognitive activity that occurs at a team level" [76]. Team cognition has also been described as a "collective cognitive structure" that supports team interactions and behaviors [90]. Importantly, the relationship between team cognition and team interactions is cyclical as repeated interactions and processes foster the development of cognitive structures, which serve as a foundation to support subsequent team interactions [90, 214].

Research has consistently shown team cognition to be an important construct to teamwork with its ability to have a positive influence on team performance [90, 263, 55, 79, 76]. For instance, Mathieue et al. (2000) used a teamwork simulation program involving a fixed-wing aircraft and found that shared team-based mental models positively influenced team performance [244]. Salas et al. (2004) has described the ways that team cognition can serve as a guiding framework to investigate factors relating to team performance [330]. Marks et al. (2002) utilized a computer simulation methodology and found that team cognition improved team performance with coordination as a mediator [237]. And in a meta-analysis on team cognition, Dechurch

& Mesmer-Magnus (2010) found that team cognition has a positive relationship to team performance [90].

In addition to performance, team cognition is also a key predictor of task-related processes (e.g., team decision-making, team coordination) and motivational states (e.g., trust) [90]. McNeese et al. (2016) investigated how team cognition related to decision support for remotely piloted aircraft systems (RPAS). Their results pointed to team cognition facilitating collaborative activities in RPAS and they advocated for collaborative technologies to support team cognition [255]. Jackson et al. (1995) found that team cognition serves as a mediator of diversity in decision-making for teams [162]. Prior research has pointed to team cognition leading to improved team coordination [113, 255]. In addition to pre-planning and communication (i.e., explicit coordination), teams often rely on anticipation and dynamic adjustment (i.e., implicit coordination) which require team cognition [320].

As researchers have delved into the cognitive aspects of teamwork, it has become important to understand *what* exactly researchers are referring to when they reference the construct of team cognition. Although there are many sub-constructs that fall under the team cognition umbrella, researchers commonly use two sub-categories to describe team cognition including team cognition as (1) ecological interaction (a *process*) and (2) shared awareness (a *product*) [214, 113, 90, 263].

First, team cognition has been viewed through the lens of the process of ecological interaction (e.g., transactive memory [395], interactive team cognition [77, 253], group learning [11]). For instance, the construct of transactive memory has been used to describe how teams collectively encode, store, and retrieve information by knowing who possesses what information [395, 219, 300]. This form of team cognition sometimes involves viewing teams as information-processing units [154]. Improving team cognition in this way promotes increased efficiencies in teams as they are able to appropriately use information and allocate tasks [15].

Second, and more commonly, team cognition has been viewed as the product of shared awareness (e.g., team mental models [263], shared situation awareness [396], strategic consensus [190]). Most popular of these constructs, and most relevant to this dissertation, are team mental models (TMMs). TMMs are organized mental representations regarding the team environment that are distributed or shared by team members [263, 201]. These mental models are important to teamwork in that they: (a) provide a framework for compatible task allocation and duties and (b) allow team members an effective way to interpret changes to the performance environment [238]. A detailed description of TMMs, their importance, and how they are developed will be provided in the subsequent subsections.

2.2.2 Team Mental Models

Team members collectively being able to adapt to changing circumstances within their environment has long been considered an important skill in teamwork [52, 144]. But how do teams adapt to such change in an efficient and coordinated manner? Cannon-Bowers et al. (1993) have suggested that "team members hold compatible mental models that lead to common expectations for the task and team" (p. 236) [74]. In other words, TMMs put team members on the "same page" regarding what is happening, what is going to happen, and being able to predict what other team members will need so that the team's actions are coordinated and efficient with better support for decision-making [263, 74]. Mental models are organized mental representations of the world that allow individuals to predict what will occur next [324]. The construct of TMMs is used to describe how these knowledge structures are shared and used to promote team functioning [201]. Much of this work has been based on shared mental model theory which suggests that team members are able to predict the actions and needs of their teammates which can increase the team's performance [263, 74, 201].

Although many of the studies referenced in this section use the term *Shared Mental Model*, for the purposes of this dissertation, the term *Team Mental Model* will be used as a more general term to remove the ambiguity associated with the term 'shared' similar to prior research (e.g., [263, 201]). For instance, mental model *sharing* could refer to having overlapping models, having identical models, or even "dividing up" the cognitive aspects of teaming [317, 55], although there is usually an emphasis on the first category of overlapping mental models in prior literature [263]. Importantly, most researchers agree that mental models do not have to be identical in many teamwork environments. Rather, there is an emphasis on the mental models converging, having consistency, and being compatible [74, 316, 182].

2.2.2.1 Team Mental Model Content and Measurement

Before delving into the teamwork literature and describing the studies relating TMMs to performance and processes, it is important to note what these mental models *contain* and how these mental models are *measured*. First, as team members must hold multiple mental models simultaneously [323], researchers have organized the mental model content into various domains. For instance, early research commonly organized mental models into four domains including the *Equipment Model* (e.g., knowledge of technology and tools required), the *Task Model* (e.g., knowledge of work procedures and strategies), the *Team Interaction Model* (e.g., knowledge of role interdependencies and communication patterns), and the *Teammate Model* (e.g., knowledge of teammate preferences and skills) [74, 55]. However, more recent literature often simplifies and collapses these four domains into two to include the broader categories of *Task Model* and *Team Model* [244, 78, 263, 223, 245, 335]. This two domain categorization is consistent with parallel research that suggests teaming behavior often includes two tracks (i.e., a teamwork track and a taskwork track) [328, 215, 162, 267]. With this binary distinction, *task* TMMs include "work goals and performance requirements", while *team* TMMs include the "interpersonal interaction requirements and skills of other team members" (p. 880) [263]. A list of knowledge and information pertinent to each of these models can be found in Table 2.1 which was inspired by and adapted from previous writings and tables (e.g., [74, 335, 244].

Task Model	
Equipment	**Task**
Equipment Functioning	Procedures
Operating Procedures	Scenarios
System Limitations	Contingencies
Likely Failures	Strategies
	Task Component Relationships
	Environmental Constraints

Team Model	
Team Interaction	**Teammate**
Roles/Responsibilities	Teammates'...
Interdependencies	Knowledge
Interaction Patterns	Skills
Communication Channels	Attitudes
Information Sources	Preferences
Information Flow	Tendencies

Table 2.1: The Two Domains of TMMs

Second, TMMs are often measured or referred to using two properties including similarity and accuracy [244, 238, 227]. Whereas the former refers to how similar two teammates' knowledge structures are [244], TMM accuracy refers to how closely the mental models reflect the "true state of the world" (p. 728) [103]. Although researchers measure these two properties of TMMs separately, the combination of convergent and high quality models promote the greatest team benefits [243, 103, 347].

2.2.2.2 Team Mental Models and Team Performance

The positive relationship between TMMs and performance has firmly been established by researchers over the past four decades [263]. Some research has focused on TMM *similarity*. For instance, in a teamwork flight simulation study, Mathieu et al. (2000) found that task and team TMMs (similarity) related positively to both team processes and performance [244]. However, the task TMM similarity only had an indirect effect on team performance through team processes [244]. In a study involving project-based learning and college teams, Jo (2011) found that team and task TMMs were positively associated with team performance [172]. In Rentsch & Klimoski's (2001) teamwork study involving naturalistic work teams and paired comparison ratings, they found that task TMM similarity were related to team performance [315]. In the context of air traffic control teams, Smith-Jentsch et al. (2005) found that two factors of TMM similarity combined and interacted to influence team performance [349]. In a field setting, Kellerman et al. (2008) found a main effect of TMM similarity on decision quality [189].

Other studies have looked at both TMM *similarity* and *accuracy*. In a study involving dyadic teams working on a complex skill task, Edwards et al. (2006) found that TMM similarity and accuracy both predicted team performance with TMM accuracy also partially mediating the relationship between team ability and performance [103]. Using a command-and-control simulation, Ellis (2006) found that team interaction TMMs (similarity and accuracy) partially mediated the negative effects of acute stress on team performance [105]. Lim & Klein (2006) utilized a field study with action teams and found that both task and team TMM similarity and team TMM accuracy predicted performance [227]. Using three-member teams that participated in a tank simulation, Marks et al. (2000) found team-interaction TMMs positively influenced both communication and team performance [238]. However, they found that similarity was more important than accuracy regarding performance [238]. In Webber et al.'s (2000) study involving basketball teams, they found that task TMM similarity, but not accuracy, was significantly related to team performance [393].

In summary, TMM similarity has consistently shown to have a positive relationship to team performance [78, 79, 103, 105, 227, 237, 238, 243, 244, 315, 349, 189] including both taskwork (e.g., [227]) and teamwork (e.g., [244]) TMMs. Additionally, research on TMM accuracy typically indicates a relationship to team performance [78, 79, 103, 105, 227]; however, some studies suggest that this relationship is not as strong as TMM similarity's (e.g., [238] or have not found a relationship between TMM accuracy and performance at all (e.g., [393, 243]. However, it is likely that the teaming context plays an important role in how important specific types (i.e., task vs. team) and measurements (i.e., similarity vs. accuracy) of TMMs are. For instance, Marks and Zaccaro (2000) found that mental models "predicted performance more strongly in novel than in routine environments" (p. 971) [238]. In any case, multiple meta analyses have strongly documented TMM research and conclude that there is a strong relationship between TMMs and performance regardless of team type or measurement type [263, 90, 91].

2.2.2.3 Team Mental Models and Team Processes

TMMs are also positively associated with team processes including both taskwork (e.g., [244, 243] and teamwork (e.g., [138, 237]). In a computer simulation study, Marks and colleagues (2002) found that TMM similarity was associated with improved coordination and backup behaviors [237]. These findings were complimented by Schmidt et al. (2014) who found that TMMs improved backup behaviors in Information Systems development teams [336]. Waller et al. (2004) investigated TMMs in nuclear power plant control room crews and found that TMMs improved communication [389] which compliments similar findings by Marks et al. (2000) [238]. Importantly, the ability of TMMs to improve processes such as coordination and communication are of particular interest to teams that work under stressful, time-sensitive, or unusual situations where time constraints do not allow teams to freely communicate and strategize [54, 238]. In addition to communication and coordination, other studies involving TMMs have shown a relationship to other team processes such as strategy implementation [138], collective efficacy [245], confrontation norms [189], situational awareness [357], and engagement [259].

2.2.3 Techniques for Development of Team Mental Models

As mentioned in the previous subsections, TMMs are of great importance to teams in that they support both team performance and team processes. Thus, many researchers have focused on how TMMs are developed and supported. At a high level, mental model convergence typically begins when team members begin interacting with one another and continues to develop throughout the task through subsequent interactions and observations [368, 249]. This process has previously been described to contain three different phases where team members: (1) orient themselves to their teamwork situation (orientation); (2) create their personal view of the situation (differentiation); and (3) adapt their personal view into a team view (integration) [256, 250].

Some research has pointed to the importance of certain factors that are predictive of teams having improved TMMs. For instance, in a study involving student groups working on research projects, Peterson et al. (2000) found that collective efficacy (i.e., a group's judgement of their ability to perform a task) had a positive effect on TMMs (including both teamwork/taskwork TMMs and similarity/accuracy measurements) later in the semester [302]. Rentsch & Klimonski (2001) identified other various factors that correlated with TMM similarity including similar education level among team members, similar levels of team experience, and smaller team size [315]. Although these factors have been important to identify, other researchers have typically focused on team-level interventions to improve TMM development such as leadership, planning, experience, and training [263].

First, some research has pointed to the importance of leadership and planning. Gurtner et al. (2007) found that TMMs were more similar on teams who received guided reflexivity interventions and when commanders communicated task strategies [138]. Another study found that leader briefings had a positive effect on TMM development [238]. Research involving the esports context revealed that players perceive TMM development to be supported by planning sessions between games and by leaders sharing a unifying vision for task strategy [272]. Importantly, other research has pointed to the importance of high-quality planning (over low-quality planning) in having improved TMMs [358]. The same holds true for leadership quality as leaders with inaccurate TMMs might cultivate high TMM *similarity* with low TMM *accuracy* [272] which could have detrimental effects on team performance [227].

Second, researchers have investigated the importance of experience to support TMMs. Smith et al. (2001) explored the relationship between experience and TMMs for Navy service members and found that members with higher rank and time in service had more similar TMMs, while members with higher rank had more accurate TMMs [347]. Similarly, Edwards et al. (2006) found that team ability was related to TMMs, but the relationship was stronger for TMM accuracy than to similarity [103]. Notably, experience with the task is not the only kind of experience that supports TMM development. In addition to experience with the task, researchers in the esports context found that experience with teammates provides support for TMMs in novel tasks [272]. Similarly, a study involving project-based learning for college student teams found that team member interaction predicted both team and task TMMs [172]. Blickensderfer et al. (2010) investigated sports teams and found that experience playing together improves team TMMs (e.g., skills of teammates and how the team operates) which supported implicit coordination [36]. Further, simply having experience with teamwork is positively related to TMM similarity [315]. It should be noted that not all experience results in the same benefits to TMM development. Research has pointed to the importance of intentional interactions during teamwork (e.g., group learning) to facilitate TMM development [262, 381]. Group learning involves group interactions that support development, modification, and reinforcement of TMMs [262].

Third, the largest amount of research attention to enhance TMM development has been placed on team training and development [263, 342] which are seen as highly effective and efficient ways for teams to converge their TMMs [53, 341]. As described by Salas et al. (1997), the purpose of team training is "to foster in team members an accurate and sufficient mental representation of the team task structure, team role, and the process by which the two interact" (p. 362) [327]. For instance, Smith-Jentsch et al.'s (2008) research found that guided team self-correction resulted in more accurate TMMs [348]. In another study, teams that participated in team-interaction training had improved similarity in their team-interaction TMMs [238]. Further, computer-based training that involves teamwork competencies has been shown to improve both accuracy and similarity of TMMs [347]. As discussed in the previous paragraphs (i.e., leadership/planning and experience), the quality of the intervention matters. Findings by Van Boven & Thompson (2003) give evidence that experience-based training is superior to instruction-based training in developing TMMs [380].

In addition to the forms of training mentioned above, a particular type of training, cross-training, has received repeated interest in the teamwork literature. Cross-training is defined as "an instructional strategy in which each team member is trained in the duties of [their] teammates" (p. 87) [386]. Through this process, team members are able to acquire knowledge of other roles and perspectives on the team [56, 386]. This knowledge supports awareness of other team member's roles and interdependencies which, therefore, supports more accurate and similar TMMs [35, 263]. Some research has pointed to cross-training improving similarity for team-interaction TMMs [237]. While other research has shown that cross-training contributes to the accuracy and similarity of both taskwork and teamwork TMMs [79]. Marks et al. (2002) suggested that cross-training is particularly useful for developing TMMs on action teams which are categorized by highly interdependent roles [237].

2.2.4 Development of TMMs on Temporary Teams

A perplexing challenge for temporary teams is that TMMs are often more important for their teamwork context, yet they can be harder to develop. On one hand, TMMs are typically thought to be essential for time-constrained or emergency environments where explicit communication cannot be easily utilized [74, 293]. This is also true for fast-paced virtual environments that involve teaming with temporary or pickup groups [272]. Temporary teams also typically perform tasks in novel environments [362, 86]. As research has shown that TMM similarity is more predictive of performance in novel than in routine environments [238, 389], temporary teams often stand to benefit more from TMMs than ongoing teams.

On the other hand, factors that are typical for temporary teams often have negative effects on TMM development (e.g., unknown teammates, short time period, disbanding). Full descriptions of these characteristics are provided in Subsection 2.1.2 and include: (1) teams are composed of unknown teammates [230, 86]; (2) teams work together for a short period of time [134, 351, 86, 60, 92, 332]; and (3) the team typically disbands after the task is completed [151, 16, 163, 86, 251, 332]. These characteristics can pose obstacles for TMM development. First, experience with teammates through previous interactions inside or outside of the team environment can promote TMM development [272, 172]. Since interactions between teammates are the main way in which TMMs are developed [368, 249], teams with limited teammate interaction prior to the commencement of the task may be limited. Second, the short time period associated with temporary teams working together limits their ability to gain experience with one another "on-the-job" which makes establishing teammate TMMs challenging [213, 272]. Third, the inherent nature of disbanding temporary teams removes the benefits of performance cycles that allow for the refinement of TMMs for future tasks [236, 213, 242, 161]. In addition to these TMM development challenges that most temporary teams face, many temporary teams must deal with stress in their team environments (e.g., medical trauma teams [200], emergency response [115], military teams [159]), which can have a negative influence on TMM similarity and accuracy [105].

2.2.4.1 Developing Specific TMM Domains on Temporary Teams

Although the challenges for developing TMMs on temporary teams may seem daunting, there are many different types of TMMs that can still be supported naturally or with typical interventions. It is helpful to refer back to 2.2.2.1 and Table 2.1 to note that researchers typically categorize TMMs into two domains including the *task model* and *team model* [244, 78, 263, 223, 245, 335], which can be thought to contain two sub-domains (i.e., *equipment/task* and *team interaction/teammate* respectively) [74, 55]. The following paragraphs as well as Table 2.2 provide an overview of each of these sub-domains, the challenges that temporary teams face in developing these TMMs, and the ways that temporary teams can be supported.

Model	**Contains (e.g.,)**	**Support**	**Challenges**
Task - Equipment	Equipment Functioning, Operating Procedures	Training, Experience	Novel Equipment
Task - Task	Procedures, Scenarios, Contingencies	Training, Experience, Leadership	Generalizing, Novel Environments
Team - Team Interactions	Roles, Responsibilities, Interdependencies, Information flow	Training, Cross Training, Experience, Leadership	Generalizing, Novel Roles or Environment
Team - Teammate	Knowledge, Skills, Attitudes	Selective Composition, Sharing Teammate Information	New Teammates, Limited Task Time, No Performance Cycles

Table 2.2: Challenges and Support for TMMs on Temporary Teams

First, the *equipment* (e.g., equipment functioning, operating procedures) and *task* (e.g., procedures, scenarios, contingencies) sub-domains of TMMs (particularly their accuracy) can be supported on temporary teams through training [348] and experience [348, 103]. For instance, temporary military teams can be trained on procedures and equipment ahead of time [119] (i.e., *equipment* TMM) or medical trauma teams can use simulation training [165] to improve their *task* TMM. Although training and experience can greatly support *equipment* and *task* TMMs, it should be noted that challenges can occur when temporary teams must generalize their TMMs from the specific tasks and environments that training involved (e.g., emergency response training) [115].

Second, the *team model* contains both *team interaction* and *teammate* TMM sub-domains. Similar to *equipment/task* TMMs, training and experience can support *team interaction* TMMs (e.g., roles/responsibilities, interdependencies, information flow). For instance, esports players that have experience with the game and roles can quickly develop TMMs with new teammates [272]. In addition to experience, cross-training can particularly be helpful to teams in developing an understanding of roles and interdependencies [35, 263, 79] and have been shown to be useful for temporary teams [237]. Importantly, the *teammate* TMM sub-domain (e.g., knowledge, skills, and attitudes of teammates) is challenging to support for temporary teams. This is perhaps due to the team-specific nature of this TMM compared to the generalizability of equipment, task, and team interaction TMMs [52, 326]. Interactions between teammates are the main way in which *teammate* TMMs are developed [368, 249, 173] and these interactions on temporary teams are limited [351, 60, 92]. Notably, the three main characteristics of temporary teams that pose challenges for TMMs (i.e., unknown teammates, short time period, and disbanding) all affect the *teammate* TMM sub-domain the most.

2.2.4.2 Accounting for the Teammate TMM on Temporary Teams

As supporting the development of *teammate* TMMs provides the most challenges for temporary teams, researchers have investigated various interventions to support the acceleration of these TMMs, namely supporting team member understanding of their teammates' knowledge, skills, attitudes, preferences, and tendencies. This has been targeted through two main categories of interventions including *selective team composition* (e.g., [86]) and *sharing teammate information* (e.g., [394]).

For team composition, various approaches have been used. In research involving Olympic ice hockey teams, Dalal et al. found that teams that contained members with more shared work experiences with other members had higher team performance [86]. Their initial conclusions suggested that "all else [being] equal, choosing the individual with shared work experiences with other team members will result in better performance" (p. 573) [86]. Meanwhile, other research has shown that members on temporary teams often seek out prior social connections (higher team TMMs) during team formation to the detriment of having non-diverse teams [133]. Although these findings are useful for assembling some temporary teams, other temporary teams are composed of complete strangers (e.g., [230]). To account for this, many researchers have investigated the use of team formation algorithms to promote team cohesion including the use of a recommender system for team assembly [377]. This has involved using team formation tools such as CATME [21] to select teams based on skills, working styles, and demographics [164, 404]. Meanwhile other researchers have used factors such as collective intelligence and coalition structure generation [379] or learning styles [210] to form temporary teams. This research attempts to promote team cohesion on temporary teams by curating the "optimal" teams.

However, in many cases, temporary teams are not able to be optimized using a selection of candidates and are instead formed out of convenience based on their appropriate skills for the task at hand [45]. For these situations, other research has focused on improving team cohesion and *teammate* TMMs by providing team members with information about their teammates *after* team formation (e.g., knowledge, skills, attitudes). Sharing this teammate information is especially important as improving interpersonal understanding is predictive of team performance on temporary teams [100]. Yang et al. (2015) investigated fast-response spontaneous virtual teams (i.e., team-based online games) and found that sharing sharing skills information was positively related to perceived task cohesion which was positively related to team performance [409]. However, less is known regarding what information to share (e.g., efficacy and efficiency) and how to share it (e.g., privacy) which has inspired the work of technology solutions (to be described in subsequent sections).

2.2.5 Summary

A review of the team cognition and TMM literature emphasizes the importance of the team cognitive aspects of teamwork and their influence on team processes and performance [90, 76]. The importance of TMMs is further emphasized on temporary teams which often involve novel environments, fast-paced decisions, and/or communication challenges that necessitate TMMs [74, 293]. Although much research has investigated how TMMs can be supported, even on temporary teams, research is limited regarding how specifically the development of *teammate* TMMs can be accelerated on teams. These members often work with unfamiliar teammates and are limited by time and task cycles that limit interactions that would support *teammate* TMM development [86]. Although preliminary research points to teammate information as a way to support *teammate* TMMs, more research is necessary to understand what to share and how best to share it.

2.3 Collaborative Technology and its Role in Teaming

2.3.1 Computer-Supported Cooperative Work and Teamwork

Either due to the complexity of teaming in the modern world or perceived advantages of using technology in teamwork, natural research questions have arisen such as, "How can the coordination requirements of cooperative work arrangements be accomplished more easily, rapidly, flexibly, comprehensively, etc. with information technology?" (p. 5) [337]. To address this and parallel questions, the field of research known as Computer Supported Cooperative Work (CSCW) (sometimes referred to as Computer-Supported Collaborative Work [106]) emerged and has become an established field of research in its roughly 35 years of existence [338]. The field of CSCW research is continually in flux due to certain inherent characteristics of the field including: (1) it is comprised of interdisciplinary researchers, (2) the research does not focus on a singular group of technology, and (3) the technology itself is constantly advancing [338]. However, certain characteristics of the research field have emerged. According to Bannon (1992), CSCW research should focus on proactively improving the design of technology to support collaboration rather than reacting to poorly designed existing technologies [18]. In this way, CSCW research puts cooperation first rather than a technology-driven approach [337]. Succinctly put, CSCW has been described as "an endeavor to understand the nature and characteristics of cooperative work with the objective of designing adequate computer-based technologies" (p. 360) [17].

To organize the factors and considerations relevant to CSCW researchers and practitioners, various researchers have attempted to classify different components of CSCW research and propose taxonomies (e.g., [84, 80, 137, 387, 301]). In the meta-analysis conducted by Cruz et al. (2012), their work resulted in a classification model to organize both technological and social requirements of CSCW systems [84]. This classification [84] includes: (1) time and space (i.e., synchronous/asynchronous and co-located/remote distinctions) [289, 34]; (2) CSCW characteristics (e.g., cooperation, coordination, communication, division of work) [120]; (3) group issues (e.g., size and task types) [67]; (4) technical criteria (e.g., scalability) [246]; and (5) complementary features (e.g., usability, awareness) [142].

Although the broad CSCW research umbrella focuses on how technology can support collaboration, much of this research has specifically focused on the teamwork context. As such, teamwork is one of the most consistently mentioned keywords in CSCW research [80] as CSCW researchers have been investigating the teamwork context for decades [67, 120]. This body of research has investigated a multitude of teamwork contexts including domains such as healthcare [149, 104, 312, 9, 235], manufacturing [265], education [344], software development [142, 143], and online games [221, 361, 403]. Factors important to teamwork have been investigated such as lifespans of teams (ongoing [332] and temporary [212]), composition (dyads [117], larger teams [322], and even human-agent teams [254, 108, 121]), distance (collocated [313] and distributed [305]), and stage of teamwork (e.g., team formation [184]).

Notably, there are numerous factors that are important to CSCW teamwork researchers making it an expansive field to review; therefore, the scope of this section will be limited to important cognitive aspects of CSCW teamwork including awareness, team cognition, and, most important to this dissertation, *teammate* TMMs. These topics will be discussed in detail in the following subsections, 2.3.2 and 2.3.3.

2.3.2 Technology - Supporting Awareness and Team Cognition

2.3.2.1 Awareness

There has been a significant amount of research dedicated to the cognitive aspects of teamwork in CSCW including awareness and team cognition [353]. First, research has focused on the importance of technology supporting awareness in teams (e.g., [141, 140, 139]). Awareness in CSCW is commonly defined as "an understanding of the activities of others, which provides a context for your own activity... [which] allows groups to manage the process of collaborative working" (p. 107) [98]. Importantly, awareness has been identified as a way to facilitate team cognition by providing members a general awareness for what the team is doing as a whole as well as specific knowledge of team members who share role interdependencies [142]. For instance, research involving shared displays and shared workspaces is a popular area of CSCW research (e.g., [47, 268]). Prior studies have identified the importance of shared displays in supporting teamwork through monitoring group awareness and conversational grounding through observation of body language and gaze [388, 126, 94]. Other research has focused on distributed teams. Guzzi et al. (2015) studied software developers and found that they rely on information from their integrated development environment to maintain awareness of their teammates' progress in order to coordinate timing of tasks [143]. In virtual environments, tools are designed to support spatial awareness so that members maintain awareness of where their teammates are as well as other objects relevant to the task within the environment [283, 334]. Much of this research has focused on esports which highlights the importance of awareness in both temporary teams and fast-paced environments (e.g., [228]. Players utilize pings (non-verbal spatial markers) [221] as well as other annotations [403, 7] to improve awareness in the team regarding member intentions, enemy locations, and other information relevant to the task [402].

2.3.2.2 Team Cognition

Second, research has shown promise regarding ways in which technology can be involved in or support team cognition [400, 399, 114]. Much of this research has highlighted the importance of team cognition in virtual environments (e.g., [196]) while also teasing out the relationships between team cognition and factors such as experience, awareness, and communication.

As mentioned earlier, esports research has shown that experience with teammates (teammate TMMs) as well as experience with the game (task and team interaction TMMs) support team cognition in virtual environments [272]. For awareness, Convertino et al. (2009) provided numerous insights from a study comparing face-to-face teams and distributed teams performing emergency management planning [75]. Using a shared map, team cognition was supported by members being aware of other actions taking place by teammates which facilitated implicit sharing [75]. In a laboratory setting involving collocated teams, McNeese & Reddy (2017) found that search, information, and social methods of awareness were important factors for developing team cognition during collaborative information seeking tasks [256].

Regarding communication, its involvement with team cognition is twofold: communication supports team cognition and team cognition often takes the form of implicit communication in virtual environments. Schelble et al. (2022) investigated both all-human teams and human-agent teams and identified the importance of supporting communication for accelerating the development of team cognition in both types of team composition [333]. Similarly, other research involving human-agent teams showed that team and task TMMs are related to the agent's verbal and non-verbal communication ability [147]. When teams participate in team cognition, it can take the form of teams being able to limit their verbal communication so that they can make team decisions quickly [272]. This finding aligns with other research which shows the importance of team cognition through nonverbal communication such as interpreting objects in joint work [313] or observing teammate actions [364]. Gergle (2004) noted that "action replaces explicit verbal instruction in a shared visual workspace" [125].

Thus, CSCW research has shown that experience [272], awareness [256], and communication [333] support team cognition, which often takes the form of implicit communication in computer-mediated environments [125]. In line with these findings, numerous CSCW researchers have attempted to design platforms and simulations to specifically support team cognition such as a simulated fire emergency response for distributed teamwork [373] and an emergency management planning task [401]. This line of inquiry has even extended to supporting team cognition between humans and AI on human-agent teams (e.g., [412, 270, 269, 410]. Although CSCW researchers have consistently investigated how to support team cognition with technology and have even investigated how humans can participate in team cognition with AI teammates, less is known regarding how AI can support team cognition between human teammates, specifically their *teammate* TMMs.

2.3.3 Technology - Supporting Teammate TMMs and Trust Through Information Sharing

Most important to this dissertation is understanding how technology can support *teammate* TMMs, particularly on temporary teams. As described earlier in Section 2.2.4.2, some technology research has focused on interventions to change team composition (e.g., [86, 404]; however, supporting *teammate* TMMs by selectively picking team members based on familiarity or compatible personalities is not always feasible [45]. Thus, CSCW researchers have pointed to the utilization of sharing teammate information to support *teammate* TMMs (e.g., [394]. It is important to note that high-performing teams often exchange personal information during the early stages of teamwork [169]. But how has this information sharing been facilitated by technology?

The teamwork and technology literature provides examples of sharing *team-*

mate information, including skills and personal information, to support *teammate* TMMs. Yang et al. (2015) conducted research on fast-response spontaneous virtual teams (FRSVTs) and found that supporting *teammate* TMMs positively related to perceived task cohesion, which was positively related to FRSVT performance and teammate satisfaction [409]. In this study, *teammate* TMMs were supported by technology that shared teammate skill levels (obtained through skill-profiling tools) as well as playing tendencies (obtained through clan membership and governance rules) [409]. In a study involving esports, Freeman and Wohn (2019) investigated various team formation strategies so that teams could know and judge their teammates before the team was formed [118]. This teammate understanding is particularly valuable in esports where teams must coordinate and communicate under time pressure [118, 272]. Their findings suggest that teams often use a computer-mediated trial process to play together and gain experience to understand each other's skills and temperaments [118]. Additionally, the authors provided valuable design implications including suggesting a system that could provide teams with each other's social cues and tendencies (in addition to skills and competencies) to better understand one another during team formation [118].

In line with this, a recent article has attempted to address this issue by suggesting the use of AI to provide team recommendations based on member personalities to facilitate and strengthen teamwork after team formation [394]. However, less is known about how such a system would be perceived in practice by team members regarding acceptance and privacy concerns. Of interest is a study that involved designing an interactive visualization tool to configure which personality traits to share [391]. Although their findings indicated that the tool was effective, this research focused more on general workplace sharing rather than sharing within teams in addition to focusing on visual user-interface elements [391].

The CSCW literature is fairly thin with regard to the specific aim of supporting *teammate* TMMs by sharing teammate information. However, more CSCW literature has investigated how trust can be supported on temporary teams by sharing such information, and a review of such literature provides valuable insights to teammate information sharing. Calefato and Lanubile (2013) presented a social awareness platform to facilitate trust and establish interpersonal connections by sharing teammate personal interests [50]. They predicted that team members were likely to adjust their working styles to accommodate each other due to computer-mediated accelerated social awareness [50]. Similarly, other research on virtual teams has suggested that opportunities such as team-building activities can reduce negative biases and improve trust in teams [181, 158] by allowing team members to "accumulate personal knowledge of each other" [158]. These findings are supported by other research involving virtual teams which has shown that making information about teammates more available can increase trust during the initial phase of collaboration [325]. In an empirical study focused on online communication, results indicated that providing users with information that highlighted similar experiences could promote empathy and build interpersonal trust [111]. Schumann et al. (2012) found that sharing teammate information including domain expertise and personal hobbies enhanced cognitive and affective trust respectively, and could lead to members sharing more and better ideas [339]. However, their research also points to some potential side effects of teammate information sharing such as misconstruing professional competency [339].

2.3.4 Summary

The field of CSCW is a well-established field of interdisciplinary research that aims to promote collaboration in groups through improved design [338]. This body of literature has made many contributions to the computer-mediated teamwork context. Specific to this dissertation, there is a well-established precedence for using technology to support the cognitive aspects of teamwork (e.g., awareness, team cognition, TMMs) due to their importance in team processes and performance [272]. This body of research has pointed to the importance of sharing teammate information in order to support *teammate* TMMs as well as improve trust on temporary teams [118, 50]. However, based on this literature, two important literature gaps must be addressed. First, prior literature on teammate information sharing has revealed few insights as to *what* information elements are most important and appropriate to share to support temporary teams and their *teammate* TMMs [325, 339]. Second, just as prior research has emphasized the importance of considering the flexibility and nuance of sharing task information in CSCW systems [1], so too should considerations be made as to *how* to best share and present *teammate* information to meet the needs of temporary teams.

2.4 Group Recommender Systems and Information Sharing

2.4.1 Group Recommender Systems and an Information-Sharing Recommender System

Prior research has pointed to the importance of recommender systems as a technology in their ability to suggest items or information that a particular user might be interested in [319, 318]. Many applications of recommender systems involve suggesting items to buy, entertainment content to consume (e.g., music, movies), or online news [319]. Recommender systems utilize various approaches for generating recommendations including content-based [229], collaborative filtering [131], demographics [37], knowledge-based [44], and hybrid recommender systems [48]. A fairly consistent component of recommender systems is that they are created for users who often do not have the adequate experience or ability to sift through a seemingly overwhelming number of choices that are available [318]. Thus, recommender systems provide an opportunity to utilize large datasets and make recommendations regarding what information about teammates is helpful and appropriate to share.

A highly relevant sub-class of recommender systems for this dissertation is that of *group recommender systems*. A group recommender system involves making recommendations to a group rather than to a single user (individual recommender) [167, 87]. Although this change from individual to group might seem slight on first impression, the implications for generating and presenting recommendations heavily increases the complexity of the system [167] and has opened up a large area of research interest [87].

In literature reviews of group recommender systems, numerous domains have been identified that could involve a group seeking a recommendation that assists in group decision-making [87, 167] such as movies/TV (e.g., [294], music (e.g., [83]), tourism/travel (e.g., [10, 248, 57, 183], restaurants/food (e.g., [247], etc. Additionally, Boratto & Carta (2010) conducted a review and found that group recommender systems typically involve four types of groups [38]: (1) established groups: members explicitly choose to be in the group based on shared, long-term interests (e.g., [195]); (2) occasional groups: members perform occasional activity together with a common aim (e.g., [122]); (3) random groups: members share an environment at a given time without a particular interests that links them (e.g., [83]); and (4) automatically identified groups: members are selected based on preferences and/or resources available (e.g., [377]).

According to Jameson & Smyth (2007), group recommender systems involve four sub-tasks: (1) acquiring information about user preferences; (2) generating recommendations; (3) explaining recommendations; and (4) helping users come to a group decision [167]. Much of the previous research has focused on two of these sub-tasks including generation (to be described in this paragraph) and explanation (requires its own subsection, 2.4.2) [167]. For generating group recommendations, research has pointed to two broad methods involving either aggregating individual profiles to make a group profile to recommend to or generating individual recommendations and aggregating them into a group recommendation [6, 87, 241, 194]. For aggregating individual preferences, various strategies have been used such as average, fairness, least misery, most pleasure, dictatorship, and without misery [239, 241, 276]. Importantly, there is typically no best way to aggregate and reach a group decision as each method has its disadvantages [13]; thus, aggregation methods are typically decided based on the group context [276].

2.4.2 Group Recommender System Explanations

An important feature of many types of recommender systems is explanation. Recommender systems utilize explanations to assist users in gaining an understanding for *why* a recommendation was made (i.e., understanding the recommendation process) and can assist users in choosing a better solution or increasing their acceptance of the recommended item(s) [64, 307, 110, 371, 374]. Further, the design of explanation can serve one or more of seven aims including effectiveness, satisfaction, transparency, scrutability, trust, persuasiveness, and efficiency [372, 369, 370]. Typically these recommendations fall under one of two categories: (1) collaborative explanations that indicate similar users selected an item [152] or (2) content-based explanations that provide descriptions of the recommendation's properties [385, 360]. Much of this research has focused on single-user recommenders and their ability to increase user trust through transparency [123, 152, 345]. However, the importance of explanations is also important in group recommender systems and contain unique challenges [279].

Just like single-user recommender systems, group recommender system explanations can be used to understand how the recommendations are generated [109]. However, group recommender system explanations must often account for conveying why a recommendation was made when it seems undesired by particular group members (i.e., clarifying a solution that accounted for discrepancies between group member preferences) [109]. In these circumstances, explanations can articulate trade-offs and assist members in accepting items they do not like to help the group reach a decision [374, 20, 278]. Thus, certain researchers have focused on how to best explain the aggregation process and convey fairness (e.g., [166, 248]). For instance, Tran et al. (2019) found that explanations that describe how all member or a majority of member preferences were considered achieved the best results in terms of fairness perception, consensus perception, and satisfaction [374]. Other researchers have investigated how natural language explanations can be used for high divergence scenarios in contexts such as music and tourism [279, 273]. In an exploratory study comparing repair-related to reassuring explanations and vital information to complete information, Najafian & Tintarev (2018) found that reassuring explanations with vital information (category 2) had the highest satisfaction; however, more complicated explanations were acceptable when the recommendation resulted in maximal misery [279]. Participants explained their preference for category 2 explanations by describing traits such as clarity, brevity, simplicity, and friendliness [279].

In addition to the challenge of explaining a more involved recommendation generation process, group recommender systems also face the issue of balancing privacy issues associated with disclosure. Specifically, disclosing more information in the explanation about user preferences can increase the effectiveness of the explanation, but this disclosure might result in encroaching on group member privacy [240, 279, 277]. In a group tourism recommender study, Herzog & Wörndl (2019) found that some members preferred to keep their preferences from being shown on the public display, which highlighted the importance for privacy in group recommendation explanations [153]. Quijano-Sanchez et al.'s (2017) research pointed to the need for 'tactful' explanations when the information is personal such as relationships [309]. In evaluating group music recommendations, Najafian et al. (2020) found that users disclosed less information in explanations (i.e., their name, rating, and personality) in low-consensus group scenarios [277]. Much of this research has pointed to the need to understand various factors that influence whether or not members choose to disclose information to be used in group recommender system explanations (e.g., [278]). The following two subsections (Subsections 2.4.3 and 2.4.4) will further explore this decision-making process and factors involved.

2.4.3 Privacy Calculus and User-Tailored Privacy

Group recommender system explanations require a trade-off when dealing with personal information disclosure such that "(a) generating effective explanations to group members and (b) keeping each group member comfortable by not disclosing private preferences to other group members" (p. 14) [274] are balanced. Thus, it is important to look to prior technology literature which has pointed to people deciding whether they want to trade off the anticipated benefits with perceived risks when disclosing information [363]. This privacy decision-making process is often referred to as *privacy calculus* [220, 85]. In this calculation, the factors of privacy risk and disclosure benefits must be considered [278].

Privacy has previously been described as a multi-faceted concept including being left alone [384], secrecy, controlling personal information, personhood, and intimacy [350]. However, research in online contexts typically narrows the focus of privacy to controlling personal information including its disclosure, storage, and use [398, 363, 135]. Thus, privacy concern has been defined as concern about losing privacy from sharing personal information to an external agent (e.g., technology, company) [407, 95, 406]. For the group recommender system context, these definitions have been altered so that privacy concern is defined as "(each) group member's concerns about a possible loss of privacy as a result of the group recommender system presenting an explanation to the whole group" (p. 15) [274]. When privacy risk or privacy concern increases, users often decrease their willingness to share their information [188, 232, 282].

On the other hand, users must consider the benefits of self-disclosure (i.e., context-specific gains from disclosure) [177]. Prior work in other online contexts has revealed the perceived benefits from self-disclosure such as monetary rewards from location-based services [408], social benefits from blogging [222], curating an image on personal websites [171], and gaining a personalized experience in online shopping [62]. As users consider the benefits, they may be willing to give up a level of their privacy [405, 65, 193]. In the temporary team context, the disclosure benefit can be considered as improved team effectiveness by improving *teammate* TMMs on the team.

However, when researching the privacy-related decisions of technology users, it is important to note that some researchers take issue with privacy calculus and other decision theories. For instance, decision theories like privacy calculus can be considered incomplete as they over-assume the rationality of users and their decision-making process [343, 128, 187, 186]. In response to this, more recent research as suggested moving past privacy calculus in favor of *user-tailored privacy* which involves providing privacy decision support by "first predicting users' privacy preferences and behaviors and then providing adaptive nudges (e.g., automatic initial default settings)" (p. 3) [202]. When implemented correctly, this approach can alleviate the burden placed on users to calculate the risks and benefits (e.g., [30]). The algorithm can potentially consider factors such as the user's characteristics, their decision history, the context, etc. [202].

Importantly, there are many factors that algorithm decisions should consider for user-tailored privacy. Many of these factors, as well as the research that has investigated them in the group recommender system context, will be described in the following subsection.

2.4.4 Factors Influencing Privacy and Disclosure in Group Recommender Systems

For group recommender systems, many factors have been examined to investigate privacy risk and information disclosure including individual differences, group context, information type, and privacy controls.

2.4.4.1 Individual Differences

First, individual differences are an important factor to consider when predicting a user's privacy concern for disclosing personal information [206]. Such differences are often measured using personality assessments such as the five factor personality model (i.e., the Big Five) which consists of five factors (i.e., extraversion, emotionality (or neuroticism), conscientiousness, agreeableness, and openness) [81].

In a study involving various online contexts, higher levels of agreeableness and neuroticism and lower levels of extraversion (in some contexts) were associated with increased privacy concerns [19]. In a location-based services study, Junglas et al. (2008) used a survey-based and found that agreeableness, conscientiousness, and openness to experience were associated with higher concern for privacy [180]. Korzaan & Boswell (2008) conducted a survey study for information privacy and found agreeableness to have a significant influence on privacy concern [211]. Meanwhile, Dinev et al. (2006) conducted a study in the e-commerce context and found trust propensity (a sub-facet of agreeableness [298]) to be a facilitator to information disclosure [95].

Specific to group recommender system explanations, few studies have investigated how personality influences privacy and information disclosure. Najafian et al. (2021) conducted research in the tourism group recommender context and found that agreeableness and extraversion related to higher concerns for privacy [274]. However, in a follow-up experiment, researchers found that these personality differences did not affect the final disclosure behavior of users [275]. To better understand the disconnect between privacy concerns and disclosure, one more study was conducted. In this study, Najafian et al. (2022) found that higher extraversion and conscientiousness relate to lower privacy concern and higher agreeableness relates to lower privacy concern [278]. Their findings also indicated that personality does not have a direct effect on information disclosure; however, they found that personality affects privacy concern which, "in turn, affects their trust in the group, which affects their perception of privacy risk and disclosure benefit when disclosing personal information in the group, which ultimately influences the amount of personal information they disclose" (p. 5) [278]. In addition to personality, research by Prasad (2019) identified conflict management styles as a factor for predicting the explanation type (different amounts of privacy) that users preferred depending on the type of group [306].

Based on this research, it seems that factors such as personality and conflict management are valuable predictors when discerning the privacy and explanation preferences for group recommender systems. Notably, there are differences in how personality relates to privacy concerns depending on context (e.g., comparing [19] with [278]). These differences are likely driven by the context the information is being shared in. For instance, a collaborative context such as a travel group recommender systems might mediate the relationship between a trait such as agreeableness and users wanting to share more information to reach a group decision [278].

2.4.4.2 Context and Relationships

Second, the context that the information is being shared in also influences privacy concern and disclosure. In online contexts, the sensitivity of the context (e.g., finance, e-commerce, and health) can impact privacy concern and intent to disclose [19]. When choosing to disclose private information to a group recommender system, the type of group and the relationship that members have to one another are factors since social relationships are a contextual factor that can impact privacy concern [107, 136, 153, 257, 392]. For instance, Mehdy et al. (2021) found that the receiver's relationship (i.e., family, friend, colleague, or stranger) to the user had a significant relationship with intent to disclose [257]. The closer the relationship (e.g., family compared to colleague), the more positive attitude users had toward information disclosure [257].

Research in group recommender systems have shown similar results. In a study by Prasad et al. (2019), no significant differences were found between group types (closely-related vs. loosely related members) regarding the type of explanations received (complete information vs. privacy-preserving information); however, post-hoc analysis suggested that members might prefer different explanation types depending on their conflict-handling preferences combined with the group type [306]. Similarly, Najafian et al. (2021) found that users have higher privacy concern in loosely-coupled heterogeneous groups compared to tightly-coupled homogeneous groups when using group recommender systems [274]. Group recommender system researchers have also investigated how the task design might influence information disclosure by comparing users instructed to convince others of their opinion compared to reaching a group consensus [275, 278]. Results indicated that framing the context as competitive can influence emotion-related information disclosure [275] and can mediate the relationship between privacy risk and information disclosure [278]. Therefore, contextual factors such as relationships between members and the framing of the task (competitive vs. collaborative) influence privacy concerns and information disclosure in group recommender systems.

2.4.4.3 Information Type

Third, the information type is an important factor for privacy concern and whether they choose to disclose information. Private information can fall under many categories including location, medical, emotion, personal details, and associations [51]. Prior studies have shown that both the type of information (e.g., health, finance, or relationship) [257] as well as the level of detail of the information [72] can affect disclosure behavior.

In groups, motivations for privacy concern might stem from a desire to not leave a negative impression or to conform to the group. Research in other online contexts have shown that users use various strategies to avoid sharing personal information that they perceive might leave a negative impression on others (e.g., [33, 295, 376]). In context such as corporate financial communications and personal websites, users have been known to curate the way they present themselves by displaying positive information while not disclosing information they perceive as negative [43, 171].

Much of the group recommender system research on privacy concern with information type has focused on consensus and conformity. When using music group recommender systems, users have been shown to use more privacy options in low consensus scenarios [277]. This is perhaps due to people wanting their preferences to align with the group and to match the preferences of the majority due to a phenomenon known as conformity [116, 14, 240]. Tourism group recommender system research has shown that having a minority preference in a group is associated with a higher privacy concern which can affect disclosure behavior [278], especially for emotion-related information [274].

2.4.4.4 Privacy Controls and Settings

Lastly, privacy controls and settings are important factors to privacy concern and disclosure. At a minimum, simply providing users with privacy controls can decrease privacy concerns [375, 363]. As recommender systems sometimes utilize sensitive information such as emotion to generate recommendations (e.g., [260], group recommender system research has considered allowing users to selectively disclose different types of information in order to generate explanations [277]. In this study, users were able to conceal different types of information when group explanations were made such as name, rating, or personality [277].

2.4.5 Summary

This section has provided a high-level overview of what group and single-user recommender systems involve as well as their aims. The technology described in this dissertation (i.e., information-sharing recommender systems) contains many similarities to group recommender systems; therefore, a literature review of group recommender systems is highly relevant. This review points to the importance of considering both efficacy and privacy when presenting users with group recommendation explanations [240, 279, 277]. Prior research on these group recommender explanations has emphasized the importance of individual differences (e.g., personality and conflict management) and has pointed to the need to use more specific personal characteristics for predicting disclosure behavior in future research [278]. Additionally, context of group and relationship to members (e.g., collaborative vs. competitive environments) and the sensitivity of information can influence information disclosure in group recommender systems [274, 278].

Although the group recommender system research has provided an excellent starting point for understanding the prior research in this field that is highly relevant, simply focusing on this context also points to major literature gaps. First, the information-sharing recommender system technology is new and requires significant investigation, particularly involving how to share personal information. Group recommender systems typically focus on recommending leisure content to users (e.g., movies, tourism, music) by using group member preferences rather than recommending information about members to other members (e.g., [319]. Second, group recommender systems have yet to investigate the context of temporary teams, a context which is a hybrid between two previously identified group recommender categories - established groups and automatically identified groups. It is likely that many context-dependent factors such as individual differences, group type, and information type need to be reevaluated in the team context regarding their relationship to information disclosure for explanations.

2.5 Chapter Summary

This background chapter involves descriptions of research from various domains including teamwork, CSCW, and recommender systems. A review of teamwork literature points to the challenges that temporary teams face, especially in their need to accelerate the development of *teammate* TMMs. The research on *teammate* TMMs in the CSCW community suggests that these mental models can be supported through teammate information sharing; however, the amount of information shared might be overwhelming to members and the content shared might create privacy concerns. These challenge motivates the use of recommender systems to intelligently share teammate information between team members to promote *teammate* TMMs. Group recommender system research provides numerous insights for how recommendation explanations can be presented while considering privacy.

A review of these domains has highlighted significant research gaps, leading to the development of the research questions investigated by this dissertation:

1. Both teamwork and CSCW research have pointed to the value of using technology to share teammate information to improve teamwork on temporary teams; however, the lens and motivation of promoting teammate TMMs has yet to be explored including what information to share. ([409, 118])

2. The primary focus on previous tools to share teammate information has been on improving teamwork with little attention paid to privacy concerns and how

these can be reduced through the sharing process. ([393, 409])

3. Much of the group recommender system explanation research has focused on sharing preferences to explain the group recommendation. The concept of sharing personal information as the recommendation in recommender systems is novel and requires preliminary understanding and guidelines to promote efficacy while reducing privacy concerns. ([109, 279, 240])

4. Disclosure behavior is an important concept in the group recommender system literature including how factors such as individual differences differences, information type, and group type influence disclosure. Prior recommender system research has only investigated leisure group contexts with the specific teamwork context yet to be examined and how it might influence privacy concerns and disclosure. ([278, 274])

I now turn our attention to the following chapters which describe studies that examine these issues.

Chapter 3

Research Platform Criteria, Design, and Development

To perform the studies in this dissertation, a research platform had to be designed and developed that could actually be used with real teams and not just experimental teams. Specifically, a system had to be designed that could intelligently share teammate information that is relevant to teamwork to members on the team (i.e., Teammate A receives information about Teammate B and Teammate C; Teammate B receives information about Teammate A and Teammate C; etc.).

This chapter is organized as follows. This chapter begins with a high-level description of the technology (1). Then, the subsequent sections describe the many factors that had to be considered during the design and development of the system including: (2) information type and source, (3) creating and validating recommendations, (4) ranking algorithm and validation, (5) how users interact with the platform, and (6) admin features for assigning conditions and exporting data.

3.1 Technology Description

The technology described in this dissertation and developed as a research platform draws on the design of single-user and group recommender systems (described in Section 2.4). However, there are notable differences between these technologies which are outlined in Figure 3.1. For generating recommendations, an information-sharing recommender shares in the complexity of group recommenders (compared to single-user recommenders) in that they must account for multiple users in determining recommendations. However, three important differences exist. First, an information-sharing recommender must generate interaction models (e.g., identifying similarities and differences of an interaction pair) and a user model (what a particular user might find helpful) rather than a group model. Second, information-sharing recommenders must take privacy into account at the generation phase since the recommendation itself involves personal information. This is in contrast to group recommender systems that usually only need to take privacy into account at the explanation phase. Third, this type of recommender mirrors single-user recommenders in that it is creating recommendations for individuals, whereas group recommenders create recommendations for the group as a whole. Although there is some precedence for group recommender systems being used to make recommendations to individuals (e.g., to address cold-start problem), this is not what most group recommender systems are designed for [241, 240].

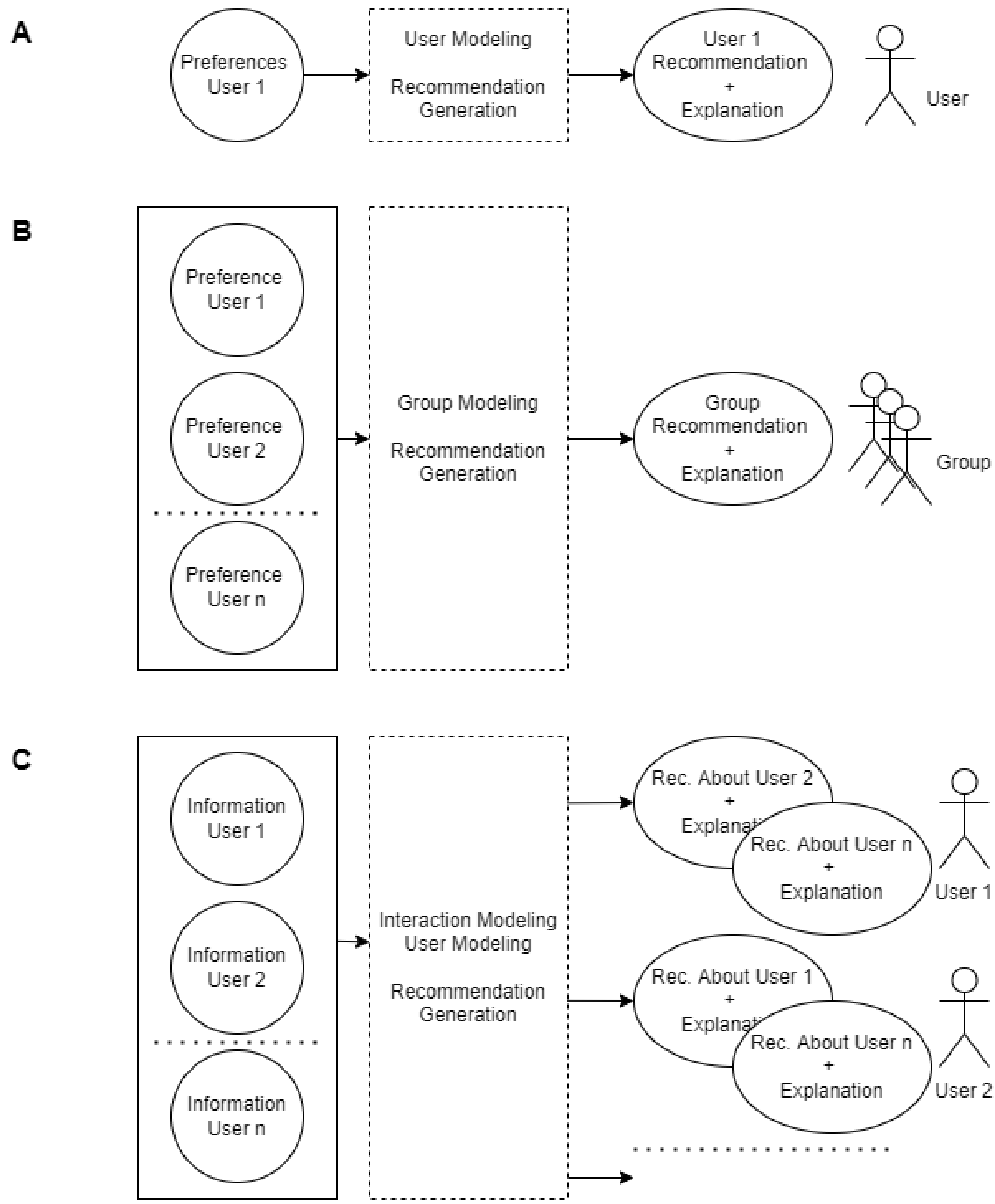


Figure 3.1: Comparing Recommender Systems: A) Single-User, B) Group, C) Information-Sharing. Adapted from multiple sources: [122, 66, 87, 6, 414]

3.2 Information Type and Source

The goal of this technology and research platform is to facilitate teammate information sharing to accelerate the development of *teammate* TMMs on temporary teams. As described in Section 2.2.2.1 and Table 2.1, *teammate* TMMs contain knowledge of teammates including their knowledge, skills, attitudes, preferences, and tendencies. Future implementations of this technology might value information sources such as performance histories, preference surveys, or team evaluations. However, in planning the dissertation studies, it became evident that the system needed to account for various teaming contexts (i.e., general teammate information) and had to be able to acquire the information quickly and easily. These requirements motivated the use of commonly-used and established personal assessments that provide users with information relevant to teamwork. The final selection for these assessments included the Big Five Personality assessment [81] and Rahim & Bonoma's 1983 Conflict Management Styles assessment [310]. These assessments as well as the motivations for using them are described below.

3.2.1 Big Five Personality Assessment

Personality assessment results are of interest to this technology as they provide a high-level overview of how an individual works and interacts with others on a team (e.g., tendencies, preferences, etc.). Particularly, the Big 5 personality assessment was selected as it is the most frequently used personality theoretical model and assessment in teamwork and psychology research [192, 383, 261, 23, 46, 299]. This model gives users insight regarding how their personality fits onto five factors including extraversion, emotionality (or neuroticism), conscientiousness, agreeableness, and openness [22]. Prior research has shown that the Big Five is stable on temporary learning teams [356] and that team members on these teams are able to better assess the personality of their team members over time [355].

Although there are various versions of the Big Five and assessments used to measure it, the 30 facet scale (i.e., 6 facets per personality factor) [81] is often utilized as it provides more granular information and is better able to predict behavior compared to the broad five categories alone [298]. A list of the 30 facets and the Big Five trait they are associated with can be found in Table 3.1. Based on Costa & McCrae's (1992) research on the 30 facets [81], a 300-item inventory was created to measure constructs similar to these facets [132]. Johnson (2014) went on to create a shorter 120-item measure and showed that it resulted in acceptable reliability in measuring the 30 facets [174]. This research platform utilizes this measure (see Table A.1 in Appendix A) to collect personality data of team members.

Big Five Traits	Facets
Extraversion	Activity Level, Assertiveness, Cheerfulness, Excitement-Seeking, Friendliness, Gregariousness
Emotionality	Anxiety, Frustration, Immoderation, Melancholic, Self-Consciousness, Vulnerability
Conscientiousness	Achievement-Striving, Cautiousness, Dependability, Orderliness, Self-Efficacy, Self-Discipline
Agreeableness	Altruism, Cooperation, Modesty, Morality, Sympathy, Trust
Openness	Adventurousness, Artistic Interests, Imagination, Intellect, Liberalism, Sentimentality

Table 3.1: Big Five Personality and 30 Facets

This dissertation is motivated to use the 30 facets as they are able to provide detailed information of team members that are highly relevant to *teammate* TMMs. Although the assessment results do not contain information relevant to teammate knowledge and skills, they do contain information regarding teammate attitudes, preferences, and tendencies. Examples of such information and how they relate to *teammate* TMM content can be found in Table 3.2.

Teammate SMM	Big Five Sub-Facets
Attitudes	Cheerfulness, Cooperation, Self-Efficacy, Trust
Preferences	Activity Level, Cautiousness, Cooperation, Orderliness
Tendencies	Assertiveness, Anxiety, Dependability, Vulnerability

Table 3.2: Examples of Personality Facets and How They Relate to *Teammate* TMM Content

Prior research has pointed toward the value of reflecting on and sharing personality information on temporary teams. For team training, reviewing and discussing different personality styles in general as a team can help team members value diversity [397]. Research involving student software engineering teams suggests that taking and reflecting on personality assessments improved interpersonal relations and enhanced trust within teams [303]. This particular study emphasized the importance of collaboratively looking at team profiles to see how similar or different the team is regarding various attributes [303]. Similarly, another study found that members knowing their teammates' personality types were valuable in understanding team member behaviors and managing team dynamics [69].

3.2.2 Conflict Management Styles Assessment

Second, conflict management styles was selected as an information source for this system. Conflict management styles refer to how individuals deal with and handle interpersonal conflicts [310]. The assessment results in individuals understanding what styles they use to handle conflict including five categories: integrating, accommodating (obliging), dominating, avoiding, and compromising which are categorized using two dimensions regarding a 'concern for self' and a 'concern for others' as shown in Figure 3.2 [310]. These results can be obtained by taking a 26-item assessment (see Appendix A, Table A.2) which results in scores for each of the five different conflict management styles [367].

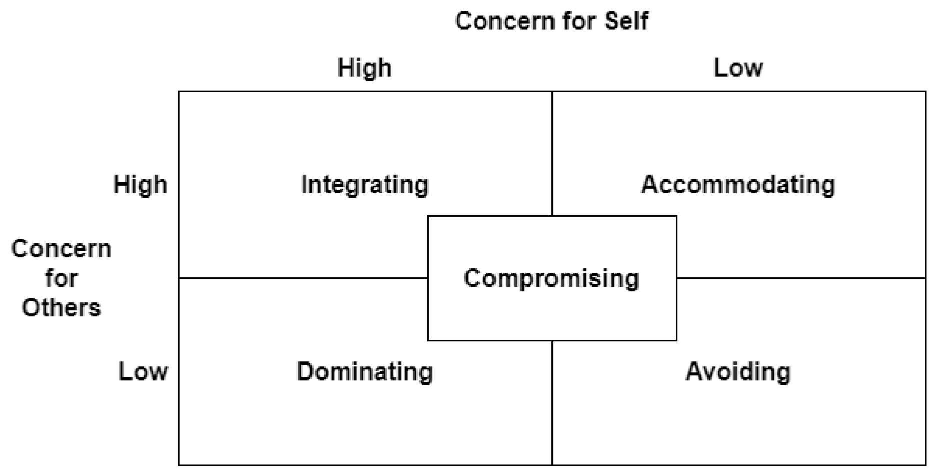


Figure 3.2: Conflict Management Styles and Concern Dimensions (adapted from [310])

Like the 30 facets of the Big Five personality model, conflict management style information is relevant to *teammate* TMMs. For instance, this information can result in an understanding for a teammate's tendencies or preferences for handling conflict (e.g., avoiding compared to dominating). Prior research has shown that understanding various conflict management styles can improve communication and collaboration on teams [40, 27, 24, 290, 63]. Research has shown that team members understanding how they and their teammates manage conflict can assist in essential team processes such as communication and decision making [290]. Compared to personality assessments there is less research regarding member perceptions of sharing conflict management style information. However, the first study in this dissertation indicates that team members are more likely to perceive sharing conflict management style information as appropriate and helpful than sharing personality information on temporary teams.

3.3 Creating and Validating Recommendations

Once the information source for this technology was established, recommendations had to be created and validated. In order to increase the efficacy and validity of these recommendations, inspiration and content were drawn from ITP metrics. ITP metrics contains a suite of online assessment tools that have been curated and implemented to promote effective teamwork including personality, conflict management styles, leadership, team health, and peer feedback assessments [292, 168, 346, 378].

Importantly, the conflict management styles and personality assessments already contain *individual* recommendations in the reports that are generated on ITP metrics. When a user takes the Big Five personality assessment on the ITP metrics website, raw scores are generated for the 30 facets based on how individuals answer Likert questions associated with each facet. Next, scores are presented to users as percentiles where percentile scores compare users to a "normative sample" (i.e., compared to 20,000 respondents for ITP metrics) [292]. These scores are displayed categorically as 'low', 'moderate', or 'high' based on the percentile value. For the personality assessment, 'moderate' refers to the 25th to 75th percentile, while 'moderate' refers to scores between the 33-66 percentile range for conflict management styles. To compliment these percentile scores and categories, individual recommendations are presented that are associated with the facet and percentile category. For instance, a user who scores in the 78% for 'gregariousness' is placed in the 'high' category for this facet and are presented with an individual recommendation:

You likely prefer to work in a group than on your own and you enjoy the *feeling of belonging to a team. Take advantage of your sociable nature to share all your unique ideas and perspectives with the team but be careful not to be overbearing or interjecting your thoughts at the expense of others.* [292]

Since there are 30 facets for personality and three recommendations per facet (i.e., one for each percentile category - low, moderate, and high), ITP metrics contains 90 unique recommendations for the personality assessment. A similar recommendation archive is associated with the conflict management styles assessment on ITP metrics which results in 15 unique individual recommendations. These recommendations were created by teamwork experts and were iteratively improved upon by the ITP metrics team as they received feedback from numerous users over the years. Although these recommendations cannot be considered 'perfect' due to the nuance of human personality, the expertise and iterative improvement on them point to an acceptable validity for use as a starting point in fostering an understanding in individual differences for team members.

Although these individual ITP metrics recommendations provide an excellent starting point for the system, changes had to be made to account for a system sharing this information *about a teammate* rather than *about oneself*. These changes involved a rewording of the recommendations so that they would be about someone else. Additionally the wording had to account for how two team members categorically compared for a given facet. For instance, a recommendation might account for how someone who scores 'low' on 'gregariousness' relates to someone who scores 'high'. By this logic, nine different interaction recommendations had to be extrapolated from the original three ITP metrics individual recommendations. An example of nine 'gregariousness' recommendations is provided in Table 3.3. Based on 30 personality facets and 5 conflict management styles (35 attributes in total) and 9 potential category relations, this process resulted in 315 unique recommendations. These interaction recommendations were created by the collaboration of two researchers. These researchers would look at how two recommendations (e.g., low and high) related for a given facet before combining and rewording the recommendations to produce a reasonable teammate recommendation. A training period was conducted so that consistency was established in generating the recommendations. Quality was assured collaboratively through additional checks and iterations to ensure that the recommendations were consistent, accurate, and helpful. These recommendations were further validated by additional teamwork experts who checked the recommendations during the ranking process (to be described in the next section).

Self Score - Teammate Score	Gregariousness Recommendation
Low - Low	Both you and this teammate may find it difficult to work in a group and prefer to do work on your own but remember most work is done as a team. Capitalize on your ability to be productive on your own by taking on focused tasks and being well prepared.
Low - Moderate	This teammate is slightly more interested than you in group work and being a part of the team. Take advantage of their sociable nature and ability to share with the team. Also be mindful that they might not be as productive as you while working on individual tasks.
Low - High	This teammate is much more interested than you in group work and being a part of the team. Take advantage of their sociable nature and ability to share with the team. Also be mindful that they might not be as productive as you while working on individual tasks.
Moderate - Low	This teammate might find it more difficult than you to work in a group. Take advantage of their ability to be productive on their own while simultaneously encouraging them to share and work together with you as a team.
Moderate - Moderate	Both you and this teammate can work alone or in a group, and can likely succeed in either situation. Remember that others may not be as flexible as you two.
Moderate - High	This teammate is more interested than you in group work and being a part of the team. Take advantage of their sociable nature and ability to share with the team. Also be mindful that they might not be as productive as you while working on individual tasks.
High - Low	This teammate might find it much more difficult than you to work in a group. Take advantage of their ability to be productive on their own while simultaneously encouraging them to share and work together with you as a team.
High - Moderate	This teammate might be slightly less interested than you in working as a group. Take advantage of their ability to be productive on their own while simultaneously encouraging them to share and work together with you as a team.
High - High	Both you and this teammate likely prefer to work in a group more than on your own and you enjoy the feeling of belonging to a team. Take advantage of each other's sociable nature to share all your unique ideas and perspectives with the team but be careful not to be overbearing or interjecting your thoughts at the expense of others.

Table 3.3: Gregariousness Recommendations Based on Teammate Score Relations

3.4 Ranking Algorithm and Validation

As shown in Table 3.3, the recommendations generated often contain 2-3 sentences. If a user were to receive all 35 of these recommendations per teammate, they would likely become overwhelmed or fatigued. Further, many of these recommendations are not that helpful compared to others. Thus, this system had to be designed to filter through and present the 'best' recommendations to teammates. Building a true recommender system that contains an AI system that improves its algorithm over time was beyond the scope of this dissertation. Instead, an expert system was created that can filter recommendations with enough efficacy to be perceived as a recommender system by participants.

To create this expert system, six teamwork experts took a survey where they indicated how useful they thought each attribute and associated recommendation was using a 5-point Likert scale (Not At All Useful – Extremely Useful). Although they did not do this for all 315 recommendations, they did this for a representative sample of recommendations which included one recommendation for each of the 35 attributes (30 personality and 5 conflict management styles). The recommendation provided for each attribute was based on a consistent category comparison (i.e., each recommendation was based on the low-high percentile category comparison of two teammates). Although this is not a perfect solution, this representative sample of recommendations resulted in acceptable data regarding how these 35 attributes compared in helpfulness for the temporary learning team context.

The scores for each attribute were averaged and a ranking system was created based on the average score for each attribute. For example, the personality attribute 'activity level' ranked the highest and 'sentimentality' ranked the lowest. However, the usefulness of these recommendations is not solely reliant on the attributes themselves. How teammates relate on these attributes contributes greatly to how useful the information is. For instance, if two members both rank ‘moderate’ on a given attribute, they are unlikely to find the information very useful. Thus, each of the nine interaction possibilities were ranked with the combinations ‘high-low’ and ‘low-high’ ranking the highest and ‘moderate-moderate’ ranking the lowest. There are, of course, limitations to this rudimentary ranking system. For instance, a recommendation describing two members rating ‘high’ on ‘dominating’ might be much more useful than two members rating ‘high’ for ‘liberalism’. However, the resulting rankings resulted in acceptable results for the research purposes of this dissertation. Taking these two ranking systems in combination resulted in an algorithm that could rank all 315 recommendations by scaling the weights of the two ranking systems. Pilot testing was conducted with teams to determine initial perceptions of the recommendation ranking. Based on feedback, adjustments were made to the algorithm to change how ‘attributes’ were weighted compared to the weight of ‘interactions’ rankings. This process was iteratively performed until the system consistently produced acceptable rankings for users.

3.5 Platform Description

The research platform took the form of a website that participants could visit when instructed to by researchers. An undergraduate member of the lab group who has significant development experience created the application. The backend for the application was made using a Python framework called Django. While the front-end uses Bootstrap for styling and JavaScript for interactive elements. The application contains five pages including register/login, home, assessments, results, and recommendations.

Participants begin using the platform when they receive a join code from a researcher. The join code can be associated with an experimental condition and/or a team. Users can create an account with the join code before logging in with their credentials on the log in page shown in Figure 3.3. Once logged in, users are directed to the home page (see Figure 3.4) which provides a high-level descriptions of the other pages (i.e., assessments, results, and recommendations).

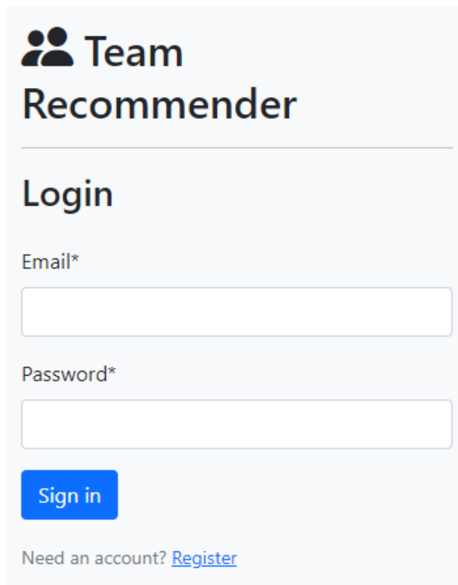


Figure 3.3: Platform Login Page

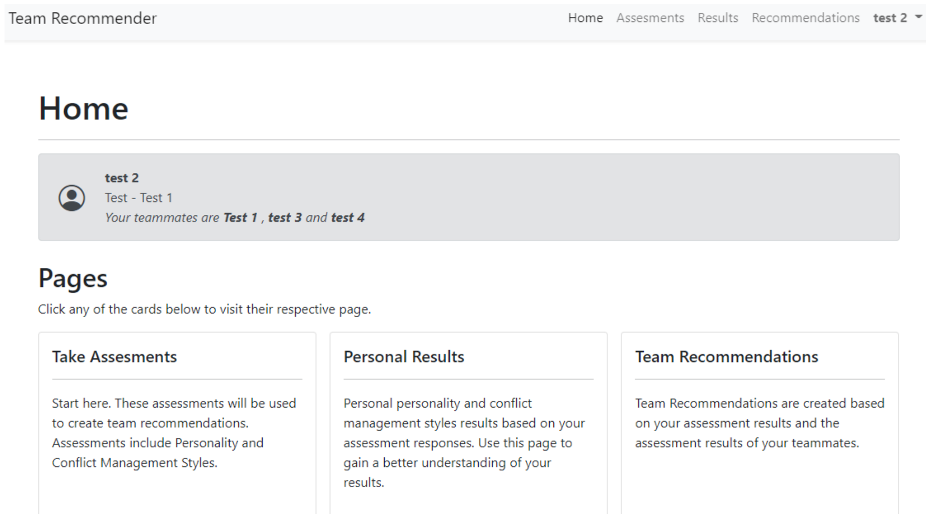


Figure 3.4: Platform Home Page

Users are first directed to the *assessments* page. The assessments page has cards for both personality and conflict management styles assessments. Each card provides a description and a link to take the survey for each respective assessment. The personality assessment contains 120 items on a five-point Likert scale ranging from 1, “Strongly Disagree” to 5, “Strongly Agree”, (see Appendix A, Table A.1). The conflict management styles assessment contains 26 items answered on a five-point Likert scale ranging from 1, “Strongly Disagree”, to 5, “Strongly Agree.” An example of one of the assessment pages, the conflict management styles assessment, is shown in Figure 3.5.

Conflict Management Assesment

Please use the rating scale below to describe how accurately each statement describes you.

Question	Very Inaccurate	Inaccurate	Neutral	Accurate	Very Accurate
I try to investigate an issue with others to find a solution acceptable to everyone	○	○	○	○	○
I generally try to satisfy the needs of everyone	○	○	○	○	○
I attempt to avoid being 'put on the spot' and try to keep my conflict with others to myself	○	○	○	○	○
I try to integrate my ideas with others to come up with a decision jointly	○	○	○	○	○

Figure 3.5: Platform Assessment Page - Conflict Management Styles

Once users complete their assessments, they are directed (and able to) visit the *results* page. The results page is intended to roughly mirror some of the features of the ITP metrics results page. Users can read more detailed information regarding what the assessments are meant for and how the results can be interpreted. For each facet/style, a percentile score is displayed that is color coded so that users can quickly distinguish between low, moderate, and high percentile scores. Additionally, a brief individual recommendation is given for each facet/style to provide additional context as to what each attribute-percentile combination might mean. These individual recommendations came directly from ITP metrics. In study 3, this page also contains interaction options for users to indicate which attributes they are comfortable sharing with their team. A portion of a results page is shown in Figure 3.6.

Conscientiousness - Moderate 32%

Facet	Percentile (25-75% = Moderate)	
Achievement-Striving	Low - 16	You restrict your time and effort into tasks and may accept a passable standard of work. This may help your team avoid doing unnecessary work that does little to contribute to the overall objective. However, you risk producing sub-par work and not meeting the expectations of your team.
Cautiousness	Moderate - 44	You are reasonably cautious and consider both sides of a decision before taking action. Help your team take calculated risks while also ensuring adequate time is given to discuss decisions where the risks could outweigh the benefits.
Dependability	Low - 23	You do not take issue with breaking a few rules or failing to meet some obligations. Be mindful that team members are counting on you to attend meetings and complete your tasks on time. Breaking promises can lead others to see you as unreliable or untrustworthy.
Orderliness	Low - 23	You tend to be unconcerned with tidiness and organization. This allows you to focus regardless of the work environment. Be careful that your disorganization is not disrupting your team's workflow or leading to wasted time looking for shared physical or virtual documents and resources.
Self-Efficacy	Low - 5	You may find yourself doubting your ability to get the job done. You should inform your team members of your strengths when the group is assigning tasks in order to exploit your skillset, but be willing to push yourself to learn and try new things to build on your current knowledge.
Self-Discipline	High - 87	You are often prepared and able to execute your tasks without procrastinating. Take advantage of your self-discipline by helping the team set goals and execute tasks. Be careful that your self-restraint and dedication does not come across as an inability to relax by remembering to celebrate your accomplishments.

Figure 3.6: Platform Individual Results Page

Once all users on a team have completed their assessments, teammate recommendations are generated. Users can view these recommendations on the *recommendations* page (a portion of an example is shown in Figure 3.7). Depending on the condition, a number of recommendations (see Table 3.3 for examples) are displayed for each teammate. In addition to the recommendation being shown, other information like rationale can be displayed (i.e., "In the category of compromising, you scored low and they scored high").

Recommendations are organized by teammate below:

Test 1:

Recommendation #1	This teammate will not likely push hard for their ideas especially when you are pushing hard for your ideas. Consider proactively seeking out the viewpoints of this teammate to make sure you are not missing anything in the decision-making process.	In the category of **dominating**, you scored **high** and they scored **low**.
Recommendation #2	This teammate prefers working on many tasks at the same time. Be sure to communicate your workload preferences so as to manage their expectations.	In the category of **activity level**, you scored **moderate** and they scored **high**.
Recommendation #3	Your teammate is much less interested in compromising than you are. Though there are benefits to whichever other form of conflict management they prefer, try to see if you can still encourage compromise on your team. Or, even better, try to integrate this teammate's ideas with other team member ideas if time allows.	In the category of **compromising**, you scored **high** and they scored **low**.

Figure 3.7: Platform Recommendations Page

3.6 Admin Features

In order for this application to be used for research, a suite of admin features had to be created. From the admin page, researchers can create teams and users. The admin can control the pacing of the experiment by indicating when recommendations are released (e.g., once all team members have joined and completed the assessments) or if they should be displayed automatically (e.g., for experiments that involve hypothetical teammates). Importantly, the admin can set and edit which experiment and experimental condition users are in so that multiple studies and conditions can run simultaneously.

Although a more detailed description will be provided for differing conditions, examples of condition variation within the application will be provided here. On the *results* page, various condition settings result in users being able to indicate which attributes they are comfortable sharing. While on the *recommendations* page, some conditions contain anonymous recommendations while others contain rationale associated with them. Additionally, some studies involve the ability for users to indicate which recommendations they found helpful on this page.

In addition to conditional variation, the research platform contains the ability to export participant data in the form of a CSV or JSON file. The participant data in these files includes information such as username, team, condition, and assessment results. For some experiments, this file also contains user data regarding sharing preferences and recommendation perceptions.

In summary, the research platform contains a user experience that involves taking assessments and receiving recommendations. This is powered by algorithms that calculate attribute scores for users as well as algorithms for ranking which recommendations to share. The admin features facilitate differentiating the user experience for various conditions and the ability to export robust data relevant to the experiments.

Chapter 4

Study 1: Exploring Teammate Information Sharing to Promote *Teammate* TMMs

4.1 Overview and Research Questions

Alhough prior research points to the possibility of sharing teammate information, less is known regarding what information is appropriate and helpful to share to promote *teammate* TMMs. This first study takes a highly exploratory approach to understand temporary team member perceptions regarding what information they perceive as helpful to support *teammate* TMMs and how this sharing can be better supported by technology. The aim of this study is to create a solid foundation for future studies and for the development of a research platform through this improved understanding.

In this mixed-methods exploratory study, Study 1 uses actual temporary teams working on semester-long projects. Measures were taken to understand how two popular personal information sources, personality and conflict management style assessments, are perceived by team members including their accuracy and how helpful and appropriate sharing such information amongst the team is. Two conditions were used including a sharing condition and a non-sharing condition to understand how experience with sharing influences such perceptions. Qualitative data was collected to understand what information types are perceived as helpful to support *teammate* TMMs and how technology could support the sharing of such information. Relevant to the dissertation-level research questions, this first study addresses the following study-specific research questions:

RQ1.1: What information is important to share to promote *teammate* TMMs on temporary teams?

RQ1.2: How can an information-sharing system be designed to promote teammate understanding?

RQ1.3: How do team members perceive the sharing of personal assessment data in terms of accuracy, helpfulness, and appropriateness?

RQ1.4: How does experience with sharing personal assessment data influence perceptions of helpfulness and appropriateness?

4.2 Methods

4.2.1 Experimental Design

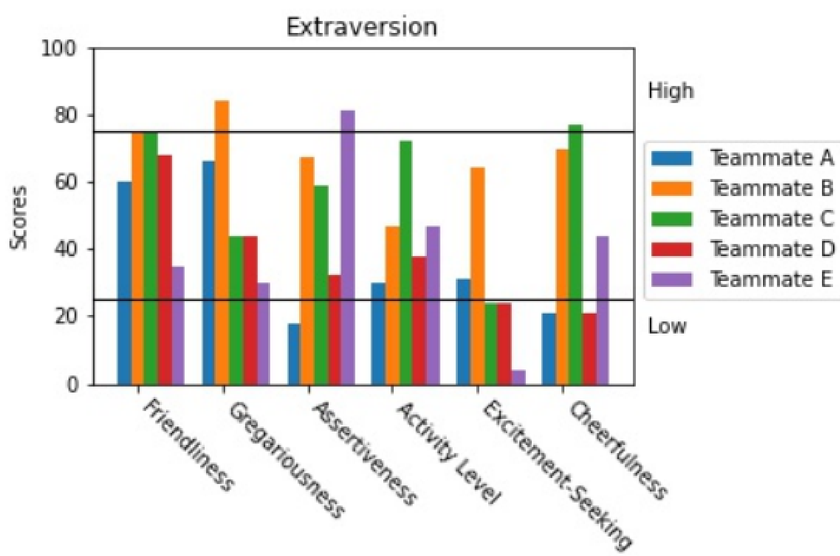
The research questions for this study follow two strands of inquiry. First, this study is exploratory in nature in trying to understand what information team members require in order to accelerate their *teammate* TMMs on temporary teams as well as an understanding of how technology can facilitate this information sharing. In pursuit of this research strand, qualitative data was collected from university student team members working on an industrial engineering capstone course project. Second, this study investigated perceptions of sharing results from two popular personal assessments (i.e., personality and conflict management styles) within the team in terms of accuracy, helpfulness, and appropriateness. These perceptions were further investigated by creating two experimental conditions (see Table 4.1, a sharing condition and a non-sharing condition, to understand how some of these perceptions are influenced by experience with sharing.

Conditions	Description
Sharing	Received a summary of teammate personal assessments in addition to individual reports
Non-Sharing	Only received individual reports of personal assessments

Table 4.1: Study 1 Conditions

This study involved three stages. First, toward the beginning of the project, participants were instructed to take personal assessments including the Big Five Personality assessment [81] and Rahim & Bonoma's 1983 Conflict Management Styles assessment [310]. After completion, participants were instructed to review their results and the associated reports.

Shortly after everyone completed the surveys in stage 1, the individual personality and conflict management style assessment results were compiled and shared with the respective teammates in the sharing condition. Sharing was conducted through a Python script that used all assessment result data for a team to generate a PDF report specific for that team. An example section of a sharing report is shown in Fig. 4.1 where a graph indicated the relative percentile each team member scored for the conflict management styles assessment and each of the sub-facets of a Big Five personality measure (in this example, Extraversion). Additionally, highlights were provided that described when team members ranked high for a particular facet that one of their teammates ranked low on. The complete report included six sections, including a section for conflict management styles and five sections for personality. After sharing was completed (if applicable), all participants completed stage 2 surveys that collected their perceptions of assessment results and sharing such results regardless of whether they were in the sharing or non-sharing condition.



Highlights:
• Teammate E ranks high in Assertiveness, whereas Teammate A ranks low in Assertiveness.
• Teammate C ranks high in Cheerfulness, whereas Teammate A & Teammate D rank low in Cheerfulness.

Figure 4.1: Example Section of Sharing Report

For stage 3, qualitative data in the form of short-answer questions was collected at the end of the project. These questions targeted an understanding of what these team members perceived as important information to share in order to improve *teammate* TMMs on these temporary teams. Other questions investigated how sharing teammate information can be improved and facilitated by technology.

4.2.2 Task Design

Teams participating in the study were assigned to solve complex applied industrial problems submitted by regional industry partners. For example, one team was challenged to significantly improve the inbound and outbound logistics at a tire manufacturer's largest manufacturing facility. Teams were given 15 weeks to address the problem with several milestones/check-ins throughout the project to help guide teams through the course's learning objectives. The professor in charge of the course also ensured that each of the projects given to the class were of similar difficulty and scope. At the project's conclusion, the teams were expected to present their solution to the relevant industry professionals that proposed it.

4.2.3 Participants and Demographics

This study, as well as some of the subsequent studies in the dissertation, use semester-long student projects as a context (or inspiration for scenarios) for temporary teams. Student project teams meet the four criteria used for classifying teams as temporary including unfamiliarity with one another [86], work together for a short period of time [351], work on specific and complex tasks [146], and they disband after the task is completed [163]. Although some might call into question the second criteria involving a 'short period of time', Bradley et al. (2003) classified teams based on the "intensity and duration" (p. 358) of member interactions instead of the length of the team's existence [41]. Since student teams are limited by how often they can meet due to other course requirements [148], these teams have a relatively small number of interactions for being on the team for an entire semester. Thus, teams of this nature have previously been classified as temporary and have been used in temporary team research (e.g., [100]).

A power analysis was performed to determine the number of participants required for an independent t-test analysis. This analysis determined that 102 participants was required to reach a reasonable power for a medium effect size. Therefore, an upper-level undergraduate project-based course was sought after.

Participants of this study were students of an industrial engineering capstone project course, a methodology common to teaming literature [176]. The current study recruited 103 individuals, which each took part in a semester-long team design project for regional business clients. The 103 individuals were divided into 20 teams, with 5.15 individuals per team on average. 89 individuals from this course elected to participate in data collection for this study (59 identified as men, 30 identified as women). All participants were Industrial Engineering majors with 88 Seniors and 1 Junior.

4.2.4 Measurements

4.2.4.1 Personal Assessments

Participants took two personal assessments including the Big Five Personality assessment involving 30 facets [174] and a Conflict Management Styles assessment [310]. These assessments were not used in analysis and were simply used as part of the task design which required participants to view their personal results (and sometimes their team members' results depending on their condition). For a description of these personal assessments, see Section 3.2.1 and 3.2.2. For a full list of questions in these assessments, see Appendix A, Tables A.1 and A.2.

4.2.4.2 Survey Questions

Stage 2 was primarily composed of a survey completed by participants in both conditions. The survey began with descriptive demographic questions (see Appendix B, Table B.4). Afterward, the survey primarily utilized a series of Likert-scale questions designed to better understand how team members perceived the assessments themselves (e.g., *"My personality assessment results were accurate"*) as well as their perceptions regarding the sharing of such information (e.g., *"It is appropriate for conflict management assessment data to be shared with teammates"*). A full list of these questions can be found in Appendix C, Table C.8.

4.2.4.3 Qualitative Questions

Qualitative short-answer and free-response questions were used in both stage 2 and 3 of this study. Stage 2 qualitative questions focused on understanding why team members thought the reports were or were not helpful (e.g., *"What information (if any) from the personal reports did you find useful and why?"*). Additionally, these questions sought to understand how the sharing could be improved by technology in the future (e.g., *"How could the report be improved so that you would find it more helpful?*). A full list of these free-response questions can be found in Appendix C, Table C.8.

Stage 3 qualitative questions, asked at the conclusion of the project, were knowledge elicitation questions investigating what information should be shared to promote *teammate* TMMs on temporary teams. As these teams had just finished a team project, they had likely formed somewhat accurate *teammate* TMMs. Thus, they were asked questions such as *"I would have worked better with teammate X if I had done _____ differently during this project"* and *"I will work better with teammate*

X in the future now that I know _____" in order to understand what information they found pertinent to their mental model of their teammates. A full list of these free-response and short-answer questions can be found in Appendix D, Table D.9.

4.2.5 Analysis

This study involved both quantitative and qualitative methods of analysis. First, analysis of the quantitative data involved descriptive statistics to show general perception trends and comparisons, a paired samples t-test to show perception comparisons between assessments, and independent samples t-tests to determine if sharing assessment results has an effect on perceived helpfulness and appropriateness.

Second, some of the qualitative data was analyzed using thematic analysis based on grounded theory [130]. This data set came from four free-response questions (see Appendix C, Table C.8) collected during stage 2 of this study. In line with prior research involving thematic analysis [365], the following steps were taken to analyze the data: (1) the first author read through all the question responses to obtain a basic understanding of participant perceptions of assessment reports and the sharing of such reports; (2) the first author iteratively generated codes based on various patterns that the data contained; (3) the first author categorized participant responses by major themes and sub-themes and extracted quotes; and (4) three authors discussed and refined themes to ensure that participant perceptions were thoroughly understood and summarized.

Third, a different set of qualitative data from stage 3 was analyzed using content analysis to understand what information temporary team members identify as important to promote their *teammate* TMMs. Although three questions were asked in this data collection, only one was used (i.e., *"I will work better with teammate*

X in the future now that I know _____") as it produced responses most reflective of *teammate* TMMs and also contained the most robust and consistent data set. To analyze this data, both qualitative and quantitative procedure steps were followed based on prior research involving content analysis [216] including the following: (1) two researchers independently read through the data to generate codes that represented various information types described by participants; (2) the two researchers reviewed and discussed the codes to generate a codebook to be used for analysis; (3) the two researchers independently coded 20% of the data, with some responses receiving no code, one code, or more than one code to determine inter-rater agreement. Inter-rater agreement was calculated as a raw percentage which resulted in an acceptable overall agreement of 82.6%. (4) The data set was split between the two researchers to assign codes for all responses.

4.3 Results

This section contains one quantitative and two qualitative subsections to address the research questions associated with this study. First, quantitative data in the form of diverging stacked bar charts and statistical analysis is used to describe and analyze perceptions regarding the sharing of personal-assessment data (RQ1.3 and RQ1.4). Second, qualitative data is presented through thematic analysis to understand the *why* behind perceptions of the assessments (RQ1.3) and how technology can be used to improve the sharing of this information (RQ1.2). Third, thematic analysis is used once again to present qualitative data related to what information temporary team members find important to promote *teammate* TMMs.

4.3.1 Quantitative: Assessment Perceptions

4.3.1.1 Comparison of Perceptions of Personal Assessment Data

A series of Likert-scale questions were used to determine how users perceived the accuracy of personality and conflict management style assessment reports and their perceptions of the helpfulness and appropriateness of sharing this information with their team. First, a look at response distributions and means reveal high-level findings. All participants were asked whether they thought the reports were accurate. Fig. 4.2 shows the distribution of responses for both the personality (top) and conflict management style (bottom) assessments. Meanwhile, Table 4.2 provides means and standard deviations for participants' perceived accuracy of the assessments as well as other perceptions. Note that these responses were on a 7-point Likert scale (0 = strongly disagree; 7 = strongly agree). These results indicate that overall, team members perceive these assessments to be accurate (M = 5.45 for personality and M = 5.51 for conflict management).

DV	Assessment Type	Mean	SD
Accuracy	Personality	5.45	0.97
	Conflict Management	5.51	1.07
Helpfulness	Personality	4.80	1.38
	Conflict Management	4.93	1.31
Appropriateness	Personality	4.18	1.40
	Conflict Management	4.49	1.41

Table 4.2: Perceptions of Personality and Conflict Management Styles Assessments. Mean values range from 1 (strongly disagree) to 7 (strongly agree).

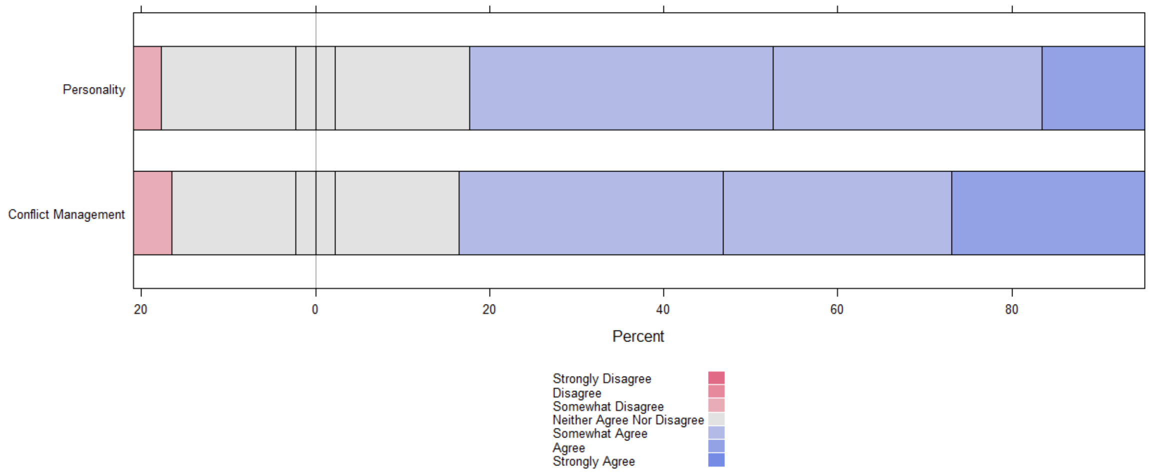


Figure 4.2: Perceived Accuracy of Assessment

Additionally, participants from the sharing condition were asked whether they thought sharing assessment data was helpful. Fig. 4.3 and Table 4.2 show the results for perceived helpfulness for both assessment types (M = 4.80 for personality and M = 4.93 for conflict management). Although many participants felt neutral or disagreed that sharing was helpful, a large majority of participants perceived sharing this information to be helpful. Relative to helpfulness, participants were less likely to agree that sharing these results was appropriate (M = 4.18 for personality and M = 4.49 for conflict management). Fig. 4.4 and Table 4.2 show the perceived appropriateness of sharing both assessment types.

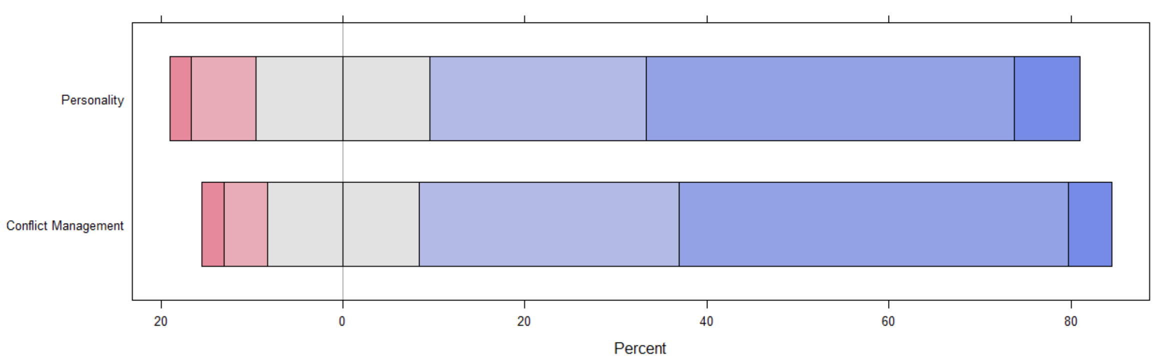


Figure 4.3: Perceived Helpfulness of Sharing Assessments

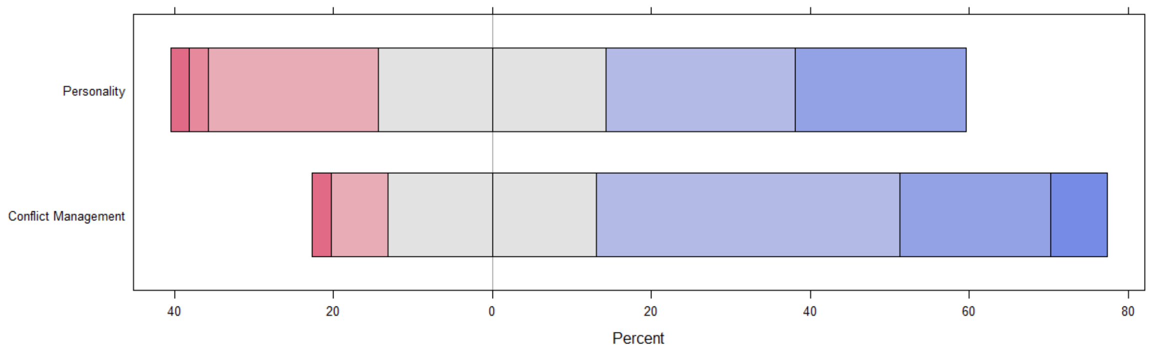
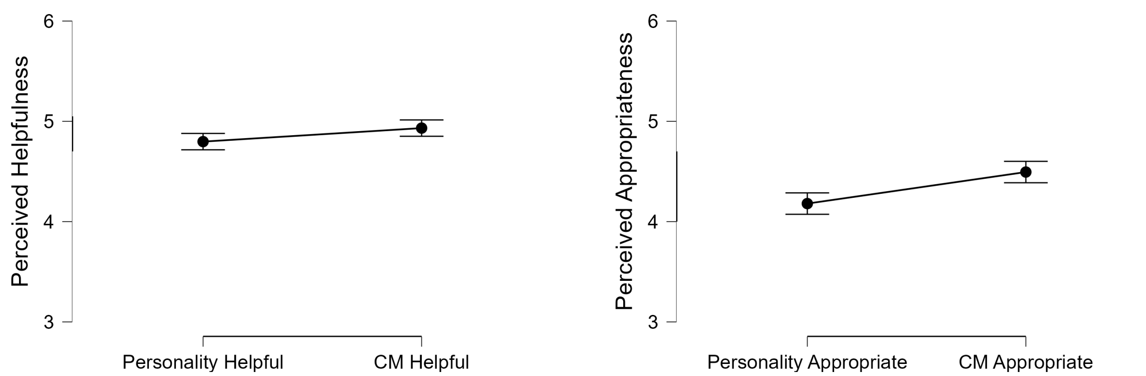


Figure 4.4: Perceived Appropriateness of Sharing Assessments

Second, a paired samples t-test of all participants showed a preference for sharing conflict management results. Participants had a significantly lower perception of the **helpfulness** of sharing **personality** results (M = 4.80, SD = 1.38) than sharing **conflict management** results (M = 4.93, SD = 1.31), $t(88)$ = -2.32, p = < .05, r = .24. Participants also had a significantly lower perception of **appropriateness** of sharing **personality** results (M = 4.18, SD = 1.40) than sharing **conflict management** results(M = 4.49, SD = 1.41), $t(88)$ = -4.14, p < .001, r = .40. A visualization of these two comparisons is shown in Figure 4.5.

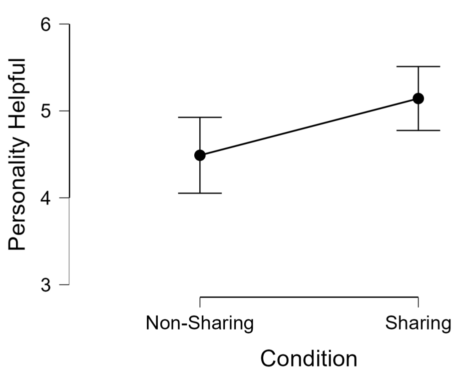


(a) Perceived Helpfulness (b) Perceived Appropriateness

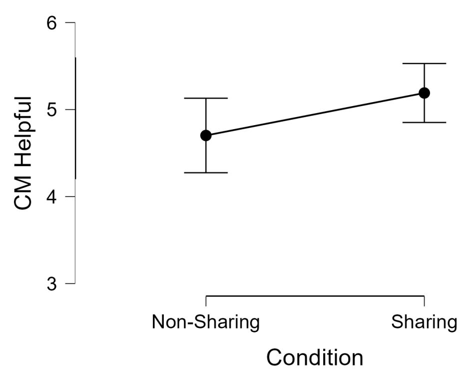
Figure 4.5: Comparison of Perceptions of Sharing Personality and Conflict Management Assessments

4.3.1.2 Sharing Experience and Perceptions of Sharing

Helpfulness Between A comparative analysis of the data also revealed interesting differences between the sharing and non-sharing conditions. I used independent samples t-tests to determine if sharing assessment results had a significant effect on perceived **helpfulness** of sharing. On average, participants in the non-sharing condition (M = 4.49, SD = 1.49) had a significantly lower perception of helpfulness regarding sharing **personality** results than participants in the sharing condition (M = 5.14, SD = 1.18), $t(85.85) = -2.31$, $p < .05$, $r = .24$. A similar comparison can be made regarding **conflict management** results, as participants in the non-sharing condition (M = 4.70, SD = 1.46) had a near-significantly lower perception of helpfulness than participants in the sharing condition (M = 5.19, SD = 1.08), $t(84.39) = -1.80$, $p = .075$, $r = .19$. A visualization of these two comparisons is shown in Figure 4.6.



(a) Perceived Helpfulness Personality

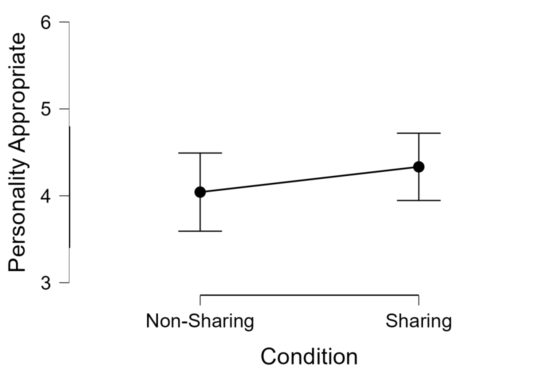


(b) Perceived Helpfulness Conflict Management

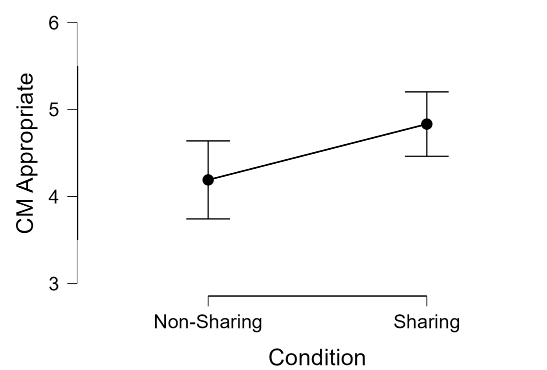
Figure 4.6: Comparison of Perceived Helpfulness of Sharing Personality and Conflict Management Assessments Between Conditions

Appropriateness Between Next, I used an independent samples t-test to determine if sharing assessment results had a significant effect on perceived **appropriate-**

ness of sharing. On average, participants in the non-sharing condition (M = 4.04, SD = 1.53) had a lower perception of appropriateness regarding sharing **personality** results than participants in the sharing condition (M = 4.33, SD = 1.24), but this difference was not significant $t(86.23)$ = -0.99, p = .33, r = .24. However, regarding the appropriateness of sharing **conflict management style**, participants in the non-sharing condition (M = 4.19, SD = 1.53) had a significantly lower perception of appropriateness than participants in the sharing condition (M = 4.83, SD = 1.19), $t(85.43)$ = -2.23, p = < .05, r = .11. A visualization of these two comparisons is shown in Figure 4.7.



(a) Perceived Appropriateness Personality



(b) Perceived Appropriateness Conflict Management

Figure 4.7: Comparison of Perceived Appropriateness of Sharing Personality and Conflict Management Assessments Between Conditions

4.3.2 Qualitative: Useful Features and Desired Improvements for Sharing Assessment Data

In order to better understand why team members had certain perceptions about the sharing of this information, participants responded to open-ended questions. These questions investigated what features participants liked about the assessments, why they liked or did not like sharing this data, and probed for information regarding what improvements they wanted to see to a system that shared such information. Thematic analysis revealed three major themes pertaining to these questions: (1) uncertainty of accuracy; (2) the perception that certain assessment data is more helpful to share; and (3) proposed improvements regarding how this information could be presented better.

4.3.2.1 Uncertainty of Accuracy

Data presented in the quantitative findings indicated that most participants perceived the assessments to be accurate. However, for those who were neutral or disagreed with the accuracy of these assessments, a common theme from the free-response questions emphasized their uncertainty regarding the accuracy of these assessments. This data provides insight into why participants might think the assessments are inaccurate or simply feel neutral regarding the assessment accuracy. Some of these participants expressed distrust for a computer's ability to classify such personal human traits:

> *I just personally believe that it is difficult to have a computer program try to define someone's personality.* -P27

P27 described disbelief that a computer would be able to classify or describe a person's personality. Without trust that the generated reports and classifications are accurate, users would be unable to utilize any subsequent recommendations or information provided. Other participants described *why* they might not trust the computer's output regarding the assessments:

> *The only suggestion I would have would be to ask questions that are more specific and scenario based versus the ones you asked which seemed broad*

and vague because I don't think the questions you asked previously would give accurate results to show who people truly are. -P63

The questions don't offer flexibility in regards to situations. It's either one way or the other. Sometimes the question may apply but other times it may not. It didn't always account for that. -P21

Since participants knew the assessment scores were driven by question responses, much of their trust for the assessments were based on how they perceived the quality of the questions themselves. P63 mentioned "scenario based," and P21 referred to "situations." It was clear that many participants understood that context matters when it comes to teamwork and how teammates might behave. Thus, participants were looking for better or additional questions to capture their personalities and how they handle conflict.

Additionally, participants who received assessment information about their teammates were unsure how to assess the accuracy of the information:

I feel that I don't know them quite well enough to validate their results. This is mostly due to the fact that I have not been in every situation in which each of their results could be distinguishable. -P35

P35 was part of the sharing condition. Although many participants perceived their own personality results to be accurate, many participants were unsure how to perceive the accuracy of their teammates' assessments. Although individuals are likely to have self-awareness and an opinion regarding the accuracy of their own report, they have much less experience with their teammates and do not know if their assessment results are accurate.

4.3.2.2 Certain Assessment Data is More Helpful to Share

Next, a review of responses revealed that participants had preferences for different types of information being shared with them and certain information *not* being shared about them. For instance, many participants found the sharing of conflict management style information to be beneficial. The preference for having this data shared compared to personality data was described often by participants. The following quotes describe how this conflict management information is helpful to them on teams:

> *I found it interesting to understand their conflict management results. This may be used to explain some team member's reactions to tough situations when it comes to the project.* -P43

> *I think that the conflict management section is useful (over using any personality information). Knowing how my teammates respond to conflict allows me to understand how my actions may affect them. Knowing their response tendencies, I can strive to ensure that no teammate dominates over the other and that all ideas are heard.* -P34

In these quotes, P43 and P34 describe their preference for utilizing conflict management data. P43 described how this information can allow them to understand their teammates better and how they react to situations. P34, on the other hand, described the ability to use this information in leadership to ensure that all ideas are heard. For instance, if they knew that one teammate ranked much higher in "dominating" for conflict management, they could be cognizant that additional effort would be necessary to ensure that less assertive voices were heard and understood.

Participants were less likely to describe the utilization of team personality information. In fact, P11 described a negative consequence of sharing such information:

> *I do think that some parts of the personality test shouldn't be shared with the team, especially on sections such as anxiety and other emotional aspects.* -P11

P11 perceived that some personality information was too sensitive or personal to share with teammates (i.e., emotionality scores). In addition to the quotes above describing practical uses of conflict management data, this description of hesitancy to share personality data helps explain why participants were more likely to perceive sharing conflict management information to be more appropriate than sharing personality information (see quantitative findings, Section 4.3.1). Importantly, not all participants felt the same way. A quote from P89 stands in stark contrast to P11's perspective:

> *Seeing the emotionality levels helped me understand why some people seemed to either be overly confident or unconfident in their work.* -P89

Interestingly, P89 found the same personality metric (emotionality) to be especially helpful. However, it is essential to note that while P89 found this information to be *helpful*, P11 thought that sharing this information category to be *inappropriate*. In deciding what personal assessment information to share (especially sensitive personality categories), considerations should be made regarding helpfulness and appropriateness.

4.3.2.3 Improvements to Presentation of Information

The third theme contains several quotes describing desired improvements to how and what information is shared. For instance, P68 and P69 shared similar sentiments:

> *I think there could have been fewer categories, some seemed too similar.* -P68

> *I think a less detailed report on my teams evaluation would be useful. I personally don't care for the specifics of how my team scored on each of the extraversion scores. I would rather just see an overall score for who is extroverted, conscientious, etc.* -P69

These quotes touch on a practical limitation of these reports in that they can often be perceived as too long. P68 noticed that fewer categories could have been utilized since many of the attributes seemed similar. Similarly, P69 felt that they were overwhelmed regarding information about their teammates. Although less information might provide a less accurate picture and would not be as descriptive, it could increase the report's readability, thus increasing the amount of usable information that users take away.

Parallel to these suggestions was the desire for more helpful information:

> *The report lacked a lot of details. A list of common avoidances and tips would be helpful.* -P30

> *I think it would be more helpful if it offered examples of strategies in a team environment that would allow you to perform your best.* -P43

P30 and P43 both described a desire for actionable information. To them, the report seemed like too much surface-level information and not enough tangible details or examples. Although these quotes might seem to contradict the previous two quotes (which expressed a desire for less information), the pairing of these suggestions could complement one another to result in a report that contains fewer categories yet more actionable information. P36 described what such a recommendation could look like:

For example, if teammates have a high self efficacy, dependability, self discipline, and low friendliness, then I conclude that on smaller tasks that teammate would rather work alone. -P36

In this quote, P36 described how multiple metrics could be combined to create useful information that could inform how teammates work together. An intelligent system might use such personality features to share less information and convey only helpful information that could promote *teammate* TMMs regarding attitudes, preferences, and tendencies.

4.3.3 Qualitative: Information for Promoting *Teammate* TMMs

In this study, understanding what types of information temporary team members find relevant to promoting their *teammate* TMMs was accomplished through asking free-response questions. As these participants were not necessarily familiar with teamwork literature and terminology such as 'team mental models', the question *"I will work better with teammate X in the future now that I know _____"* was used to operationalize the construct of *teammate* TMMs. Asking this question at the end of a temporary team project allowed participants to realistically reflect on how teamwork could have been improved if they had known specific information about their teammates before the project had begun.

Responses to this question were coded as one or more types of information. An iterative process between two researchers created the codebook shown in Table 4.3. Although this table only provides brief descriptions of the codes used, more detailed descriptions were used by the researchers in their codebook including the following: (1) information related to teammate 'hard' skills relevant to project tasks or preferences for different tasks; (2) information related to how hard teammates are willing to work and how reliable teammates are; (3) information related to how teammates communicate, how they handle conflict, and how they collaboratively make decisions; (4) information pointing to preferences for leadership, leadership style, or leadership skills; (5) how teammates work on a given timeline (e.g., do they procrastinate or do they work to get tasks done ahead of time); (6) information related to when teammates are available or how many other commitments they have; (7) information that alludes to high-level personality differences; and (8) any responses that were left blank or are not usable. It is important to note that some of these categories overlap. For instance, (2) reliability and (5) proactivity can be considered as (7) general personality . However, when participants gave more specific responses, it was valuable to code these based on the more specific categories (i.e., 2 and/or 5). When participants gave more vague responses such as 'personality information', a more broad category such as 7 had to be used.

Code #	Brief Description	Count
1	Relevant task skills and preferences	21
2	Work ethic and reliability	18
3	Conflict management style	17
4	Leadership skills	4
5	Proactivity	7
6	Availability	9
7	General personality or social differences	18
8	No response, missing, or not usable	18

Table 4.3: Study 1 Content Analysis Codebook and Counts

Based on this codebook, the responses provided, and the analysis, counts for each information type were calculated as shown in Table 4.3. Although information types such as leadership skills, proactivity, and availability seem to be important to some, the categories most referenced included information related to (1) task skills/preferences, (3) conflict management styles, and (7) personality information. Particularly for personality information, participants very often described information related to (2) how reliable or dependable their teammates were.

4.4 Discussion

To answer the research questions, I have investigated how team members perceive the sharing of personal assessment data (RQ1.3). I found that team members perceive the two personal assessments, personality and conflict management styles, to be accurate overall. Further, thematic analysis revealed why some participants disagreed, felt neutral, or slightly agreed with assessment accuracy. Participants described a lack of trust in computers or a desire for more nuanced assessment questions. Next, most participants perceived that sharing these assessments was helpful, whereas only a slight majority of participants perceived this sharing to be appropriate. The within-subjects analysis also indicated that participants perceived sharing conflict management data as significantly more helpful and appropriate than sharing personality data. Data from open-ended questions supported this notion as participants often described how conflict management style reports were both more helpful and appropriate to share.

For RQ1.4, comparative analysis revealed that having experience sharing personality data increased the perception that sharing personality data is helpful, and experience sharing conflict management data increased perceptions of helpfulness and appropriateness.

Regarding how an information-sharing system can be designed (RQ1.2), qualitative data revealed interesting findings. First, varying perceptions of *what* data to share indicates that participants have differing views on what is appropriate and helpful to share. Second, data indicated that an intelligent system to facilitate team sharing should prioritize what information to share and provide more context and insights regarding the few categories that are shared. Implications of this are discussed further in the following section.

For RQ1.1, content analysis was used to determine what information temporary team members find important for promoting their *teammate* TMMs. Responses indicated that participants are particularly interested in teammate information related to task skills, conflict management styles, and reliability.

4.4.1 Design Implications for an Intelligent System to Facilitate Team Sharing

Based on the findings, I propose design implications to address challenges associated with creating an intelligent system to facilitate team sharing, including: (1) desired content and presentation; and (2) mitigating accuracy and privacy concerns. These recommendations can be viewed as promising starting points for such a new and unexplored form of technology.

4.4.1.1 Desired Content and Presentation

Our findings suggest the type of content that team members are interested in receiving and how they wish this information to be presented. First, an intelligent system to facilitate team sharing should focus on suggesting limited content (recommendations) to reduce cognitive overload. Participants described being overwhelmed by information, especially as they read through 30 different personality facets and five conflict management styles. This challenge was compounded as some participants were provided this information for 3-5 additional teammates depending on their team size. Thus, such a system should restrain how much information is presented to promote readability and usability.

Second, participants described their desire to have more actionable and helpful information about how their assessments related to their teammates. The presented information was often described as high-level or generic, which did not seem useful to some participants. An intelligent system to facilitate team sharing should focus on presenting actionable and specific content so that users know how to use the information. This design might involve providing more context or giving examples of what interactions might look like between a given pair of teammates.

Third, the type of information shared should focus on the categories most important to temporary team members in terms of promoting *teammate* TMMs. Based on this study, task skills, conflict management styles, and personality (particularly teammate reliability) are promising starting points for types of information. Additional research is necessary to understand where this information should come from (e.g., performance history or personal assessment) in order to promote trust while limiting privacy concerns.

4.4.1.2 Mitigating Accuracy and Privacy Concerns

Based on these findings, it also seems pertinent to address both accuracy and privacy (appropriateness) concerns. One design feature to mitigate such concerns would involve the implementation of a user interface that affords flexibility and more user input. To achieve this, I suggest allowing users to review any data points or features attributed to them before this information is used in sharing. As such, if users have strong opinions regarding their privacy or how appropriate they think sharing such information would be, they can give that feedback to prevent the system from sharing it. This design would promote more flexibility than blocking particular personality or conflict management attributes for all users all the time. For example, Although some users might find their 'anxiety' score to be too private, this information should not be blocked from being shared from users who do not find this information sensitive. This feature is vital since diverse populations will have varying opinions regarding what information they find appropriate to share and what is not.

4.4.2 Limitations and Future Work

Certain limitations of this study should be considered when interpreting the results. First, it is important to note that all participants were college students and a study involving participants in a professional work environment may yield different results. Second, time limitations and the exploratory nature of this study required brief surveys. Therefore, single item responses were used for perceived accuracy, helpfulness, and appropriateness measures. Future studies would benefit from using previously developed multi-item measures (if available) or developing and validating their own measures. Third, this study prioritized external validity by using actual student teams. However, the diverse nature of each participant's teammates likely created significant variation in user experience with the reports meaning future studies should also target internal validity.

Chapter 5

Study 2: Effects of Anonymity and Explanations on Team Outcomes and System Perceptions in Teammate Information-Sharing Recommendations

5.1 Overview and Research Questions

A through line of this dissertation is understanding what information to display and how to display it when sharing teammate information through a recommender system. Specifically, this study focuses on *how to display this information*. Using a mixed-methods approach, Study 2 emphasizes external validity by using actual temporary teams working on semester-long projects. Depending on the team's assigned condition, individuals on the team received recommendations pertaining to each of their teammates at the start of the semester with either: (a) anonymized information, (b) identified information, or (c) identified information with explanation provided. By manipulating the level of user privacy in the recommendations presented to team members and collecting surveys throughout the semester, a comparison could be made regarding how the privacy level of the recommendations might influence perceptions of the system as well as team outcomes. Thus, this first study addresses the following study-specific research questions:

RQ2.1: How does presentation (anonymity and explanations) influence perceptions of a teamwork information-sharing recommender system?

RQ2.2: How can teammate information recommendations be presented (anonymity and explanations) to promote associated characteristics of *teammate* TMMs on temporary teams?

RQ2.3: How do users perceive the balance of privacy concern to the benefits of information sharing regarding how the information is presented?

5.2 Methods

5.2.1 Experimental Design

The research questions for this study pertain to how teammate information recommendations can be presented to promote *teammate* TMMs and positive user perceptions of the system. These research questions dig into the potential trade-off between privacy and efficacy. For these recommendations to be effective, they need to share teammate information in a way that is potentially revealing while providing a sufficient explanation for recipients to foster trust in the recommendations. To better understand how to present these recommendations, two factors were manipulated including anonymity and explanations. These factors were used to create a continuum of privacy which was represented by three conditions ranging from low to high privacy (see Table 5.1). This study utilizes a 3x1 repeated measures design with actual student teams in order to capture how the privacy level of the system relates to participant perceptions regarding their team (i.e., satisfaction, psychological safety, cohesion, and perceived effectiveness) and the system (i.e., privacy, trust, and satisfaction). Measures were taken using surveys during team formation, at the midpoint of the project, and at the end of the project. Additionally, qualitative interviews were conducted to understand *why* participants felt that certain ways of presenting were helpful or invaded their privacy.

#	Condition	Level of Privacy	Description
1	Anonymized	High Privacy	Anonymous recommendations with no explanations
2	Identified	Medium Privacy	Identified recommendations with no explanations
3	Identified & Explanation	Low Privacy	Identified recommendations with explanations

Table 5.1: Study 2 Conditions

In all three conditions, participants received three recommendations for each of their teammates (e.g., for a team of 4, each member would receive 9 recommendations, 3 for each teammate). The recommendations displayed were based on actual personality and conflict management styles assessment scores of team members, so tangible privacy concerns could exist. For a full description of how personal assessment data was used to create the recommendations, see Chapter 3. See Section 3.4 for a description of the algorithm used to select more helpful recommendations to display.

An example set of three recommendations is shown in Table 5.2. Note that the middle column contains the recommendation and the third column contains the explanation. For this study, explanations focused on the comparative personal information that motivated the recommendation (i.e., how the receiver and the teammate who the recommendation was about compared on a given attribute) rather than a deep explanation for how the algorithm works. The explanations were only provided for the third, 'Identified & Explanation' ('Low Privacy') condition. For condition 1 ('Anonymized'), recommendations were anonymized by displaying recommendations in their ranked order rather than grouping them by teammate. Thus, members knew that the recommendations applied to someone on their team, but they did not know exactly who they referred to. For conditions 2 and 3 (Medium and Low Privacy), recommendations were identified. This means that recommendations were grouped by teammate and had a name label above each grouping to indicate who the three recommendations referred to.

#	Recommendation	Explanation
#1	Your voice may be overshadowed by this teammate when making decisions. If the consequences of the decision are important to you or if you are aware of a blind spot in your teammate's decision making, consider asserting yourself more.	In the category of **dominating**, you scored **low** and they scored **high**.
#2	This teammate is highly self-disciplined and is able to execute on tasks without procrastinating. They are a great resource to utilize when setting goals and expectations. While they are reliable and can provide great support, they struggle with being perceived as unable to relax. Encourage them to take time to celebrate their own personal accomplishments, as well as team accomplishments.	In the category of **self-discipline**, you scored **moderate** and they scored **high**.
#3	This teammate is much more likely to address confrontation in a team setting. Try to take their arguments constructively and not personally. Although you are good at promoting harmony, try to also stand up for your opinions or challenge your teammate's ideas.	In the category of **cooperation**, you scored **high** and they scored **low**.

Table 5.2: Study 2 Recommendations with Explanations

5.2.2 Task Design

In order to capture actual teams and teamwork, this study utilized student teams who were working to complete projects for their course. In order to recruit enough participants, three different School of Computing courses were used. These courses involved both upper-level undergraduate students as well as graduate students. A high-level project description for each of the three courses is provided in Table 5.3. Although the projects varied from course to course, all of the projects were of similar intensity and required team members to meet 2-3 times per week for the duration of a semester.

#	Student Level	Project Description
#1	Upper-Level Undergraduate Students and Graduate Students	The team must go through the design process from beginning to end (working digital prototype) with evaluation findings. This involves conducting user research, defining requirements, designing/prototyping, and conducting user evaluations.
#2	Upper-Level Undergraduate Students and Graduate Students	The team must write a term paper relevant to the topic. This involves proposing a research topic, writing a proposal with related literature, writing an IRB proposal, conduct qualitative interviews, and writing the final paper.
#3	Upper-Level Undergraduate Students	The team must go through the major phases of the software development lifecycle. This involves requirements analysis, requirements modeling, design modeling, and project management, and intermediate coverage of module-level design principles, program specification and reasoning principles, and program validation and verification techniques.

Table 5.3: Study 2 Course Team Project Descriptions

At the very start of each respective course project, participants began using the research platform (full description provided in Chapter 3). This lined up with team formation for each course at a time when participants knew what the project was and who their teammates were, but had not had time to get to know their teammates yet. Participants created an account with a join code that was specific to their team. Once their account was created, participants took both a personality and conflict management styles assessment. Once all assessments were completed, the system released the teammate recommendations. At this time, as well as at the midpoint and end of the project, participants took surveys which measured their perceptions of their team as well as the system.

5.2.3 Participants and Demographics

Participants for this study were recruited from the three course projects described above. For each of the course projects, initial recruitment occurred a few weeks into the semester. Participants were required to use the research platform including taking personal assessments (15 minutes), and take the three surveys which took 5-10 minutes each. It total, 30-45 minutes were required of participants over the course of the semester. Each of the respective instructors offered extra credit for their course as incentive for participation. Students who participated in the interviews at the end of the project did so on a volunteer basis and were not provided with an incentive for this aspect of the study.

A power analysis was performed to determine the number or participants required for a between-subjects repeated measures design. This analysis determined that 120 participants were required to reach a reasonable power for a medium effect size. However, based on course availability and the number of students who volunteered from the three courses, 105 students participated in the study with 101 of these participants completing the entire study. Of these 101 participants, there was a mix of upper-level undergraduate (12 sophomores, 22 juniors, and 43 seniors) and graduate students (24). In terms of gender, 29 participants identified as women, 69 as men, 2 as non-binary, and 1 preferred not to say. 14 of these participants elected to participate in the interviews including 10 who identified as women, 3 as men, and 1 as non-binary. A table of interview participants, their gender, and condition is provided in Table 5.4.

PID	Gender	Condition
2	Woman	Identified Condition
5	Man	Anonymized Condition
6	Man	Anonymized Condition
8	Woman	Anonymized Condition
12	Woman	Identified & Explanation Condition
13	Woman	Anonymized Condition
15	Woman	Anonymized Condition
16	Man	Identified & Explanation Condition
20	Woman	Identified & Explanation Condition
30	Woman	Identified Condition
37	Woman	Identified Condition
44	Woman	Identified & Explanation Condition
48	Non-Binary	Anonymized Condition
51	Woman	Identified & Explanation Condition

Table 5.4: Gender and Condition of Interviewees

5.2.4 Measurements

The measurements for this study include repeated measures through surveys as well as qualitative interviews. For RQ2.1, understanding how recommendation presentation can promote associated characteristics of *teammate* TMMs, team measures were taken. For RQ2.2, understanding how recommendation presentation can promote positive user perceptions of the system, system perception measures were taken. Both team measures and system perception measures were taken at three points throughout the project. In order to understand *why* recommendation presentation influences associated characteristics of TMMs (RQ2.1) and system perceptions (RQ2.2) as well as understanding *why* the teaming environment influences privacy concerns (RQ2.3), qualitative interviews were conducted with participants. Descriptions of each of the measures used are provided in the following sections.

5.2.4.1 Demographics and Personal Measures

Demographic and personal measures were taken at the start of the project only and not administered during the midpoint and end of the project like the other measures. Basic demographics were collected for descriptive purposes including gender, year of study, and co-op/internship experience (see Appendix B, Table B.4. Additionally, the personal measure of *Trust Propensity* was collected. Since this study deals with measures of trust related to a system, it is important to measure how likely an individual is to trust a person or thing. This trust propensity scale was originally created by McKnight et al. (2002) [252] and has been used in previous recommender system research [209, 29, 390]. This scale involves 4 items and has been adapted for this study to use a five-point Likert scale ranging from 1, strongly agree, to 5, strongly disagree (see Appendix B, Table B.7).

5.2.4.2 Team Measures

Although TMMs were not measured directly, other team measures that are known to be associated with *teammate* TMMs were measured including perceived team effectiveness, team satisfaction, team cohesion, and team psychological safety.

Perceived Team Effectiveness As described in Section 2.2.2, research has consistently shown a relationship between TMM similarity and team performance (e.g., [263, 244, 237] as well as between TMM accuracy and team performance (e.g., [78, 103, 105]. Due to the varied nature of the team tasks, objective team performance measures were not collected. Instead, perceived team effectiveness measures were taken throughout the semester. Perceived team effectiveness was measured using a scale developed by Rentsch & Klimoski in 2001 [315]. The scale's three dimensions targeted client satisfaction, team viability, and team member growth and included 9 items (adapted to 8 items for this study), which were answered on a seven-point Likert scale that ranges from 1, strongly disagree, to 7, strongly agree. A list of the questions used in this measure can be found in Appendix D, Table D.13. Compared to the other measures, perceived team effectiveness was only measured at the mid-point of the project and at the end of the project (not at the start of the project) since most of the questions in this survey were not relevant to a team that had only recently formed.

Team Satisfaction Team satisfaction has been shown to be associated with TMM similarity [415]. Team satisfaction was measured using the scale developed by Vegt and colleagues in 2001 [382]. The scale includes three items answered using five-point Likert scales ranging from 1, strongly disagree, to 5, strongly agree. Each participant provided answers to the questions, which were summed and averaged together to produce an overall team satisfaction metric. A list of the questions used can be found in Appendix D, Table D.10.

Team Cohesion Team cohesion is known to be associated with TMMs [112]. To study team cohesion, a survey is administered using a six item scale. The scale was originally developed by Michalisin and colleagues in 2004 [258]. The scale includes six items, which are answered on a Likert scale ranging from 1-5 with anchors of 1, strongly disagree, to 5, strongly agree (see Appendix D, Table D.12. Each participant completed the measure, which were summed and averaged to produce a metric for team cohesion.

Team Psychological Safety Prior research has shown an interdependence between team cognition and psychological safety [49]. For instance, teams with higher psychological safety are able to foster TMMs due to an environment that promotes sharing [59]. In the other direction, research suggests that TMMs can support teams in their ability to understand what issues are important to discuss to promote team psychological safety [287]. In addition to understanding any differences in team outcomes from recommendation presentation, it is important to understand if there are any negative side effects from presentation. For instance, not anonymizing teammate information could result in negative perceptions of teammates and have a negative effect on team psychological safety. Thus, team psychological safety was measured throughout the team projects using a scale developed by Edmonson in 1999 [102]. This scale includes seven items answered using a seven-point Likert scale that ranged from 1, very inaccurate, to 7, very accurate. All team members provided responses to the questions, which were summed and averaged to produce an overall team psychological safety metric.

5.2.4.3 System Perception Measures

In addition to understanding how changing recommendation presentation can influence team outcomes, it is important to understand how these changes influence user perceptions of the system (RQ2.2). This includes perceptions of the system's privacy which was measured through participant's *system-specific privacy concern* and their *perceived over-sharing threat*. Other perceptions were measured including their trust in the system and their satisfaction with the system.

System-specific Privacy Concern System-specific privacy concern relates to how much concern an individual has for their privacy while using a certain system. To measure this, a three-item survey was used involving a five-point Likert scale (strongly disagree to strongly agree). The questions in this survey can be found in Appendix E, Table E.14. Created by Knijnenburge et al. (2012), this survey has been used in recommender system research to understand user perceptions of the system [205].

Perceived Over-Sharing Threat Another aspect of privacy is the user's perception as to whether or not the system is causing them to share too much information or *perceived over-sharing threat*. In this study, a measure created by Knijnenberg and Kobsa (2014) was used [207]. This survey involves six questions and a five-point likert scale ranging from strongly disagree to strongly agree (see Appendix E, Table E.15 for the full survey).

Trust Trust is a multidimensional concept. In addition to propensity, McKnight et al.'s (2002) framework includes factors such as competence (i.e., ability to accomplish the task), benevolence (i.e., care for the trustor's interests), and integrity (i.e., honesty and good faith) [252]. Measures based on this framework have been created and validated for the recommender system context [209, 29, 390] and were further adapted for this study. Trust competence, benevolence, and integrity are measured on a five-point Likert scale (strongly disagree to strongly agree) using five, three, and three items respectively (see Appendix E, Tables E.16, E.17, and E.18).

Satisfaction with the System An important component to adoption to systems is user's satisfaction with the system. Satisfaction was measured throughout the project using an 11-item survey created by Knijnenburg & Kobsa in 2013 [203]. This survey utilizes a five-point Likert scale and can be found in Appendix E, Table E.19.

5.2.4.4 Interviews

For this study, 14 interviews were conducted using Zoom calls. In each interview, up to 21 pre-defined open-ended questions were asked. Since questions often overlapped, had follow-up questions, or were answered by participants before the question was asked, *21 questions* is an approximation. First, participants were asked about their perceptions of receiving the recommendations (e.g., *"Did you think the recommendations were helpful? Why or why not?, Did the recommendations seem accurate?, Did your perceptions of the recommendations change through the semester?"*). Second, participants were asked how they felt about information being shared to their teammates about them (e.g., *"Did this feel like an invasion of privacy? Why or why not?*). Last, participants were asked about any ways the system might have affected teamwork throughout the semester (e.g., *"Were there any positive/negative outcomes from using this system?"*). The average length of these interviews was around 15.3 minutes.

5.2.5 Analysis

This study involved both quantitative and qualitative methods of analysis. First, analysis of the quantitative data involved a repeated-measures, between-subjects ANOVA to determine any differences between conditions over time regarding system perceptions and team outcomes. Additionally, a linear mixed-effects model was used in order to determine what factors were significantly related to system satisfaction.

Second, the interview data was from this study was analyzed using thematic analysis based on grounded theory [130]. In line with prior research involving thematic analysis [365], the following steps were taken to analyze the data: (1) two researchers read through all the participant narratives to obtain a basic understanding of participant perceptions of the sharing system; (2) two researchers iteratively generated codes independently based on various patterns that the data contained; (3) two researchers categorized participant responses by major themes and sub-themes and extracted quotes; and (4) two researchers discussed and refined themes to ensure that participant perceptions were thoroughly understood and summarized.

5.3 Results

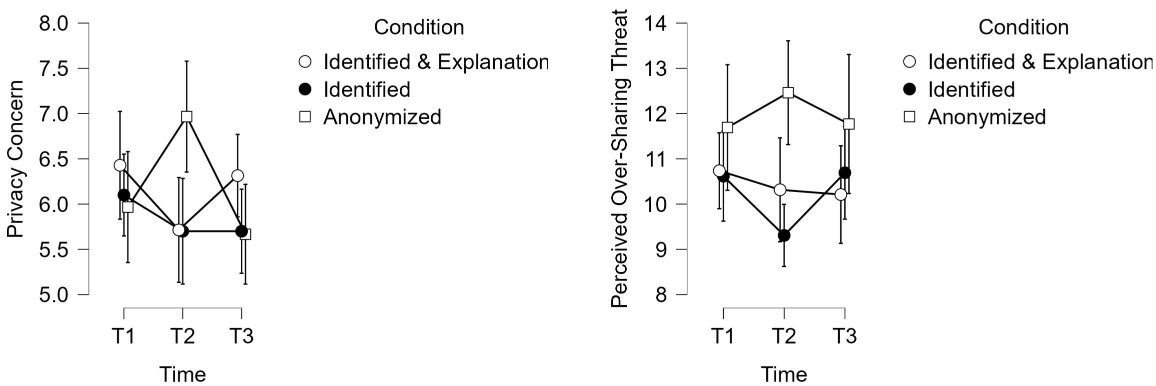
This section contains a quantitative and a qualitative subsection to address the research questions associated with this study. First, statistical analysis was used to understand how presentation can influence system perceptions (RQ2.1) and team outcomes (RQ2.2). Second, qualitative findings are presented using thematic analysis to better understand how users perceive the balance between the benefits of using the system and their privacy concerns (RQ2.3).

5.3.1 Quantitative Results

5.3.1.1 System Perceptions

In order to determine if significant differences existed between conditions regarding system perceptions a repeated measures ANOVA was conducted for each of the measures including privacy concern, perceived over-sharing threat, trust (competence, benevolence, and integrity), and system satisfaction.

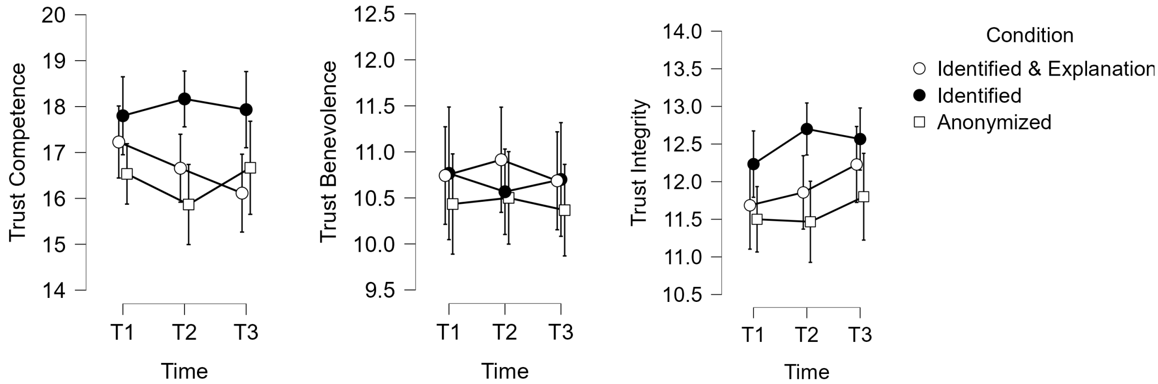
First, privacy perception results were analyzed including privacy concern and perceived over-sharing threat. A visualization of these two measures is shown in Figure 5.1. Of particular interest was understanding if anonymizing recommendations would decrease negative privacy perceptions of the system. However, this was not the case. If anything, there was a slight trend showing *more* negative privacy perceptions in the anonymized condition. To measure this difference, planned contrasts comparing the anonymized recommendation condition to the two identified recommendation conditions were performed for each of the two privacy measures. Planned contrasts revealed that anonymized recommendations increased **privacy concern**, compared to identified recommendations at $T_2 : t(95) = 1.86$, $p = .066$ with near-significance. However, this trend was reversed (and not significant) at T_1 and T_3 as anonymized recommendations decreased **privacy concern**, compared to identified recommendations at $T_1 : t(97) = -0.64$, $p = .524$ and $T_3 : t(96) = -0.80, p = .425$. For **perceived over-sharing threat**, there was a trend toward increased over-sharing threat for the anonymized recommendation condition at all three times; however, there was no significance. Planned contrasts revealed that anonymized recommendations increased **perceived over-sharing threat**, compared to identified recommendations at $T_1 : t(97) = 0.33$, $p = .742$; $T_2 : t(95) = 1.55$, $p = .125$; and $T_3 : t(96) = 0.28, p = .780$.



(a) Privacy Concern (b) Perceived Over-Sharing Threat

Figure 5.1: Privacy Perceptions by Condition Over Time

Second, trust results were analyzed including trust competence, trust benevolence, and trust integrity to understand how presentation aspects such as anonymity and explanations influenced different types of trust in the system over time. A visualization of these three measures is shown in Figure 5.2. Analysis revealed no significant difference between conditions for trust benevolence and no meaningful trend. However, there was a trend for both trust competence and trust integrity in comparing the Identified condition (i.e., identified recommendations with no explanations) to the other two conditions. Planned contrasts revealed that identified recommendations with no explanations increased **trust competence**, compared to anonymized recommendations without explanations and identified explanations with explanations at $T_1 : t(97) = 0.84, p = .404$; $T_2 : t(95) = 1.91, p = .059$; and $T_3 : t(96) = 1.62, p = .108$. Planned contrasts revealed that identified recommendations with no explanations increased **trust integrity**, compared to anonymized recommendations without explanations and identified explanations with explanations at $T_1 : t(97) = 1.17$, $p = .245$; $T_2 : t(95) = 2.20$, $p = .031$; and $T_3 : t(96) = 1.05, p = .296$.



(a) Trust Competence (b) Trust Benevolence (c) Trust Integrity

Figure 5.2: Trust Perceptions by Condition Over Time

Third, system satisfaction data was analyzed. A visualization comparing system satisfaction for the three conditions over time is shown in Figure 5.2. Analysis revealed an interesting interaction effect between condition and time as satisfaction increased for the Identified condition (i.e., identified recommendations with no explanations) and decreased over time for the other two conditions. Planned contrasts revealed that for timesteps 2 (halfway) and 3 (at the end), participants who received identified recommendations with no explanations had a higher **system satisfaction** than those who received anonymized recommendations without explanations or identified recommendations with explanations at $T_1 : t(97) = 0.58$, $p = .566$; $T_2 : t(95) = 2.62$, $p = .010$; and $T_3 : t(96) = 2.84, p = .006$. The results related to Team Measures (Section 5.3.1.2) and the qualitative results (Section 5.3.2) shed light on why users might be more satisfied with the system in the Identified and Identified & Explanation conditions compared to the Anonymized condition. However, it was expected that participants in the Identified & Explanation condition would have higher system satisfaction compared to participants in the Identified due to the benefit of having explanations [374].

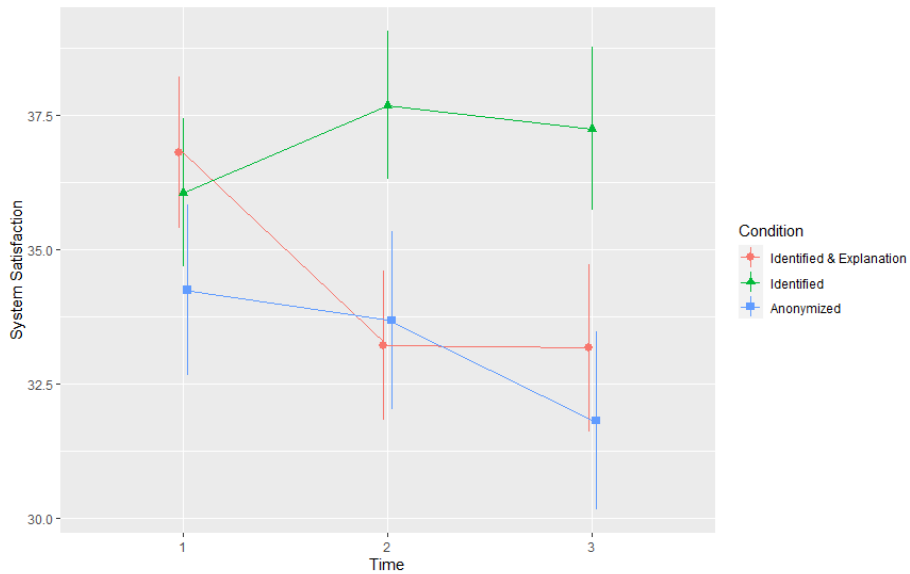


Figure 5.3: Satisfaction with the System Over Time

To better understand these differences in **system satisfaction**, a linear mixed-effects model was created to include factors such as trust competence, privacy concern, condition, and time. Table 5.5 summarizes the results of the model. This model indicates that both lower privacy concern ($p < 0.001$) and higher trust competence ($p < 0.001$) have a significant effect on satisfaction of the system. Additionally, there is main effect of time on system satisfaction ($p = 0.009$) and an interaction effect between time and condition ($p = 0.019$). These results indicate that the difference in system satisfaction between Identified and Identified & Explanation conditions might be partially due to users having *less* trust in the system when it provided explanations.

	B	t	χ^2	p
Trust Competence	0.99	10.30		< 0.001
Privacy Concern	-0.46	-3.25		< 0.001
Condition			4.26	0.119
–Condition Contrast [2 v 1,3]	-1.23	-0.74		0.460
–Condition Contrast [1 v 3]	-0.87	-0.47		0.640
Time	-0.72	-2.64		0.009
Time*Condition			8.73	0.013
–Time*Contrast [2 v 1,3]	1.71	2.93		0.004
–Time*Contrast [1 v 3]	-0.26	-0.40		0.692

Table 5.5: Linear Mixed-Effects Model Results for System Satisfaction

In summary, this study found that identifying the recommendations did not increase privacy concerns with the system, and this study did not find evidence that providing explanations increased trust in the system. Additionally, data indicated that providing identified recommendations without explanations resulted in the best perceptions regarding system satisfaction. This type of recommendation (i.e., identified recommendations without explanations) resulted in significantly higher system satisfaction at T_2 and T_3. In addition to time and condition influencing system satisfaction, higher trust competence and lower privacy concern resulted in increased system satisfaction.

5.3.1.2 Team Measures

Next, a repeated measures ANOVA was used for each of the team measures associated with TMMs including (A) team satisfaction, (B) team psychological safety, (C) team cohesion, and (D) perceived team effectiveness. It was anticipated that the condition with anonymous recommendations might have worse team outcomes due to the recommendations being more ambiguous. To analyze this data, a linear mixed-effects model was run on the repeated measures that accounted for the participant's team as a random intercept. Planned contrasts were used to compare the two conditions with identified recommendations to the one condition with anonymized recommendations.

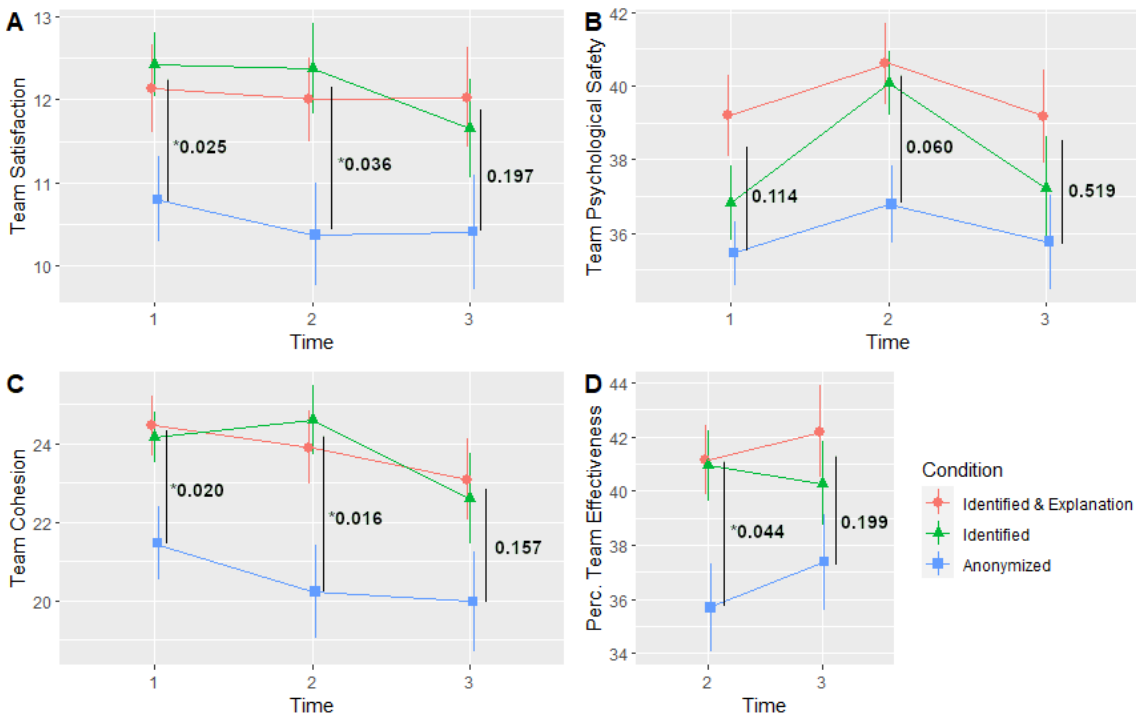


Figure 5.4: Team Measures by Condition Over Time. Vertical black lines and associated numbers refer to the p-value of the planned contrast comparing the two identified conditions to the anonymized conditions at each time.

(A) Planned contrasts revealed that participants in the two identified recommendations conditions (Identified and Identified & Explanation) had significantly higher levels of **team satisfaction**, compared to participants in the Anonymized condition, $t(23) = 2.07$, $p = .049$. (B) Planned contrasts revealed that participants in the two identified recommendations conditions (Identified and Identified & Explanation) had significantly higher levels of **team psychological safety**, compared to participants in the Anonymized condition, $t(23) = 1.71$, $p = .100$. (C) Planned contrasts revealed that participants in the two identified recommendations conditions (Identified and Identified & Explanation) had significantly higher levels of **team cohesion**, compared to participants in the Anonymized condition, $t(23) = 2.29$, $p = .032$. And (D), planned contrasts revealed that participants in the two identified recommendations conditions (Identified and Identified & Explanation) had significantly higher levels of **perceived team effectiveness**, compared to participants in the Anonymized condition, $t(23) = 1.87$, $p = .074$.

A visualization of all of these measures, by condition over time, can be found in Figure 5.4. In this visualization, p-values are provided for the differences between the conditions at each timestep. These results suggest that providing identified recommendations can improve team outcomes associated with TMMs, particularly at the start and midpoint of temporary team projects.

In summary, identified recommendations significantly increased team satisfaction and team cohesion compared to anonymous recommendations. This effect of condition was nearly significant for team psychological safety and perceived team effectiveness. Figure 5.4 also shows that for all team measures, significance between the identified recommendation condition and the anonymized recommendation condition diminished between time 2 and time 3.

5.3.2 Qualitative Results

In this section, I present the qualitative findings for how temporary team members perceive the balance of privacy concern to the benefits of information sharing regarding how the information is presented (RQ2.3). Based on the interview data from this study, three themes emerged including: (1) perceived strong benefits from understanding how other members interact in a team environment from the project's onset; (2) polar views exist in privacy concerns regarding teammate information sharing; and (3) attempts to alleviate privacy concerns associated with teammate information sharing create issues of ambiguity and assumptions.

5.3.2.1 Perceived Strong Benefits from Understanding How Other Members Interact in a Team Environment from the Project's Onset

To understand how temporary team members perceive the balance of privacy concern to the benefits of information sharing, it is important to understand what these team members perceive as the benefits to sharing this information. Two subthemes regarding benefits emerged including: (1) teammates appreciate improved awareness and preparedness and (2) teammates interact differently based on improved understanding.

Teammates Appreciate Improved Awareness and Preparedness Many team members expressed appreciation for the shared teammate information through recommendations as it assisted in providing an understanding of their teammates. This is shown in the following quotes:

> *I think it was a good primer. Sometimes when you get a new team it's hard to tell who you're going to be with and you don't really have a good read on everybody.* -P44, Identified & Explanation Condition

> *Working in a team for many months you develop relationships, you see people's weaknesses... you work around it to achieve goals in the most efficient and robust manner. And I think a system like this kind of helps on-board that and accelerate that process.* -P48, Anonymized Condition

It gave me a little bit of awareness as to what I could expect from my teammates. Just 'hey maybe this person is going to be a little bit more outgoing than myself' and stuff like that. I think being aware was very useful. -P16, Identified & Explanation Condition

As described by P44, temporary team members are often unfamiliar with one another as they start a new project on a new team. P48 describes how teams are more efficient once they gain an understanding of teammates; however, this often takes teams time as they must form relationships and understand differences. In-line with this, P16 gave a specific example of awareness in knowing how their teammate compared in terms of extraversion. Thus, sharing personal information like this is a way to accelerate understanding of one another.

For some, this awareness centered on not being surprised by certain differences between team members:

It was more just like when that behavior did come up, I was like 'oh that's just how they work, I guess. -P20, Identified & Explanation Condition

In this quote, P20 provided a general quote indicating that they were less surprised when their teammates worked differently than them. This is in opposition to the possibility of attributing the behavior as negative if they were surprised by the behavior. Other participants pointed to awareness that potentially lessened the blow of issues caused by differences:

So I think the big thing is... being prepared for when things aren't done when they're expected to be. -P5, Anonymized Condition

P5 had received a recommendation describing how their teammate might not work on the same timeline or proactivity as them. Thus, they were able to prepare or anticipate for different expectations for deadlines within the team. For other participants, the awareness created by recommendations.

Teammates Interact Differently Based on Improved Understanding The prior sub-theme speaks to how participants used the information from recommendations to create awareness and not be surprised by behaviors. In this sub-theme, many participants spoke to understood differences in their behavior or interactions with teammates based on that understanding. For some, this took the form of knowing how to operate, navigate, or organize with their team:

> *Like if you have a bunch of people who are kinda like 'I tend to just wait until the last minute', you know you have to push to front load stuff. And then if you have people who are kind of like 'I'm super type A and I'm going to take control and I'm going to do xyz' - you might have to carve yourself out a position earlier in the group.* -P15, Anonymized Condition

> *I think in practical use it is nice to know [that] this person is going to be more accommodating. So if you ever run into issues or you need an extra hand on something, it's nice to know this person fits that category. And then vice versa, like if I know I have this very large and major aspect of a project I probably shouldn't leave it in the soul hands of the people who have low levels of self-discipline.* -P5, Anonymized Condition

These two quotes highlight how participants perceived they could use the information about their teammates to make better team-level decisions. P15 emphasized the utility of knowing how proactive members are so that the project can be front-loaded if necessary. P15 also discussed how knowing a team is full of type-A members (e.g., competitive, goal-oriented, aggressive) requires members to be more assertive.

For P5, this awareness can help teams make decisions regarding assigning tasks if they are mission-critical.

For others, the actionable information from the recommendations influenced how they communicated as a team:

> *Especially [the recommendations] that said, like 'I'm not willing - I'm not as ready to speak up about things.' If they have an opinion [I made] sure that we didn't just walk all over them kinda... It was good to know that the people who weren't as ready to voice their opinions got time to speak.* -P37, Identified Condition

> *[One teammate] was maybe a little bit more timid... waits for quiet time in conversation to jump in, that kind of thing. So I think that particular recommendation was actionable. Because I would consciously say, 'Oh [name] - what do you think? Like can you give an idea, or what's your take on what we're talking about right now?' So I use that to try to actively include her.* -P2, Identified Condition

These two quotes illustrate how recommendations provided to team members who are more extroverted and outgoing can be helpful in promoting quieter, less aggressive voices on the team. Both P37 and P2 (who were not on the same team) described how they were able to better include a team member who was perhaps more shy. This inclusion can promote more diverse ideas being heard in the decision-making process for teams. On the other hand, recommendations like these can be useful for team members who are less forceful:

> *I usually let the others have their say... And the recommendation of one of my teammates was that they are good at pushing their agenda. And*

they can be headstrong about it. And the recommendation for me was like you know - I should speak up more because that's expected. So whenever there was a situation where we agreed or disagreed I felt it helped me put my ideas forward -P48, Anonymized Condition

For me it helped me to be able to know that this is who the people I'm dealing with, this is who they are. So that helps me to learn to adjust - if I know that I need to be more forceful, then you know, and so on, so for me it was useful. -P6, Anonymized Condition

These quotes from P48 and P6 highlight how lesser-heard voices can be encouraged to speak in the opposite direction. If more passive team members know that their teammates are more aggressive than them, they are able to anticipate needing to push their opinions harder than they would otherwise. Although this is an understanding that they would gain eventually from working with their team, providing recommendations can foster this understanding earlier.

In summary, participants found benefit from teammate recommendations in the form of being aware and not surprised by personal differences related to teamwork. Additionally, these team members perceived that they were able to interact differently with their teammates based on this understanding. Although participants did not explicitly describe having "improved *teammate* TMMs", their descriptions of not being surprised, being prepared, and having improved interactions run parallel to the benefits of having accurate *teammate* TMMs.

5.3.2.2 Polar Views Exist in Privacy Concerns Regarding Teammate Information Sharing

The second theme that emerged from these interviews was that there were strong differences between individuals regarding how they thought about privacy concern for a system that shares their information with their teammates. To better understand this theme, sub-themes have been organized as follows: (1) some find sharing certain traits as sensitive; (2) individual differences influence perceptions of sharing; and (3) expectations of teamwork influence willingness to share.

Some Find Sharing Certain Traits as Sensitive Although the recommender system emphasized that there are no 'better' or 'worse' personalities or conflict management styles, there was still a lingering perception for many that the system was sharing sensitive or negative information about themselves:

> *It was a little bit weird having your personality just laid out pretty much for strangers I've never met, you know. Like 'hey just so you know, this person is really anxious and really bad with timing...' It's not that the information is wrong, it was more just like, oh it's a little bit weird that we just kind of gave all this information out at first.* -P20, Identified & Explanation Condition

> *When I first saw the recommendations I did feel kind of weird about it, I was kind of like - it thinks I'm mean and now my team is gonna have an impression of me that I'm mean.* -P44, Identified & Explanation Condition

For P20 and P44, there was a realization that the system was sharing negative/sensitive information about them. As team members had not had time to get to know each other, sharing such information can create an awkward or strained dynamic within the team. Thus, there is a tension created in using such a system at the start of a temporary team project. For the system to be effective, personal information, potentially information perceived as negative, must be shared at the start of the project to accelerate *teammate* TMMs. However, sharing information early on can lead to uneasiness with creating a bad first impression. This tension was realized by some participants:

> *I would like to hide the parts that are negative on me. Like for instance I've scored by far the lowest in terms of compromising. That's not something I necessarily want my group members to know but it's something that they should know.* -P5, Anonymized Condition

> *And so I think that information would definitely be helpful for the group, but at the same time it's like - if this system didn't exist, I would not literally go and tell someone, 'hey this is how I operate', you know I mean? So it did make me feel kind of like 'Oh, this is kind of awkward.'* -P30, Identified Condition

These quotes get to the crux of a teammate information-sharing recommender system: sharing teammate information is beneficial for teamwork, but comes at the cost of privacy concern to some. Importantly, this privacy calculus is different at an individual level. Thus, the following sub-themes explore how various individuals can look at privacy concern differently in this context.

Individual Differences Influence Perceptions of Sharing In contrast to some of the concerns represented in quotes in the previous sub-theme, there were many participants that strongly felt that there was not any privacy concern. Examples include the following:

> *I mean I don't care about that stuff personally... As far as privacy, yeah I didn't care at all.* -P2, Identified Condition

> *I'm not very private and I also think that a lot of that stuff shouldn't be very surprising to anybody who reads it and I don't really care if they read it. And part of that too is, I don't know, I like myself, I think I'm great. Like I don't get embarrassed about stuff like that.* -P13, Anonymized Condition

P2 and P13 provide an example of individuals that simply do not think sharing information related to their personality and conflict management styles create any privacy concerns. Although the reasons might differ by individuals, reasons might include not perceiving their traits as negative or being proud of who they are (P13), personally not caring about privacy (P2), or expecting their teammates to eventually see these traits in them anyway (P13).

However, like in the quotes from the previous sub-theme, there are certain individuals that find this type of information disclosure uncomfortable:

> *The one thing I was thinking about before this was like - it was a little weird and embarrassing at first to have some of that stuff revealed.* -P44, Identified & Explanation Condition

This quote from P44 stands in stark contrast to the quotes mentioned previously (P2 and P13). As P44 and P8 feel much more uncomfortable about this sharing process, their perspective on privacy should be heavily considered when designing such a revealing system. Additional quotes shed light on *why* certain individuals feel uncomfortable sharing:

> *I have general anxiety... But I do not want to be perceived as that in the work environment. So, I would like to portray myself, or I try my best to portray myself, as being confident and without the unsure nature and all those things that come with something like anxiety. So as a result, I curate how I approach and present myself in a work environment or work situation so I'd be very careful with some of these negative [characteristics].* -P48, Anonymized Condition

> *Most of my life I tend to be a private person and an introvert so - I like to change it. But if they [know that] before the group project starts, then they would have some sort of prior understanding of my personality and they would have something like that which I obviously want to change and that might be a problem.* -MD P8, Anonymized Condition

For P48 and P8, there is an understanding that they have certain personality traits that they would prefer to portray differently to their teammates. P48 would prefer to give off a more confident impression while P8 does not want to be seen as introverted. These quotes highlight how providing teammate recommendations at the onset of a project can result in putting teammates 'in a box', or at least the perception that that is happening. Similarly, P12 voiced similar concerns:

> *Initially, I am not open to everyone and I'm a bit shy in talking. So that is one of [my traits], but that doesn't mean that I don't know how to lead or how to stick to my point or how to present myself. So they're very different things... Because they might [assume] other things if they know*

that I'm shy... that maybe I'm not good in presentation, or maybe I'm not good as a leader. So I don't want them to conclude by themselves in their minds. -P12, Identified & Explanation Condition

This quote by P12 presents a similar, yet different concern. Whereas P48 and P8 were concerned that sharing a specific trait would prevent them from portraying themselves as different, P12 was concerned that sharing a certain trait could lead to additional assumptions. As P12 points out, traits such as introversion and leadership are not mutually exclusive; however, teammates might jump to such a conclusion unwantedly.

Expectations of Teamwork Influence Willingness to Share As described above, personal differences exist that influence perceptions of privacy. An important component of these differences in this context is how participants view the team and their expectations of teamwork. For many, considering the teamwork context reduced or removed privacy concerns:

I didn't feel like my information - any information was revealed to them that wouldn't have been otherwise revealed just by getting to know me through working as a group throughout the semester... These types of traits would show up in your analysis of each other. so I don't think it was particularly invasive. -P16, Identified & Explanation Condition

I think because of all the personality attributes we were assessing were things that inherently come out in a group project setting or any setting where you're working on a team. It's not like I think you're going to be hiding those factors anyway. -P15, Anonymized Condition

Here P16 and P15 point to an important aspect of teamwork in that they expect this type of information to come out anyway through working with teammates over the course of a project. Similarly, P13 added an additional component:

> *So dominance can come across as super bossy and rude. So they're going to find out [my traits] with or without this recommender system, but I think the recommender system gives context to it and explains it and then gives suggestions on how to deal with that.* -P13, Anonymized Condition

For P13, not only did they expect this information to come out naturally anyway, they perceived that the recommender system shared the information with context to explain the differences. This way of sharing was perceived as a way to improve the understanding of their teammates in a more positive, holistic way.

Similar to the sentiment that 'my teammates are going to find out anyway' was the sentiment that 'teammates need to know':

> *I feel like you'd want your teammates to know that stuff about you. So I feel like I wasn't really concerned about that.* -P37, Identified Condition

> *I also think that if you are on a team and you are using something to increase teamwork, I don't know why you would go into that situation and be like, 'I don't want you to know anything about me.* -P51, Identified & Explanation Condition

These quotes point to the acknowledgement, as described in the first theme, that there are benefits to teammates knowing this information to improve teamwork. Thus, their expectation of privacy is mediated by what they see as beneficial for the team.

However, once again, not everyone looks at teamwork or their teammates the same. For some, there is an anticipation for the possibility of teammates working against one another:

> *If I know that this guy [might] easily give into me, then I might fall for the trap of taking advantage of that and always wanting to suggest ideas knowing that once I suggest, I know that these guys will always give in.* -P6, Anonymized Condition

In this quote, P6 described how information can be used against teammates. Although this particular quote points to the possibility of using information against another teammate, this quote was from a larger conversation that generally expressed concern for teammates using information against one another. Thus, if team members do not have trust for one another to use the information in a fruitful manner, privacy concerns will certainly exist. This sentiment was reflected in other quotes:

> *I mean I don't think I care much about concealment of any of that. But at the same time I don't know if in a typical work setting I would disclose [personal information] in a professional environment.* -P48, Anonymized Condition

The participants in this study were student teams. In this quote though, P48 acknowledges that teamwork might be different in a professional environment. Professional environments might have additional factors to consider such as working against each other in search of career advancement. Therefore, not every team environment is the same and additional motivations must be considered before assuming that a team context is enough to eliminate privacy concerns.

In summary, individuals vary greatly on how they perceive privacy concerns in using a teammate information sharing recommender system. For many, little to no privacy concerns exist based on their personality. For others, the teamwork context reduces privacy concerns based on their expectations of teamwork. Still others have great privacy concerns that must be accounted for in such a system.

5.3.3 Attempts to Alleviate Privacy Concerns Associated with Teammate Information Sharing Create Issues of Ambiguity and Assumptions

The third and final theme that emerged from this data is that trying to remove privacy concerns associated with teammate information sharing can create issues of ambiguity and assumptions. In this study, some conditions received anonymous recommendations (i.e., recommendations were not associated with teammate names). This manipulation was created to understand if privacy concerns could be reduced through anonymity settings. Although qualitative data shown in the previous theme points to the desire for concealing information or anonymity settings, quotes in this theme point to negative side effects associated with such efforts:

> *So yeah I didn't see people's names, you had to kind of infer... I was absolutely trying to guess who was who. . . .I think the first time I read them, it was more of a guess, and then, like everything became very apparent after I worked with the people for a couple of weeks.* -P15, Anonymized Condition

As described by P15, one issue with anonymous recommendations is that team members will try to make assumptions as to who the recommendation is referring to anyway. Other participants discussed the issues that can arise with such assumptions:

> *But [anonymity] also makes a different problem. Like, I have to accommodate for both kinds of personalities... So while I am interacting with them, I have to keep all of those personalities [in mind], though they might not be applicable for all of them.* -MD P8, Anonymized Condition

> *Maybe in a situation where we are further broken into a [one on one situation]... I might not be able to know how to relate with the person. So I might just apply the general result, based on the recommended system and just apply it to that person, which might not be accurate.* -P6, Anonymized Condition

For P8 and P6, there was an acknowledgement that making assumptions can result in mentally pairing a recommendation with the wrong person. Not only does this cause confusion, but it could result in some negative interactions that would not have happened had no recommendations been made to begin with. In addition to making wrong assumptions, other participants discussed how anonymous recommendations were not as actionable:

> *I think it would have been nice to know which ones were matched up with who. I just think that that adds an extra layer of understanding of how this person works... When you know who is who and what goes with who, then you can kind of gauge how you interact with that person and how you look to that person.* -P13, Anonymized Condition

> *But I mean in terms of practicality, I think you would have to keep them not anonymous because... it just helps you kind of pin like - okay this person in particular might need some reminders which is not something you'd be able to do easily if they were anonymous.* -P5, Anonymized Condition

As mentioned by P13, knowing exactly who a recommendation is paired with is helpful in knowing how to interact with that person. This sentiment was also described by P5 who wish they knew who needed reminders in order to hit deadlines. Although anonymity might be fruitful in reducing some privacy concerns associated with teammate information sharing, many participants acknowledged that anonymous recommendations were not as helpful as they could have been if they were identified.

5.4 Discussion

The quantitative data from this study provides insights to the research questions regarding how presentation (anonymity and explanation) can influence perceptions of a teamwork information-sharing recommender system (RQ2.1) and associated characteristics of *teammate* TMMs on temporary teams (RQ2.2). Based on the results in a real team setting, I found that identifying recommendations did not increase privacy concerns for a teammate information-sharing recommender system. Likewise, providing explanations with recommendations did not increase trust in this type of system. In this case, providing identified recommendations with no explanations produced the best results for trust competence and trust integrity perceptions of the system. These types of recommendations also resulted in the best system-satisfaction in the long term. Results indicated that factors such as privacy concern and trust competence influenced this satisfaction. For team measures associated with TMMs, the main takeaway was that anonymizing teammate recommendations results in significantly worse team outcomes. This was significant for team satisfaction and team cohesion and nearly-significant for team psychological safety and perceived team effectiveness.

Qualitative data was useful in understanding how users perceive the balance of privacy concern to the benefits of information sharing (RQ2.3) and how these relate to recommendation presentation (RQ2.1 and RQ2.2). Regarding benefits, participants found the sharing of this information beneficial in creating an awareness of their teammates and not being surprised by their behavior. Additionally, participants perceived that they were able to organize and communicate better with their teammates by understanding their differences. For privacy concern, thematic analysis revealed that polar differences exist at an individual level. Some participants had no concerns at all, whereas some participants had heavy concerns. These differences in perceptions were likely influenced by personal differences and outlooks on teamwork. In response to this, attempts to alleviate privacy concerns for some is necessary. However, anonymous recommendations contain various issues including team members making incorrect assumptions about their teammates and recommendations not being as actionable.

The importance of temporary teams continues to rise in organizations [362, 233]. Based on the importance of these teams and the fact that they contain different structures and processes from ongoing teams [332, 242], it is important to understand how technology can support these teams. The CSCW community has shown great interest in supporting temporary teams (e.g., [118]. In this section, I discuss how the findings contribute to this body of literature that seeks to understand how teammate information sharing can be facilitated by technology.

5.4.1 Explanations and Their Efficacy in an Information-Sharing Recommender System

Using explanations in recommender systems is a common practice as a way for users to understand the recommendation process and assist in their acceptance of recommended items [64, 307, 110]. Specific to the group recommender system context, research has placed much attention on understanding how explanations might result in privacy concerns since the group recommendation explanations might share *why* a recommendation was provided in terms of individual group member preferences [240, 279, 277]. The results of this study suggest that explanations in the information-sharing recommender system context do not increase trust in the system or satisfaction in the system, nor do they increase privacy concerns. This creates two avenues of discussion in comparing this type of system to: (a) single-user recommender system and (b) group recommender system.

First, considerations must be taken in understanding why explanations in this context did not increase trust or satisfaction in the system as explanations do increase trust and satisfaction for single-user recommender systems [285]. One possible rationale for why explanations were not effective in increasing trust or satisfaction might reside in the quality of the explanations used. Prior research has pointed to explanation quality significantly influencing perceptions of recommendation quality as well as trust in the recommendations [217]. The explanations provided in this study involved simply explaining to users why a recommendation was generated (e.g., *In the category of* ***dominating****, you scored* ***high*** *and they scored* ***low***. It is likely that participants perceived this explanation as basic since they knew that recommendations were generated based on personality and conflict management style assessment results anyway. Participants in the condition that did not receive explanations might have assumed that the recommendations were selected using a much more sophisticated algorithm that factored in numerous personality factors. Thus, it is possible that explanations were perceived as low-quality which could explain why the condition that received explanations had lower trust and satisfaction.

Second, it is important to understand why explanations did not increase privacy concerns in this study. Research in the group recommender system context has emphasized how group explanations can increase privacy concerns [153, 309, 277]. Group recommender systems create an important comparison for this research since they involve group-level interactions and sharing personal information with the group. However, crucial differences do exist between an information-sharing recommender system and a group recommender system. The goal of a group recommender system is to provide a recommendation or recommendations to a group, usually in the form of a group decision [167, 87]. For information-sharing recommender systems, the goal is to share information about others, although preferably the most helpful and least private. This is held in contrast to group recommender systems that only share information about others when necessary to formulate an explanation [279]. Therefore, privacy concerns are created by group recommender system explanations, whereas privacy concerns already exist due to the recommendations themselves for information-sharing recommender systems. It is likely that the explanations did not further encroach on privacy concerns in this study since privacy concerns already existed due to the recommendations themselves.

5.4.2 Accelerating *Teammate* TMMs on Temporary Teams

One benefit of the design of this study is that it utilized repeated measures to gain an understanding for the effectiveness of the system over time with regard to associated characteristics of TMMs. Of interest in looking at Figure 5.4 and the team measures over time is that the significant difference between the identified conditions and the anonymized condition seemed to reduce over time (e.g., Team Satisfaction: $T_1, p = 0.025$; $T_2, p = 0.036$; $T_3, p = 0.197$). As described by participants in qualitative interviews, a perceived value in the recommendations was team members having an accelerated understanding of one another. This aligns with prior research. For instance, in a study involving temporary learning teams, team members were better able to assess the personality of their teammates at the end of the project than at the beginning [355]. Thus, this system provides the most benefit to temporary teams at the beginning of a project when they would otherwise have limited understanding of one another. However, as there was still a trend for the identified conditions to have improved team outcomes compared to the anonymized condition at T_3 (although not significant), there could still be ripple effects from better understanding each other from the project's onset that influence team outcomes at the end of the project.

The results of this study provide empirical evidence that sharing identified teammate information has a positive influence on temporary team outcomes associated with *teammate* TMMs, especially team satisfaction and team cohesion. This was expected as temporary teams have more trouble developing *teammate* TMMs. Prior research has pointed toward the value of reflecting on and sharing personality information on temporary teams. For team training, reviewing and discussing different personality styles in general as a team can help team members value diversity [397]. Research involving student software engineering teams suggests that taking and reflecting on personality assessments improved interpersonal relations and enhanced trust within teams [303]. Similarly, another study found that members knowing their teammates' personality types were valuable in understanding team member behaviors and managing team dynamics [69]. Although these prior studies have established the importance of discussing such information, the current study provides evidence that sharing such information through technology is not only feasible, but effective at promoting team outcomes.

5.4.3 Design Implications for Promoting *Teammate* TMMs Through a Recommender System

As the concept of an information-sharing recommender system is novel and understudied, the findings from this study provide numerous insights regarding how such a system should be designed especially in team contexts. These design implications relate to privacy settings, improving the use of anonymous recommendations, and improved explanations. Each of these design implications are discussed in the following sections.

5.4.3.1 Opportunities for Reducing Privacy Concerns

An important finding of this study is that polar views exist regarding privacy concerns for an information-sharing recommender system. Although the type of information shared to some did not seem private at all, or was justified by team goals, certain participants expressed high concerns for sharing such information. This creates a conundrum for a system that must account for all members and their various outlooks regarding privacy. If even one member on the team is too concerned about their privacy to use the system, it should not be used [175]. One way to address privacy concerns is allowing individual users to create their own privacy settings for what they are comfortable sharing and not sharing. Although this could result in reduced disclosure, it would be better to have all members comfortable with the system than have some resent using it. An alternative could be using a smart privacy configuration in a similar approach as [391] where users' personality traits were used to predict what they were willing to share in the workplace, to automatically configure privacy settings.

5.4.3.2 Using Anonymous Recommendations to be More Fruitful

Anonymity has previously been used as a successful feature for reducing privacy concerns online [157, 321]. In this study, although some interviewed participants appreciated this design feature, both quantitative and qualitative results pointed toward this being a sub-optimal solution for alleviating privacy concerns as it negatively influenced team outcomes.

These findings suggest that anonymity reduced the efficacy of recommendations in the current team context, because the recommendations were teammate-specific. However, opportunities for using anonymous recommendations in other team contexts might exist. For instance, teams recruited for this study primarily had a size around four or five members; and the system made recommendations related to interactions at the interpersonal level (i.e., pairwise recommendations). This allowed and prompted team members to infer who the anonymous recommendations might apply to, but inaccurate inference can create problems of interaction based on wrong assumptions. An alternative context for such recommendations would be larger teams that might be able to take full advantage of real anonymity, where members can benefit from following the recommendations formulated in general terms without even trying to identify a specific team member. However, for such anonymous recommendations to work effectively, the algorithm should be designed to make recommendations at the team level. This would be similar to the successes seen by group recommender system research that creates group-level recommendations based on the preferences of individuals [166, 248]. The algorithm can be made to calculate the tendency for a team to malfunction, have an imbalanced contribution, develop conflicts, procrastinate, and the like, based on inputs of individual member's personalities and conflict management styles, as well as their various compositions, such that it will provide recommendations only when potential problems are predicted to occur to impact team outcomes. In this way, the recommendations themselves would likely not create privacy concerns. However, this design would require elaborate algorithms to create such recommendations at the team level based on individual differences.

5.4.3.3 Knowing *When* to Explain

A surprising outcome for this study was that explanations did not increase trust or satisfaction in the system. It is highly likely that the perceived quality of these explanations was the cause of this [217]. Much of this was discussed in detail in Section 5.4.1 with comparisons being made to both single-user [64] and group recommender systems [240]. As an information-sharing recommender system is different in nature from both types of recommender systems, it is important to re-evaluate *when* to provide recommendation explanations. Recommendation explanations are typically provided after recommendations have been made as a means to increase user acceptance of the recommended item(s) [307, 273]. However, drawing on the finding that perceptions of team effectiveness transcended concerns for privacy for quite a few people, it is promising that explanations can be repurposed for this context to highlight the importance of information sharing for the benefit of teamwork, *before* recommendations are provided. Prior research has highlighted how the perception of disclosure benefit can increase personal information disclosure [278]. It is likely that explanations can be used for this type of system during the information disclosure process (i.e., privacy setting selection). Explanations could describe how disclosing certain information will help team members coordinate and communicate more effectively and efficiently, avoid unexpected and unwanted conflicts, and the like. Meanwhile, explanations could elucidate potential risks involved in sharing such information so team members can make an informed decision to disclose. As such, explanations provided before recommendations can improve perceived disclosure benefit and potentially increase the amount of information team members disclose.

5.4.4 Limitations and Future Work

This study serves as an important foundation for investigating how a recommender system can be used to share teammate information to support TMMs. However, two limitations of this study should be specifically noted. First, it is important to note that this study utilized actual temporary teams as a way to increase external validity [197]. Although this was helpful in meeting the goals for this study, future work would benefit from utilizing a more controlled environment that would be less subjected to the random effects inherent to an actual teaming environment and could further validate the findings of this present study. Second, the findings of this study might be specific to its context, project-based teams (i.e., knowledge-based teams). This context was selected due to it allowing for measuring associated characteristics of TMMs over time [225]. Although TMMs are a key component of success for both knowledge-based and action-oriented teams [91], future CSCW research would benefit from understanding how action-oriented teams might benefit from a teammate information-sharing recommender system as well [118].

Chapter 6

Study 3: Recommender System Disclosure in Group/Team Contexts

6.1 Overview and Research Questions

A surprising result, or lack of result rather, from Study 2 was that there was no main effect of presentation (i.e., anonymity and explanation) on privacy concern. However, qualitative results suggested that there were differences between participants regarding there privacy concerns. Therefore, it is reasonable to conclude that some amount of privacy concern resulted from individual differences rather than from the presentation manipulation. There are likely many factors that influence privacy as prior group recommender system research has investigated how the type of relationships in a group influence disclosure as well as individual differences and the sensitivity of the information [278, 274, 278, 306]. This line of inquiry motivates this third study in trying to understand factors related to privacy concern and disclosure behavior. Additionally, results from Study 2 revealed negative outcomes for using anonymity to mitigate privacy concerns. Therefore, other avenues (i.e., disclosure controls) need to be investigated as a means to reduce privacy concerns while still using the system.

To better understand how the team context might influence disclosure and privacy concerns, Study 3 utilizes three conditions to manipulate the group/team context including: (a) members are assessed fully on their individual results (individual grade); (b) members are assessed 50% based on their individual and 50% based on their team results (mixed grade); and (c) members are assessed fully on the team's results (team grade). Participants were able to make selections as to what information from personality and conflict management style assessments would be shared with their group/team to understand how the information type relates to disclosure. Further, personality measures were taken to understand how individual differences relate to disclosure and privacy concerns. Thus, this first study addresses the following study-specific research questions:

RQ3.1: How does group context relate to system perceptions and disclosure behavior in an information-sharing recommender system?

RQ3.2: How do individual differences relate to disclosure behavior in an information-sharing recommender system?

RQ3.3: How does information type relate to disclosure behavior in an information-sharing recommender system?

6.2 Methods

6.2.1 Experimental Design

The research questions for this study relate to group context, individual differences, and information type and how these factors relate to system perceptions and disclosure behavior for an information-sharing recommender system. Individual differences were operationalized as personality differences and were measured inherently as the research platform requires the collection of personality data to generate recommendations. For information type, Study 1 had previously highlighted the perceived benefits of sharing personal assessment data in the form of personality and conflict management styles for promoting *teammate* TMMs. For this study, information type was measured as a within-subjects repeated measure as each participant made 35 selections (i.e., 30 personality facets and 5 conflict management) regarding what they would be willing to disclose to their group.

Group context was manipulated using three different group scenarios that ranged from loose to tight goals. Although there is not complete agreement in the literature regarding the difference between a group and a team, a distinction, although not always binary, can often be made in distinguishing the two. For instance, groups are more likely to be classified as teams if they have interdependent roles and if they have common goals [179, 340, 286]. In this study, the spectrum from group to team was created using three conditions that differed based on how the members would be assessed (i.e., graded). This involved three between-subjects conditions that ranged from being graded only as individuals to fully as a team. The distinction was created based on the vignette provided to participants. The prompt used for each of the three conditions is shown in Table 6.1

Condition #	Assessed	Prompt
#1	Individually Assessed	You are assigned to a **course study group**. You are to study with this group during the semester to help you and your groupmates achieve better individual grades. Your individual grade for this semester is **100% dependent on how you do on individual assignments**.
#2	Mix Assessed	You are assigned to a **course project team**. You are to collaboratively work with your team to create a project that will be graded at the end of the semester. Your individual grade for this semester is **50% dependent on what your individual contribution is to the project and 50% dependent on what the team delivers at the end of the semester**.
#3	Team Assessed	You are assigned to a **course project team**. You are to collaboratively work with your team to create a project that will be graded at the end of the semester. Your individual grade for this semester is **100% dependent on what the team delivers at the end of the semester**.

Table 6.1: Study 3 Conditional Prompts

6.2.2 Task Design

Participants began the study by taking an initial demographic survey as well as a trust propensity survey. After completing the initial surveys, participants were provided with a vignette prompt based on their condition (see Table 6.1. As participants were undergraduate students, these vignettes drew upon their experience working in groups or teams to complete course projects or to study for assessments. After reading their prompt, participants answered a manipulation/attention check that required them to describe the hypothetical situation from the previous page. Participants were able to return to the page if they needed to read the hypothetical situation again.

After answering the manipulation check question, participants were provided with a link and a code that took them to the recommender system website. The code they used was associated with their condition. Although changes specific to this study were made to the research platform, this was the same research platform used in Study 2 and was described in detail in Chapter 3. Participants used the platform in three stages including: (1) taking personal assessments, (2) receiving their personal results, and (3) receiving recommendations about their teammate.

Notable changes were made to the research platform for the purposes of this study. At a high level, participants in this study were paired with a hypothetical teammate rather than actual teammates. Additionally, conditional reminders were made at the top of certain pages to remind participants of the context that they were making selections. For (2), participants were able to indicate which of their results they would be willing to share with their teammates given the context. For (3), participants received the full 35 recommendations associated with a teammate rather than the top 3 based on the algorithm. Further, participants were asked to indicate how helpful each type of information was for the given context.

After using the system, participants returned to the survey platform to take final surveys including their satisfaction with the system and their privacy concern.

6.2.3 Participants and Demographics

Participants for this study were recruited through a university's SONA pool. This involved undergraduate students being recruited for the study and receiving course or extra credit for completing the study. Participants received the standard credit associated with participating for 45 minutes which was the anticipated length of the study.

A power analysis was performed to determine the number of participants required for a between-subjects ANOVA with three conditions. This analysis determined that 177 participants were required to reach a reasonable power for a medium effect size. 166 participants signed up and completed this study. However, 11 participants failed attention checks and 3 had missing or incomplete data. Therefore, this study resulted in 152 participants with usable data. 122 participants identified as women, 30 identified as men, and 0 identified as non-binary, third gender, or preferred not to say. Of these participants, 52 were freshmen, 35 were sophomores, 36 were juniors, and 29 were seniors.

6.2.4 Measurements

The measurements for this study include personal assessments (individual differences), disclosure selections (disclosure behavior), and system perception measures to answer the research questions associated with this study.

6.2.4.1 Demographics and Personal Measures

Demographic and personal measures were taken at the start of the survey. This began with participants answering basic demographic questions for descriptive purposes including gender, year of study, and co-op/internship experience (see Appendix B, Table B.5. Additionally, as in Study 2, *Trust Propensity* was collected which measures how likely an individual is to trust a person or thing. This scale involves 4 Likert-scale items which can be found in Appendix B, Table B.7.

In addition to these measures, like in Study 1 and 2, participants took a Big Five Personality assessment [174] and a Conflict Management Styles assessment [310].

In addition to the results of these surveys being used for creating recommendations and for disclosure selection, raw scores for each of the 30 personality facets as well as the five conflict management styles were collected and used as *individual differences* to answer this study's research questions. The full list of questions used in these assessments can be found in Appendix A, Tables A.1 and A.2.

6.2.4.2 Disclosure Selection

As described in detail in Chapter 3, the research platform involves participants taking personal assessments before receiving their individual results. For their individual results, participants viewed a page that provides their 'percentile' for each attribute (e.g., Compromising - High - 93%) based on their raw score for it. This page also provides users with a category (i.e., low, moderate, or high) based on their percentile score. To accompany this information, a description is provided as to what the attribute means, especially for how they categorically score on it. An example of this description (i.e., individual recommendation) can be found in Section 3.3.

For this particular study, each attribute was accompanied by a disclosure decision. Participants were prompted: *"Based on this hypothetical situation and your results, select how and if you would be willing to share each of these facets to inform the system making recommendations to your group"*. Next to each attribute, participants had to select one of three options including: (1) Do not share; (2) Share only if peer shares; or (3) Share. This trinary selection allowed for more particular disclosure choices instead of a simple binary selection in hopes of being able to see more granular differences between individuals/conditions. The middle option alludes to more of a reciprocity setting where participants can choose only to share if their group member was also willing to share the attribute. Therefore, disclosure selection can be categorized in two ways: (1) sharing (including reciprocity sharing) vs.

not sharing and (2) unconditional sharing (not including reciprocity sharing) vs. not unconditional sharing. This selection process took the form of a repeated measure where participants made 35 selections, one for each of the 30 personality facets and each of the five conflict management styles used in the platform.

6.2.4.3 Helpfulness Perception Measure

In addition to measuring how willing participants were to share each of the 35 types of information, they also made selections regarding how helpful they thought it would be to receive recommendations based on these information types. This was measured on the final page of the research platform. Participants received recommendations for their hypothetical teammates based on the 35 attributes the system uses. At the top of the page, participants received the question: *Based on this hypothetical situation, what information would you find helpful for the recommender system to share with you regarding 1 of the other people in your group?*. To measure how helpful they thought each of these were, a Likert-scale question was embedded next to each question using a five-point scale ranging from 'Not helpful at all' (1) to 'Extremely Helpful' (5). This resulted in 35 helpfulness perception responses.

6.2.4.4 System Perception Measures

After the completion of using the system, participants took two final surveys including their *system-specific privacy concern* and their *satisfaction with the system*. These measures were previously used in Study 2; therefore, descriptions of these measures can be found in Section 5.2.4. Additionally, the list of questions associated with each of these measures can be found in Appendix E, Table E.14 and E.19 respectively.

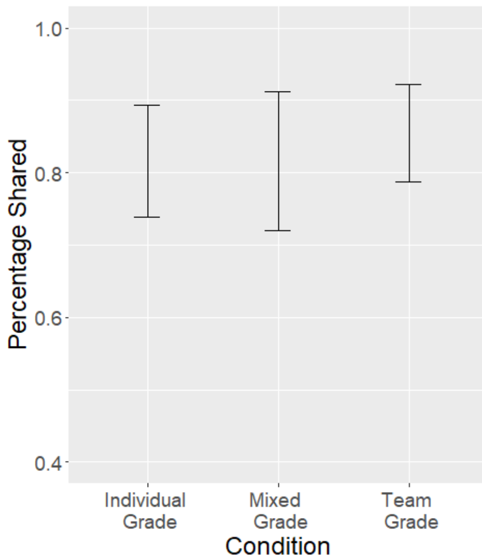
6.2.5 Analysis

This study involves quantitative analysis in the form of disclosure selection and system perception measures. First, a repeated measures ANOVA was used to determine how information type (i.e., the category of attribute) relates to disclosure behavior. Second, a generalized linear mixed effects regression (glmer) was used for each attribute category to determine how group type (i.e., condition) and individual differences relate to disclosure behavior. To compliment the analysis on information type, a *sensitivity* categorization was created. This categorization was based on anecdotal evidence from qualitative data from the previous two studies. For each attribute, a selection was made regarding which extreme rating (high vs. low) would likely be considered more sensitive. Moderate ratings were never considered sensitive. For example, a rating of 'high' for *anxiety* was considered as sensitive whereas a rating of 'low' was considered sensitive for *intellect*. This measure was included in the glmer models.

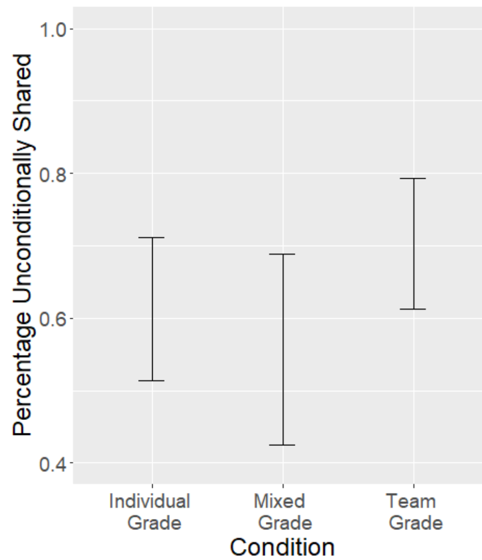
6.3 Results

6.3.1 Disclosure Behavior

To explore the hypotheses, I began by creating visualizations and exploratory statistics to determine how condition related to share settings. As seen in Figure 6.1a, there was no significant difference between conditions regarding how much personal information they were willing to disclose. However, upon visual inspection of Figure 6.1b, there appeared to be a trend regarding *how* users selected to share their information based on condition. Specifically, there was a trend for users in the *team grade* condition to unconditionally share (i.e., not use the reciprocity setting) more than those in the *mixed grade* condition. Based on this trend, I focused on unconditional (not using the reciprocity setting) sharing in the analysis.



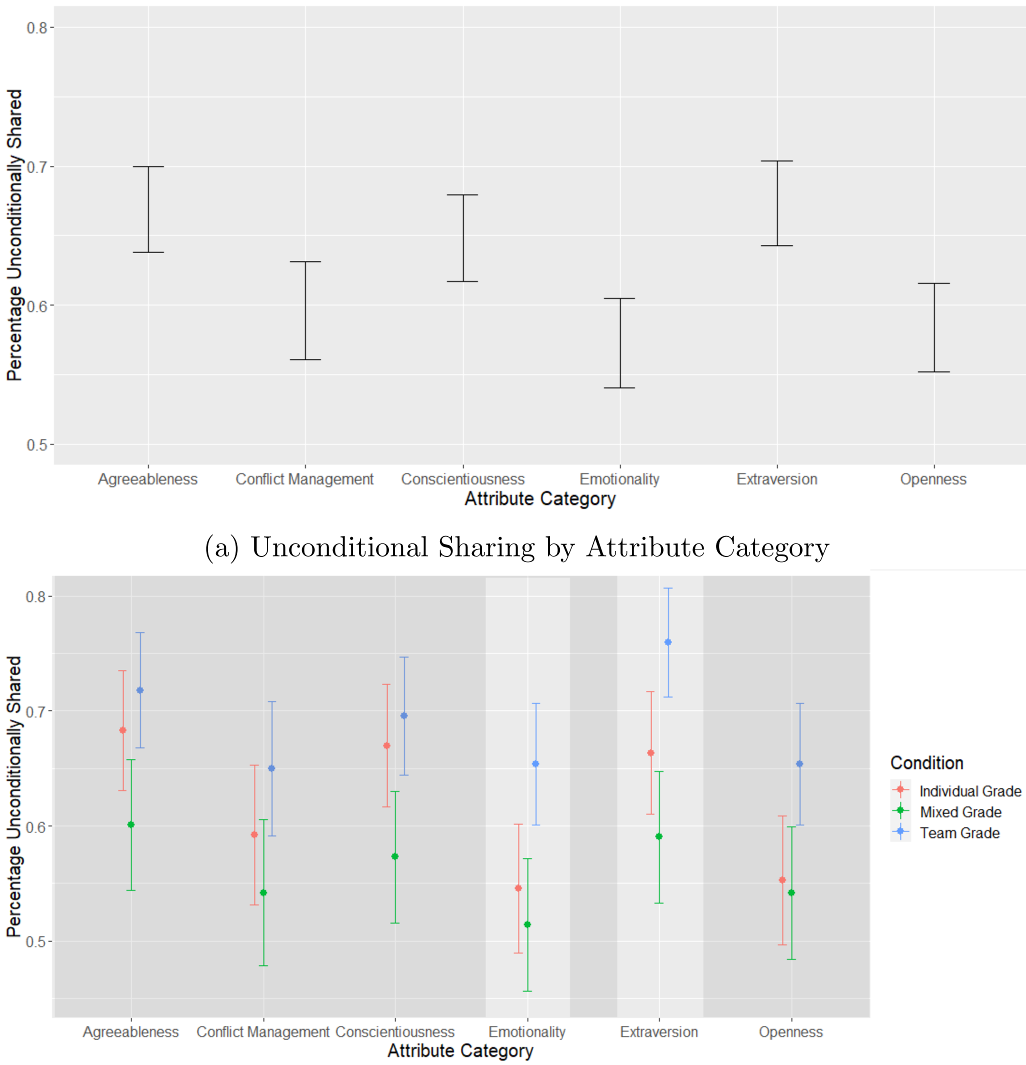
(a) Sharing by Condition (Including Reciprocity)



(b) Unconditional Sharing by Condition

Figure 6.1: Sharing by Condition Category

Next, I tested the effect of attribute category on unconditional sharing using a repeated measures ANOVA. Using the Emotionality category as a baseline, analysis revealed that each category had a positive effect on unconditional disclosure including **Agreeableness**, $t(5129) = 6.70$, $p < .001$, **Conflict Management**, $t(5129) = 1.54$, $p = .123$, **Conscientiousness**, $t(5129) = 5.24$, $p < .001$, **Extraversion**, $t(5129) = 7.01$, $p < .001$, and **Openness**, $t(5129) = 0.77$, $p = .441$. Therefore the categories of Agreeableness, Conscientiousness, and Extraversion had a significant positive effect on unconditional disclosure compared to the baseline category of Emotionality. A visualization of unconditional sharing by attribute category can be seen in Figure 6.2a which is further broken down by condition in Figure 6.2b.



(a) Unconditional Sharing by Attribute Category

(b) Unconditional Sharing by Condition and Attribute Category

Figure 6.2: Attribute Categories and Unconditional Sharing

To test the effects of assessment type (condition) on unconditional disclosure behavior, I ran a glmer with a random intercept for each of the attribute categories (Emotionality, Agreeableness, Conflict Management, Conscientiousness, Extraversion, and Openness). I used the independent variable of assessment type (Individual vs. Mixed vs. Team Grade) as well as other measures: (1) Sensitivity of the Item, (2) System-Specific Privacy Concern, and (3) Individual Differences (Openness Raw Score). I found significant effects for condition in two of the models: Emotionality and Extraversion (highlighted in Figure 6.2b). Conditional effects were not significant in the other 4 models (Agreeableness, CM, Conscientiousness, and Openness).

For unconditional disclosure of attributes in the **Emotionality** category, planned contrasts revealed that participants whose grades were **fully dependent** on the team's success resulted in a 6.16-fold increase in disclosure compared to those whose grades are only **partially or not at all dependent** on the team's success ($p = 0.040$). However, planned contrasts did not reveal a significant difference between participants whose grades were **partially dependent** on the team's success for this disclosure compared to those whose grades were **not at all dependent** on the team's success. When there is a 1-point increase in **privacy concern** for users, there is a 1.56-fold decrease in the odds that they will disclose items unconditionally ($p = 0.004$). And when there is a 1-point increase in a user's **Openness** score, there is a 8.97-fold increase in the odds that they will disclose items unconditionally ($p = 0.021$). The full summary of the glmer model for emotionality can be seen in Table 6.2.

Emotionality	OR	95% CI	p
Condition			
–Condition Contrast [Team v Mix, Ind]	6.16	(1.09, 34.88)	0.040
–Condition Contrast [Mix v Ind]	0.91	(0.12, 6.97)	0.928
Privacy Concern	0.64	(0.47, 0.87)	0.005
Openness	8.97	(1.39, 58.07)	0.021

Table 6.2: Generalized Linear Mixed-Effects Regression Model Results for Unconditional Disclosure - Emotionality Category

For unconditional disclosure of attributes in the **Extraversion** category, planned contrasts revealed that participants whose grades were **fully dependent** on the team's success resulted in a 6.06-fold increase in disclosure compared to those whose grades are only **partially or not at all dependent** on the team's success ($p = 0.046$). However, planned contrasts did not reveal a significant difference between participants whose grades were **partially dependent** on the team's success for this disclosure compared to those whose grades were **not at all dependent** on the team's success. When there is a 1-point increase in **privacy concern** for users, there is a 1.54-fold decrease in the odds that they will disclose items unconditionally ($p = 0.007$). Likewise, when items are **sensitive**, they result in a 5.26-fold decrease in the odds that the item will be disclosed unconditionally ($p < 0.001$). And when there is a 1-point increase in a user's **Openness** score, there is a 7.15-fold increase in the odds that they will disclose items unconditionally ($p = 0.051$). The full summary of the glmer model for extraversion can be seen in Table 6.3.

Extraversion	OR	95% CI	p
Condition			
–Condition Contrast [Team v Mix, Ind]	6.06	(1.04, 35.37)	0.046
–Condition Contrast [Mix v Ind]	0.58	(0.07, 4.80)	0.611
Privacy Concern	0.65	(0.47, 0.89)	0.007
Sensitive Items	0.19	(0.09, 0.42)	< 0.001
Openness	7.15	(0.99, 51.64)	0.051

Table 6.3: Generalized Linear Mixed-Effects Regression Model Results for Unconditional Disclosure - Extraversion Category

6.3.2 System Perceptions

Part of RQ3.1 was exploring whether group context also related to system perceptions. In each of the system perception measures used in this study including **system-specific privacy concern**, **perceived over-sharing threat** , and **satisfaction with the system**, there were no significant differences based on condition. Potential reasons for this lack of effect are discussed in Section 6.4.

6.3.3 Disclosure-Helpfulness Matrix

In preparing for the next study of this dissertation, Study 4, it became clear that it would be valuable to use an abbreviated version of the system where participants would not need to answer questions for all 35 attributes previously used. However, this abbreviated assessment would benefit from containing a diverse sample of attributes in terms of disclosure tendencies and perceptions of helpfulness. To assist in this, I conducted a high-level analysis of the data to determine which attributes were roughly considered more/less sensitive to share and more/less helpful to receive. If combined, this information can be visualized in a matrix that indicates which information is perceived as: (1) more helpful to share and shared more often, (2) less helpful to share and shared more often, (3) more helpful to share and shared less often, and (4) less helpful to share and shared less often. This matrix was created by determining which attributes were in the top or bottom 50% for each of the metrics (i.e., amount shared and perceived helpfulness). This matrix is displayed in Figure 6.3 and can be used in future research and development as a high-level overview of how team members perceive such information.

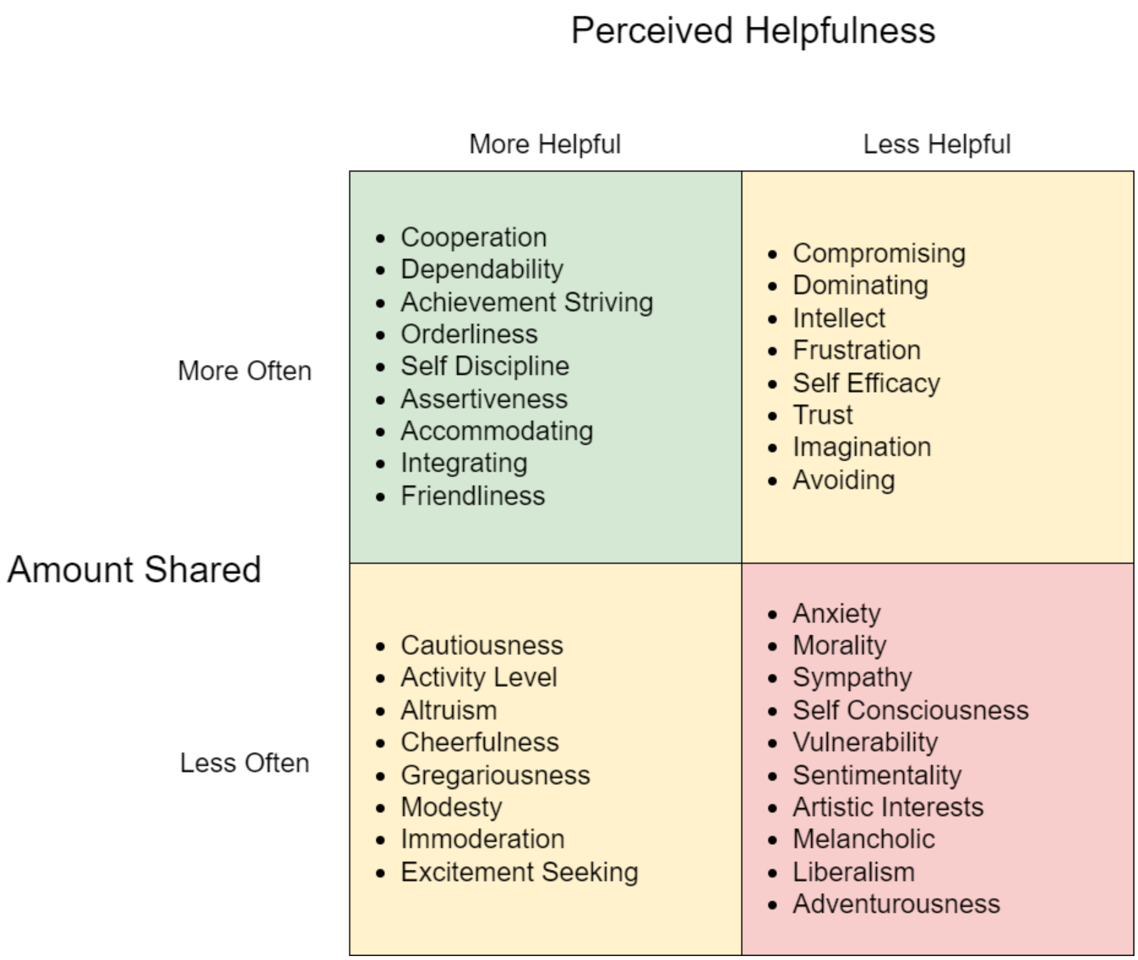


Figure 6.3: Disclosure-Helpfulness Matrix

6.4 Discussion

To answer the research questions, I have highlighted how group context relates to system perceptions and how group context, individual differences, and information type relate to disclosure behavior in an information-sharing recommender system. For **RQ3.1**, I found no significant effect of group context on system perceptions. There was also no significant difference between conditions when measuring any how much was disclosed at all levels (i.e., including reciprocity sharing). However, there was a significant effect of group context on unconditional disclosure behavior as individuals whose grades were fully dependent on the team's success were more likely to disclose information in the categories of Emotionality and Extraversion compared to participants whose grades were partially or not at all dependent on the team's success (**RQ3.1**). Regarding the other research questions, I found that the individual difference of personality-openness has a significant positive effect on unconditional disclosure of items in the emotionality and extraversion categories (**RQ3.2**). Meanwhile for information type, users are significantly more likely to disclose items in the categories of Agreeableness, Conscientiousness, and Extraversion as compared to the category of Emotionality (**RQ3.3**). Furthermore sensitive items are significantly associated with a decrease in disclosure in the category of Extraversion (**RQ3.3**).

In this section, I discuss the importance of the context of teamwork, individual differences, and information type influence disclosure behavior and what implications these findings have in designing an information-sharing recommender system.

6.4.1 The Context of Teamwork for Information-Sharing Recommender Systems

A contribution of this study is an improved understanding of how the context of teamwork influences disclosure for information-sharing recommender systems. Prior privacy research has highlighted how users have a more positive attitude toward information disclosure the closer the relationship (e.g., family compared to colleague) [257]. Specific to the group recommender system context, research has shown that users have higher privacy concern in loosely-coupled heterogeneous groups compared to tightly-coupled homogeneous groups [274]. As temporary teams are often comprised of work colleagues (e.g., temporary work project teams), it is important to understand how such colleagues might view disclosure considering the relatively loose relationships between members.

In this study I investigated how a group is assessed (individual vs. mixed vs. team) might influence disclosure behavior. This study was unable to reveal any significant differences between assessment type for disclosure in general. It is possible that this is due to the experimental design and its reliance on a hypothetical situation. There might potentially be greater differences between conditions in future studies where there are actual group members receiving their personal information and actual grades at stake.

Meanwhile, there were differences regarding unconditional (i.e., lack of reciprocity requirement) sharing. Prior research has emphasized that groups that are pro-socially motivated (i.e. motivated by the group's results) are more likely to share resources and perform better compared to groups that are egoistically motivated (i.e., motivated by their individual results) [26]. As such, the results that participants in the *team grade* condition unconditionally disclosed more information than those in the *individual grade* and *mixed grade* conditions was expected and extends these findings to the context of disclosure within information-sharing recommender systems.

However, it was expected that participants in the *mixed grade* condition would unconditionally disclose more than those in the *individual grade* condition. Prior research in the group recommender system context can shed light on this lack of significant difference. For instance, a prior study highlighted how framing the context as competitive can decrease information disclosure [275] and can mediate the relationship between privacy risk and information disclosure [278]. Therefore in the context of the current study, users in the *mixed grade* condition might have been primed to think about their individual grade, and competing with their teammates, and elected to only share if reciprocity occurred with their teammates. In this way the reciprocity setting might have served as a way to promote team outcomes while preventing their teammates from getting any kind of advantage on themself if their teammates elected not to disclose.

6.4.2 Considering Individual Differences and Information Type for Disclosure in Information-Sharing Recommender Systems

Two other factors in addition to how the group was assessed influenced disclosure behavior including individual differences and and information type. First, for individual differences, the Big Five category of *openness* had a significant effect on unconditional disclosure. Openness, also referred to as *openness to experience*, is often considered the most challenging of the Big Five personality factors to define [96]. Although based on common consensus and the scale used in this dissertation, the factor of openness can be described by characteristics such as openness to experiences, feelings, and new ideas [93, 174]. As such, it is logical for the trait of openness to be associated with a user's willingness to disclose personal information in a novel platform to new teammates which can be viewed as a new experience. However, this finding of openness augments previous research in the group recommender system context. For instance, one study found that extraversion and conscientiousness related to lower privacy concern and higher agreeableness relates to lower privacy concern, which through other mediating factors like trust in the group, perception of privacy risk, and perception of disclosure benefit influence disclosure [278]. Notably, this study did not find a significant relationship between openness and privacy concern, and therefore disclosure behavior [278].

Second, I found that information type influenced disclosure behavior. At a high level, there were categorical differences in disclosure. For instance, Figure 6.2a shows the relative amount that categories were unconditionally shared with agreeableness, conscientiousness, and extraversion being shared more than emotionality, openness, and conflict management traits. In groups, users use different techniques to avoid disclosing information to the group that might leave a negative impression [33, 295, 376]. This can take the form of users displaying positive information about themself while not disclosing information they perceive as negative [43, 171]. Although the system used in this study emphasized that "higher or lower scores are not *better* or *worse*", it is likely that users perceived some attributes to be more or less sensitive than others. For instance, if users rated low on cheerfulness or high on anxiety, they might not perceive these attributes as 'positive' and might view them as more sensitive. Thus, as expected, sensitive items are significantly associated with a decrease in disclosure while using this system. Although much of the group recommender system research has focused on conformity as it relates to information type and disclosure (e.g., [277, 116, 240]), this study contributes to these findings by providing evidence that sensitive items negatively relate to disclosure behavior as well.

6.4.3 Design Implications for Promoting Disclosure in an Information-Sharing Recommender System

This results of this study have implications for designing an information-sharing recommender system that promotes disclosure and system satisfaction. These design implications relate to: (1) using disclosure and personal data to predict disclosure preferences and (2) designing privacy settings considering their potential influence on disclosure.

6.4.3.1 Using Disclosure and Personal Data to Predict Disclosure Preferences

Online platforms have had challenges in supporting users in accurately configuring their privacy settings to allow for users to share the correct amount of information with the correct circles of people online [231]. Some of this mismatch can be blamed on the volume of data that online platforms are attempting to categorize for privacy and disclosure settings [231]. To account for this, prior research has explored the possibility of using machine learning algorithms and recommender systems to predict or suggest privacy settings [127, 352].

An information-sharing recommender system that deals with 35 disclosure choices will likely experience similar issues and could benefit from such *smart settings* to assist users in disclosure decisions. First, data from this study and future user studies could be used to filter the items to not share. This could be accomplished by identifying items that rank below a certain threshold of perceived helpfulness by receivers of the information. Additionally, data can be used to filter items that have consistently been marked as too sensitive or have a high likelihood to not be shared. Filtering these items out and not sharing them will allow users to pay more attention to the remaining items and could reduce decision fatigue [354]. Second, findings from this study could be used to support the use of factors (i.e., helpfulness rankings, context, individual differences, sensitivity of the item) for creating machine learning algorithms to predict and suggest *smart settings* for disclosure. Likewise these settings could be used to reduce decision fatigue and could potentially be used to promote sharing items that are more helpful to the team. This recommendation is in line with prior privacy research that has suggested the use of *user-tailored privacy* which can adapt and predict user privacy preferences based on the individual and the context [202].

6.4.3.2 Designing Privacy Settings Considering Their Potential Influence on Disclosure

In looking at the results of this study it is important to note that condition only had a significant effect on disclosure behavior when measuring *how* users disclosed their information (i.e., unconditional vs. requiring reciprocity). Reflecting on these results, it is important to consider the possibility that simply providing the reciprocity disclosure setting to users could have influenced users in the *individual grade* and *mixed grade* conditions to unconditionally share less. In a preference-based location sharing study, researchers found that when they removed a finer-grained sharing option, users chose the subjectively closest remaining option [204]. They also found that when an 'extreme' option was added, it can cause users to shift their sharing choice toward the added extreme option [204].

In the current study, adding a reciprocity option could have influenced users to shift their choice from an unconditional sharing to reciprocity sharing as reciprocity sharing was likely viewed as a closer option to unconditional sharing than not sharing at all. If this is the case, and the findings of [204] can be applied to the information-sharing recommender system context, certain design implications should be considered in future research and development. First, designers should only add a reciprocity setting if they find that it significantly reduces privacy concern or research reveals that adding a reciprocity setting significantly increases overall disclosure. Second, there is a design opportunity here to allow users to make disclosure selections in "batches". For instance, a developer could implement a batch of five disclosure selections for users to make. By design, this batch could contain three items that are highly valuable to the team to share and two items that are less helpful to share and perceived as highly sensitive. When comparing the three valuable items to share to the sensitive items, users might opt to disclose the items that are actually helpful to the team, therefore increasing the usefulness of the system.

6.4.4 Limitations and Future Work

This study serves as a useful investigation into how group type, individual differences, and information type influence disclosure behavior in a teammate information-sharing recommender system. However, two notable limitations serve as opportunities for future research. First, vignettes were used in this study rather than using actual teams, sharing, and assessments. As there was no significant difference by condition for system perceptions or overall disclosure, it is likely that a real scenario would invoke stronger feelings about the system and disclosure. It is excepted that a future study would reveal greater system satisfaction, less privacy concerns, and higher rates of disclosure for groups who are fully assessed as a team compared to the other two conditions. Second, this study did not measure how adding a reciprocity setting might influence system perceptions and overall disclosure. Future studies might reveal that adding a reciprocity setting reduces unconditional sharing, increases sharing overall, decreases privacy concern, and increases system satisfaction.

Chapter 7

Study 4: When and What to Explain in a Teammate Information-Sharing Recommender System

7.1 Overview and Research Questions

An interesting thread left unexplored after Study 2 is understanding why explanations did not affect trust or satisfaction with the information-sharing recommender system. Typically in single-user and group recommender system research, explanations are provided *after* or *during* the recommendation in order to increase acceptance of the recommended item(s) (e.g., [371, 374]). Additionally, the contents of these explanations are typically related to algorithmic explanations [369]. However, in exploring this novel technology, providing the explanation at the same time and with similar content as these other types of recommender systems might miss the mark. Parallel to this research thread is the need to better understand how to reduce privacy concerns with the sharing process. Prior research has highlighted the importance of users understanding disclosure benefit to increase disclosure [278].

An opportunity to combine these lines of inquiry (i.e., when to explain, explanation content, and reducing privacy concerns) is to explore *when* to provide explanations and *what* content should be included in them. Therefore, this study uses a 2x2x2 (between-subjects) design to explore three manipulations including: (1) the content in the explanation; (2) whether or not there is an explanation during disclosure; and (3) whether or not there is an explanation during recommendations. In doing so, this study investigates the following research questions:

RQ4.1: How does the occurrence of explanation provision (i.e., during disclosure or during recommendations) affect disclosure and perceptions of an information-sharing recommender system?

RQ4.2 How does the content of explanations affect disclosure and perceptions of an information-sharing recommender system?

7.1.1 Hypotheses

In conjunction with the research questions, hypotheses were made regarding explanation occurrence and content and their effect on disclosure and system perceptions.

7.1.1.1 Disclosure

Regarding disclosure, it is likely that **when explanations occur** and **explanation content** will have an influence in an information-sharing recommender system. When making decisions about disclosure, users must consider the benefits of self disclosure (i.e., context-specific gains from disclosure) [177]. Thus, users may be willing to give up a level of their privacy [405, 65, 193]. Previous work has shown that recommender systems can effectively use explanations to increase the amount of information users disclose [203]. Thus, I hypothesize:

> **H1a:** Participants using a teammate information-sharing recommender system who receive explanations during the disclosure process are more likely to disclose their personal information.

Prior research in the group recommender system context has highlighted how users who perceive a greater disclosure benefit are more likely to disclose their personal information [278]. In the temporary team context, the disclosure benefit can be considered as improved team effectiveness by improving *teammate* TMMs on the team. Thus, I hypothesize:

> **H2a:** Participants using a teammate information-sharing recommender system who receive benefit-related explanations during the disclosure process are more likely to disclose their personal information.

7.1.1.2 System Perceptions

As mentioned previously, I hypothesized that explanations provided during disclosure would increase disclosure. When explanations are provided **during the recommendation**, I hypothesize system perception benefits. Much of the previous recommender system research has evaluated explanations provided with the recommendation itself [371, 374]. In this research, explanations have been highlighted for their ability to increase perceived trust, perceived effectiveness (helpfulness), and satisfaction among many other outcomes [371]. Thus, I hypothesize:

H1b: Participants using a teammate information-sharing recommender system who receive explanations with the recommendation are more likely to perceive higher trust competence in the system.

H1c: Participants using a teammate information-sharing recommender system who receive explanations with the recommendation are more likely to perceive higher helpfulness in the system.

H1d: Participants using a teammate information-sharing recommender system who receive explanations with the recommendation are more likely to perceive higher satisfaction in the system.

Regarding the content of explanations, it is likely that there will be an influence on system perceptions in an information-sharing recommender system. Just as providing **benefit-related explanations** might influence disclosure behavior, it is likely that they will influence system perceptions. For instance, previous research has shown that user privacy concerns are related to the privacy situation [65, 2]. As such, in a team environment, explaining to users the benefit a recommendation can have to themselves and the team can remind users of the teaming context and might reduce privacy concerns. Further, prior research has shown that when users are provided with disclosure benefits they have decreased privacy concerns [411]. Thus, I hypothesize:

H2b: Participants using a teammate information-sharing recommender system who receive benefit-related explanations are more likely to perceive less privacy concerns of the system.

In a previous study involving a recommender system for disclosure, researchers found that providing justification explanations decreased user trust and satisfaction

[203]. In this study, the justification explanations were algorithmic in nature rather than explaining the actual benefit that users would gain. Thus, I hypothesize:

> **H3c:** Participants using a teammate information-sharing recommender system who receive benefit-related explanations are more likely to perceive higher trust competence in the system.

> **H3d:** Participants using a teammate information-sharing recommender system who receive benefit-related explanations are more likely to perceive higher helpfulness in the system.

> **H3e:** Participants using a teammate information-sharing recommender system who receive benefit-related explanations are more likely to perceive higher satisfaction in the system.

7.2 Methods

7.2.1 Experimental Design

The research question for this study focuses on how the occurrence and content of an explanation might influence disclosure to the system and perceptions of the system. To thoroughly explore this and to insure that the occurrence and content of the explanations do not confound the investigation, this study utilizes a 2x2x2 (all between-subjects) design. First, this includes a manipulation for content. The content of explanations for previous recommender systems typically involves algorithmic explanations (e.g., how was this recommendation produced) [369]. However, group recommender system research emphasizes that perceived disclosure benefit can increase disclosure [278]. Thus, the content for an explanation could involve describing disclosure benefit. This results in two content conditions including: (a) algorithmic rational or (b) disclosure benefit. The second and third manipulations relate to the occurrence of the explanation. Prior research typically describes explanations occurring *after* or *during* the recommendation (e.g., [371, 374]. However, if a goal is to increase the amount disclosed and decrease privacy concerns during the disclosure process, it might be beneficial to provide the explanation during disclosure selection. To explore this, both occurrence variables will be manipulated as binary conditions (i.e., yes or no) regarding whether or not an explanation will occur at that time. A summary of the manipulations is shown in Table 7.1.

Manipulation 1: Explanation Content (Between)
1 Algorithmic Rationale
2 Disclosure Benefit

Manipulation 2: When? - During Disclosure (Between)
1 No
2 Yes

Manipulation 3: When? - During Recommendation (Between)
1 No
2 Yes

Study 4: Design Matrix

	Manipulations		
Conditions	Content	During Disclosure	During Recs
1	Algorithmic	Yes	Yes
2	Algorithmic	Yes	No
3	Algorithmic	No	Yes
$\boxed{4}$	Algorithmic	No	No
5	Disc. Benefit	Yes	Yes
6	Disc. Benefit	Yes	No
7	Disc. Benefit	No	Yes
$\boxed{8}$	Disc. Benefit	No	No

Table 7.1: Study 4 2x2x2 Experimental Design. Conditions 4 and 8 will be combined to make a baseline condition as neither has explanations provided at either occurrence.

7.2.2 Task Design

The task for this study began with participants completing informed consent and pre-surveys. Part of the pre-surveys involved an abbreviated Big Five survey that measured their personality on 8 of the 30 facets. These 8 facets were selected based on the results of Study 3 which provided a Disclosure-Helpfulness Matrix (see Figure 6.3) in order to elicit more diverse preferences, responses, and perceptions from participants. Specifically, some facets were chosen due to the expectation that users will perceive them as more or less helpful and more or less sensitive based on the four quadrants from Study 3:

- More Helpful + Shared More: Dependability, Assertiveness
- Less Helpful + Shared More: Self Efficacy, Trust
- More Helpful + Shared Less: Activity Level, Cautiousness
- Less Helpful + Shared Less: Anxiety, Self Consciousness

Participants then watched and read from a video vignette (always the same for each condition) that described a worker who had been assigned to a temporary team in the workplace where none of the team members know each other (see Figure 7.1 for screen shot). The video also described the technology being used (i.e., a technology designed and developed to intelligently share information about team members to each other to accelerate their understanding of one another to improve team efficiency and performance).

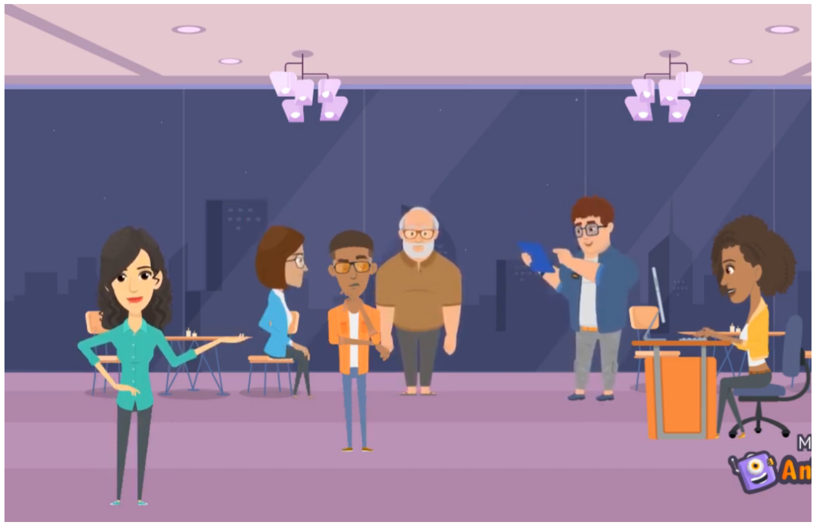


Figure 7.1: Study 4 Vignette Screen Shot

Next, participants were prompted to imagine themselves in this situation and to make selections regarding what information they would be willing to disclose to the system in order to inform recommendations to their teammates. These selections were based on the 8 personality facets (presented in a randomized order) and their own results. For some conditions an explanation was provided, although the contents of the explanation varied by condition. After participants made their selections, they were presented with 4 recommendations for working better with their hypothetical teammates (presented in a randomized order). Attributes used for recommendations included dependability, assertiveness, self-efficacy, and trust (see Table 3.3 for an example of what a recommendation might look like). For some conditions explanations were provided at this point, although the contents of the explanation varied by condition. An example for each content type based on when the explanation occurs is provided in Table 7.2. These examples are based on the same personality facet of 'self-efficacy'. See Appendix A, Table A.3 to see an example explanation for each of the 8 personality traits used in this study.

Content	Occurrence	
Algorithmic	Rationale for disclosure: Based on (1) how similar/different you and your teammate rank on this attribute and (2) similar users to your teammate have indicated they find receiving this information helpful.	Rationale for recommendation: Based on (1) how similar/different you and your teammate rank on this attribute and (2) similar users to you have indicated they find receiving this information helpful.
Disc. Benefit	Rationale for disclosure: It is helpful for your teammates to understand how confident members are in their abilities which might influence roles and responsibilities.	Rationale for recommendation: It is helpful for you to understand how confident members are in their abilities which might influence roles and responsibilities.

Table 7.2: Study 4 Explanation Examples for 'Self Efficacy'

After completing the task, participants then completed post-task measures related to their perceptions of the system.

7.2.3 Participants and Demographics

Participants for this study were recruited using Prolific, an online platform designed for recruiting participants for online research studies [296]. A power analysis was performed to determine the number of participants required for a 2x2x2 ANOVA involving main and interaction effects. This analysis determined that 146 participants would be required to reach a reasonable power for a medium effect size.

A total of 150 participants were recruited which resulted in 18-19 participants per condition. I applied the following criteria in recruiting participants: must reside be a resident of the United States, English must be their first language, and must work as part of a group at work based on established recommendations [4]. Attention checks were used to ensure quality of the data [31]; however, no participants had to be removed for failing attention checks. The average age of participants was 35.09 ($SD = 10.61$). 76 participants identified as women, 69 identified as men, 4 identified as non-binary or third gender, 1 preferred not to disclose, and 0 preferred to specify. Regarding team experience, 73.3% of participants indicated that they had experience working on ongoing project teams, 37.3% indicated that they had experience working on temporary project teams, and 20.0% indicated that they had experience working on temporary action teams. Participants were paid $3.50 as incentive for completing the survey of approximate length 20 minutes ($10.50 as their hourly rate, which is above the minimum incentive recommended [42].

7.2.4 Measurements

The measures used in this study include disclosure selections and system perception measures to answer both research questions (RQ4.1 and RQ4.2). Descriptions of each of the measures used are provided in the following sections.

7.2.4.1 Demographics and Personal Measures

Participants began by filling out basic demographic surveys including their age, education, race, language, gender, employment, and team experience (see Appendix B, Table B.6. These measures are used purely for descriptive purposes. Additionally, as in previous studies, *Trust Propensity* was collected which measures how likely an individual is to trust a person or thing. This scale involves 4 Likert-scale items which can be found in Appendix B, Table B.7.

In addition to these measures, participants took an abbreviated version of the Big Five personality assessment [174]. To alleviate survey fatigue, they only responded to questions related to the 8 facets used (i.e., dependability, assertiveness, self efficacy, trust, activity level, cautiousness, anxiety, and self-consciousness. This resulted in a personality questionnaire that contained 32 of the normal 120 questions used in the previous studies (see Appendix A, Table A.1).

7.2.4.2 Disclosure Selection

After watching the vignette, participants made selections regarding which of their 8 personality results they would be willing to disclose to the system to be used in recommendations for their hypothetical teammates. Participants made a binary selection (i.e., yes or no) regarding whether or not they are willing to share such information. The number of items that participants decided to share resulted in a 'disclosure score' that could be analyzed as a dependent variable.

7.2.4.3 System Perception Measures

After and while using the system, participants took six surveys related to their perceptions of such a system. These measures include perceived accuracy of their personality results, perceived helpfulness of recommendations, privacy concern, perceived over-sharing threat, trust competence, and system satisfaction. Perceived accuracy of personality results was measured using a 1-question survey (see Table E.20) and was asked after personal personality results were displayed. Perceived helpfulness of recommendations was measured using a 1-question survey (see Table E.21) that was asked 4 times, once after each recommendation. The other four surveys have been used in previous studies and have been described in previous chapters (e.g., Section 5.2). A list of questions used in each of the other surveys can be found in Appendix E, Table E.14, E.15, E.16, and E.19 respectively.

7.3 Results

7.3.1 Disclosure

To investigate the effect of explanation content on disclosure during system elicitation of personal information, conditions were simplified to those that provided algorithmic explanations during disclosure (Conditions 1 and 2), those that provided benefit explanations during disclosure (Conditions 5 and 6), and those that did not provide any explanations during disclosure (Conditions 3, 4, 7, and 8). Running an ANOVA, results indicate that there was a near-significant effect of providing **benefit explanations** during disclosure on **disclosure**, $b = 0.67$, $t(147) = 1.62$, $p_{one-tailed} = 0.054$. Meanwhile providing **algorithmic explanations** during disclosure had a positive effect on **disclosure**, $b = 0.21$, $t(147) = 0.51$, $p_{one-tailed} = 0.306$, though this was not significant.

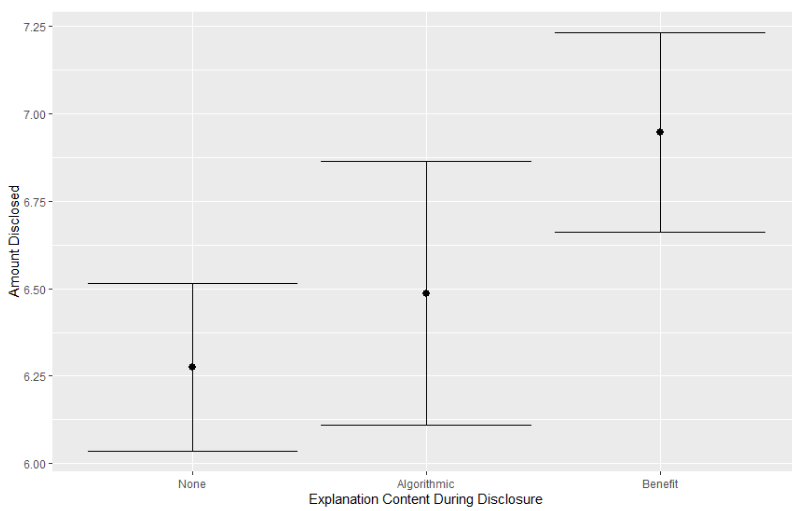


Figure 7.2: Disclosure by Explanation Content: Y-axis ranges from 0 to 8 items disclosed

7.3.2 Structural Equation Modeling

Structural Equation Modeling (SEM) was conducted to determine how various manipulations and factors relate to various perceptions of the system. SEM is an advanced statistical analysis technique that analyzes relationships between observed and latent variables [156].

Prior to running the model, I conducted confirmatory factor analysis (CFA) and examined the validity and reliability scores of the constructs measured in this study. Upon inspection of the CFA model, I removed two system satisfaction items including S1 (communality:0.399) and S9 (communality: 0.372). The remaining items shared at least 44% of their variance with their designated construct. The final factor solution has a good fit ($\chi^2(183) = 382.661$, CFI=0.921, TLI=0.909, RMSEA: 0.085, 90% CI: $[0.074, 0.097]$). Factor loadings are shown in Table 7.4 with correlations between the factors listed in Table 7.3. To ensure the convergent validity of constructs, I examined the average variance extracted (AVE) of each construct. The AVEs were all higher than the recommended value of 0.50, indicating adequate convergent validity. To ensure discriminant validity, I ascertained that the square root of the AVE for each construct was higher than the correlations of the construct with other constructs.

Table 7.3: A Summary of Correlations Between Every Two Factors. The diagonal values represent the square root of the factor's average (e.g., the square root of System Satisfaction's average is 0.87).

	AVE	Satisfaction	Privacy Concern	Trust Competence	Trust Propensity
System Satisfaction	0.75	**0.87**	-	-	-
Privacy Concern	0.87	-0.65	**0.93**	-	-
Trust Competence	0.78	0.79	-0.45	**0.88**	-
Trust Propensity	0.89	0.29	-0.32	0.27	**0.94**

Table 7.4: Survey Items Per Measurement with Item Factor Loadings. Two items from the System Satisfaction measure were removed due to low loading (shown highlighted in gray without a factor loading in the table).

Measurement	Items	Factor Loading
System Satisfaction	The system has no real benefit to me.	0.726
	Using the system is annoying.	-0.841
	The system is useful.	0.810
	Using the system is a pleasant experience.	0.882
	Using the system makes me happy.	0.890
	Overall, I am satisfied with the system.	0.957
	I would recommend the system to others.	0.922
	I would use this system if it were available.	0.922
	I would pay $2 to use this system.	-
	I would quickly abandon using this system.	-0.848
	It would take a lot of convincing for me to use this system.	-0.850
Privacy Concern	I'm afraid the system discloses private information about me.	0.921
	The system invades my privacy.	0.966
	I feel confident that the system respects my privacy.	-0.906
Trust Competence	This system is like a real expert in assessing teammates.	0.917
	This system has the expertise to understand my needs for understanding my teammates.	0.946
	This system has the ability to understand my needs for understanding my teammates.	0.871
	This system has good knowledge about my teammates.	0.834
	This system considers my needs and all important attributes of teamwork.	0.836
Trust Propensity	It is easy for me to trust a person/thing.	0.949
	My tendency to trust a person/thing is high.	0.954
	I tend to trust a person/thing, even though I have little knowledge of it.	0.920
	Trusting someone or something is difficult for me.	-0.906

Figure 7.3 presents the final trimmed model. The model's fit indices suggest a good fit: ($\chi^2(282)$ = 569.335, CFI = 0.914, TLI = 0.903, RMSEA: 0.082, 90% CI: $[0.073, 0.092]$).

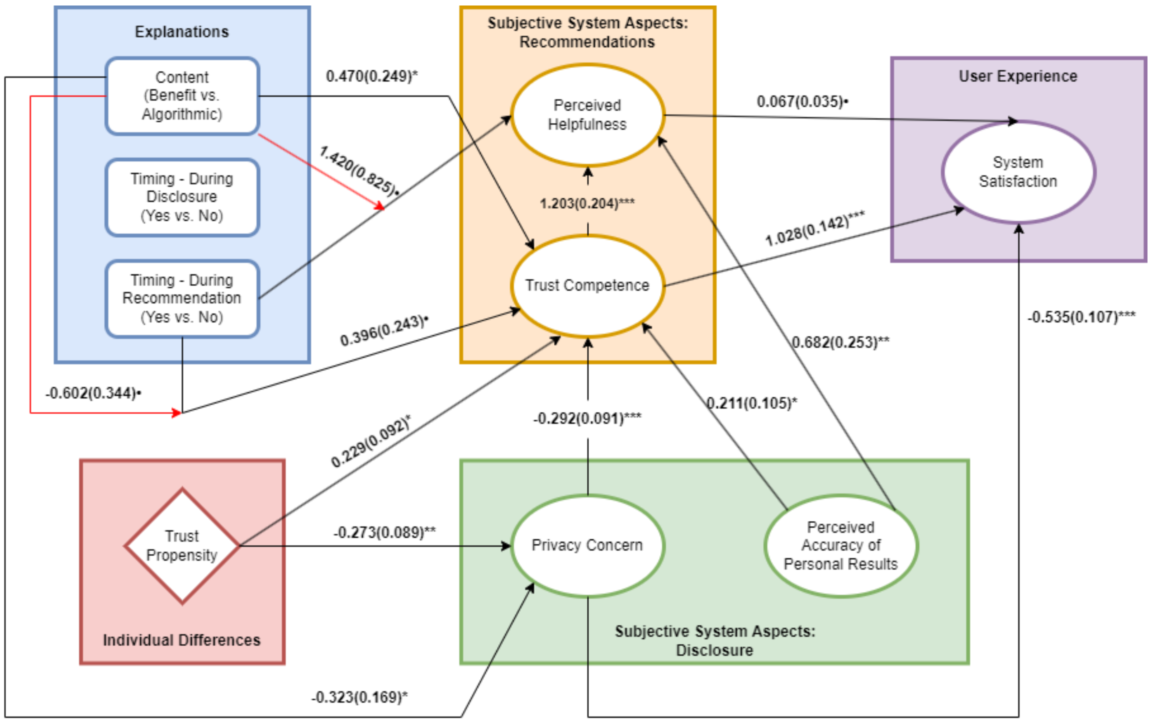


Figure 7.3: Structural model with near-significant and significant results ($\cdot$ $p < .1$, * $p < .05$, ** $p < .01$, *** $p < .001$). Numbers on the arrows represent the β coefficients with standard errors in parenthesis. Red arrows indicate interaction effects.

The model shows that providing benefit-related explanations has a negative effect on system-specific privacy concerns (β = -0.323, $p_{one-tailed}$ = .028) (see Figure 7.4). For when an explanation occurs, there was no significant main effect of explanations provided during disclosure on system perceptions. However, there was an interaction effect between benefit content explanations and the occurrence of explanations during recommendations on trust competence (β = -0.602, p = .080). This means that compared to benefit-related explanations, algorithmic explanations had a negative effect on trust competence when provided during disclosure (see Figure

7.5). There was also an interaction effect between benefit content explanations and the occurrence of explanations during recommendations on perceived helpfulness ($\beta = 1.420$, $p = .085$). This means that the influence on perceived helpfulness increased for benefit-related explanations when they were provided during recommendations more than they increased for algorithmic-related explanations (see Figure 7.6).

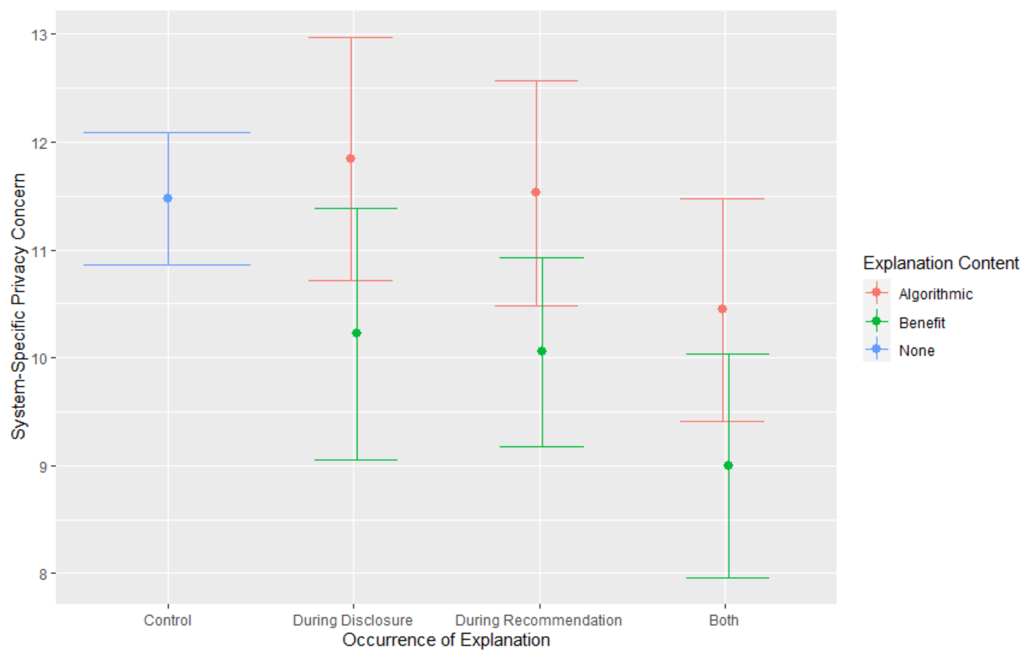


Figure 7.4: System-Specific Privacy Concern by Explanation Occurrence and Content: Y-axis ranges from 5 to 21

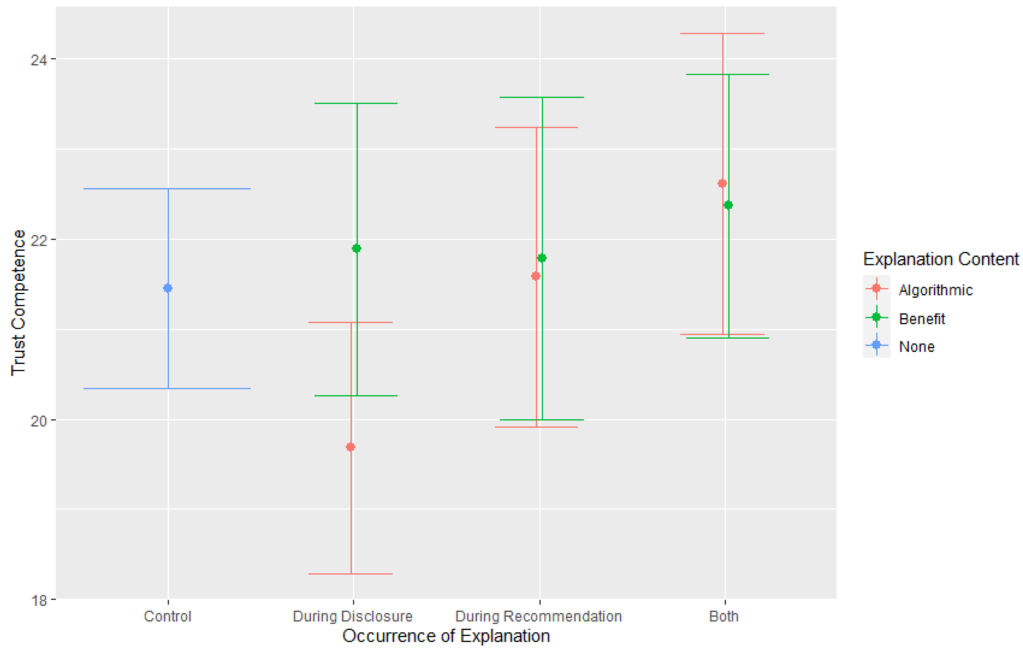


Figure 7.5: Perceived Trust Competence by Explanation Occurrence and Content: Y-axis ranges from 5 to 35

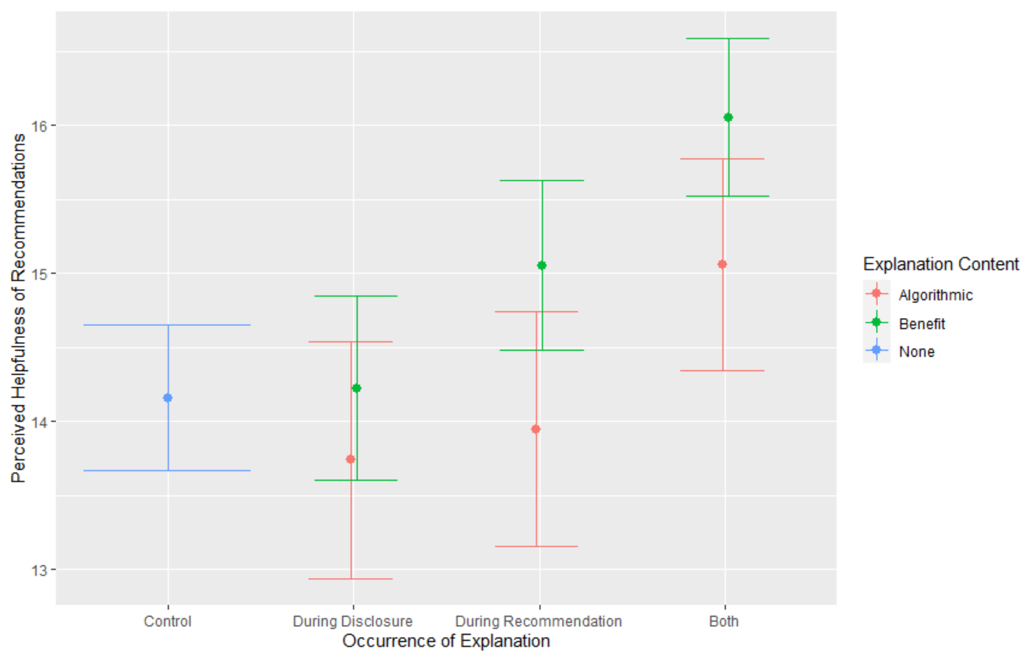


Figure 7.6: Perceived Helpfulness by Explanation Occurrence and Content: Y-axis ranges from 4 to 20

Other factors related to system perceptions include an individual's trust propensity which has a positive effect on perceived trust competence (β = 0.229, p = .013) and a negative effect on privacy concern (β = -0.273, p = .002). A user's perception of the accuracy of their personality results has a positive effect on both their perceived trust competence in the system (β = 0.211, p = .045) and their perceived helpfulness of the system (β = 0.682, p = .007). Privacy concern has a negative effect on trust competence (β = -0.292, p = .001), which in turn has a positive effect on perceived helpfulness (β = 1.203, $p < .001$). Last, perceived helpfulness has a positive effect on user satisfaction with the system (β = 0.067, p = .058) as does trust competence (β = 1.028, $p < .001$), with privacy concern being related to reduced system satisfaction (β = -0.535, $p < .001$).

7.4 Discussion

In investigating the research questions, I have identified ways in which both the occurrence and content of explanations can influence disclosure behavior and perceptions of an information-sharing recommender system. For **RQ4.1** and **RQ4.2** (disclosure) I found that providing benefit-related explanations during disclosure had a near-significant positive effect on disclosure (H2a).

Regarding system perceptions for **RQ4.1**, I found that providing explanations during the recommendations can have a near-significant positive effect on perceived trust competence of the system (H1b). Although there was not a main effect of occurrence during recommendations on perceived helpfulness (H1c) or system satisfaction (H1d), trust competence did partially mediate the relationship between occurrence during recommendation and both perceived helpfulness and system satisfaction.

In exploring the content of explanations (**RQ4.2**), I found that providing benefit-related explanations had a significant negative effect on privacy concern (H2b). Although there was not a main effect of benefit-related explanations on perceived helpfulness (H3d) or system satisfaction (H3e), both privacy concern and trust competence partially mediated these relationships. In combining **RQ4.1** and **RQ4.2**, interaction effects of content and occurrence were observed. These are discussed further in Section 7.4.2.

At a high level the SEM model also revealed relationships between trust propensity and system perception measures and how these system perception measures influence each other. Having higher trust propensity can increase perceived trust competence and decrease privacy concern. Perceived accuracy of results can increase perceived trust competence and helpfulness of the system. An increase in privacy concern is associated with a decrease in perceived trust competence and an increase in trust competence is associated with an increase in perceived helpfulness. Finally, an increase in perceptions of helpfulness and trust competence and a decrease in perception of privacy concern are associated with increased satisfaction with the system.

In this section, I discuss the numerous explanation content and occurrence considerations and what implications they have for designing an information-sharing recommender system.

7.4.1 Broadening Considerations for Explanations in an Information-Sharing Recommender System

The current study explores explanations in an information-sharing recommender system and in doing so broadens explanation considerations in three distinct dimensions including: (1) considering the likes of the receiver; (2) utilizing explanations during disclosure; and (3) emphasizing explicit benefits as part of the explanation.

First, this study utilizes **explanations that consider the likes of a receiver**. At a high level, prior recommender system explanation research has focused on a few major types of explanations such as:

- User likes items similar to item
- User is similar to users who like item
- User likes features present in item [385]

However, previous explanation categorizations like this do not account for a recommendation that involves sharing information from one user to another. Therefore in the current study, some explanations were expanded to account for the likes of the receiver (teammate). In this way, the second categorization above was expanded to *"Teammate is similar to users who like item"*. Although group recommender system research deals with disclosing information to a group through a recommender system and providing explanations, this body of research has largely focused on how explanations themselves reveal personal information (e.g., [374, 279] rather than using the explanation to encourage disclosure and/or explain the recommendation benefit to the group.

Second, explanations in this context can be **utilized during disclosure**. As a whole, recommender system explanations have often been provided during the recommendations [371]; however, other research has highlighted how explanations can be used to justify why a system is requesting information during disclosure. These justification explanations include providing rationale for requesting information [72, 5], providing potential benefits of disclosure [390, 208], or indicating that it is the social norm to disclose [3, 32, 297]. Therefore, the current study does not add a novel approach to explanations (i.e., occurrence during disclosure), but rather encompasses this additional dimension. Once again, prior group recommender system research has not investigated using explanations during disclosure (e.g., [87]).

Third, the current study emphasizes using explanations that **describe explicit benefits** to disclosing certain information or receiving a recommendation. This type of explanation has been repeatedly investigated in the context of online disclosure (e.g., [72, 208]. In one study, researchers found that giving a *why* explanation (e.g., explaining why disclosing information will help the system select a better camera) increased trust benevolence in the system [390]. The current study expands this type of explanation by also providing it during the recommendation process. Explaining benefits during the recommendation might be particularly useful to users who are not experienced in teamwork or interpersonal skills. These findings are in line with other studies that emphasize the utility of providing *justifications* (in contrast to algorithmic explanations) for why a recommendation was provided which is often more user-oriented and less algorithmic in nature [385, 123].

In summary, the current study acknowledges the complexity of the multi-faceted nature of providing explanations in an information-sharing recommender system. Although this study does not provide a complete understanding in all these dimensions, it provides essential foundational insights into this field. Notably this study highlights the importance of providing explanations during disclosure to increase disclosure, providing benefit explanations to decrease privacy concern, and providing benefit-related explanations during the recommendation process to increase perceived trust and helpfulness of the system.

7.4.2 The Interaction of Content and Occurrence in Explanations

Prior research has shown that the content of explanations must carefully be considered in recommender systems as there is often trade-offs in how users perceive them (e.g., an explanation might increase transparency of the system but decrease persuasiveness) [372]. For instance, previous research has shown that certain types of explanations might increase the perception of disclosure help at the expense of trust and satisfaction [203]. This study takes considerations of trade-offs one step further by evaluating both dimensions of content and when the explanation is provided. Two interaction effects were identified in this study that illuminate the importance of providing the right type of explanation at the right time.

First, an interaction effect between occurrence and content was identified for perceived trust competence of the system. As seen in Figure 7.5, providing algorithmic explanations during the recommendations resulted in similar perceptions of trust competence compared to benefit explanations provided during recommendations. The noticeable difference is that when algorithmic explanations are combined with the occurrence of during disclosure there is a decrease in trust competence. This suggests that algorithmic explanations should not be presented during the disclosure process if developers are interested in fostering trust with the system. Further, these findings shed light on prior recommender system disclosure studies. In a study involving a context-aware recommender system, researchers found that explanations provided during disclosure did not increase disclosure and they decreased trust and satisfaction in the system [203]. Although there are many differences between the current study and [203], it is noteworthy that most of the justification explanations provided in that study were algorithmic in nature (e.g., "[XX]% of our users told us/allowed us to use...").

Second, there was an interaction between occurrence and content for perceived helpfulness of the system. As seen in Figure 7.6, the influence on perceived helpfulness increased for benefit-related explanations when they were provided during recommendations more than they increased for algorithmic-related explanations. This suggests that if an information-sharing recommender system is desired to be perceived as helpful, benefit-related explanations should be provided during the recommendation process. This is particularly relevant in a teamwork context as users who are less comfortable with teamwork and communication might need additional assistance (explanation) in understanding why interpersonal recommendations are being provided [97].

7.4.3 Design Implications for Promoting Disclosure and Satisfaction for an Information-Sharing Recommender System

The results of this study have implications for designing an information-sharing recommender system that promotes disclosure and positive system perceptions. These design implications include the following: (1) fostering trust in the validity of the information being used before using the system and (2) creating an adaptive and intelligent explanation system.

7.4.3.1 Fostering Trust in the Validity of the Information Before Using the System

One important aspect of the SEM that has not been discussed is the importance of users perceiving that their personality results are accurate. In the presented model, *perceived accuracy of personality results* had a significant effect on both perceived trust competence and helpfulness of the system. These findings echo the findings of previous research that has highlighted how some users of personality sharing systems perceive the Big Five personality results to be inaccurate which undermines their perceptions of the system [271]. As such, there is a mismatch of perceptions and prior research as prior research has emphasized the accuracy and stability of the measure on temporary teams [355, 356].

As using an information-sharing recommender system will likely be a novel experience to many users at this point in time there will likely be a certain amount of uncertainty regarding perceptions of trust and helpfulness of such a system to begin with. Therefore, there is an opportunity to create an intervention to increase perceptions of accuracy of personality results so as to avoid creating additional uncertainty or concerns of trust. I recommend the use of training, whether digital or personal, to describe what the Big Five personality system is (or whatever information source is used by the system) as well as the accuracy and validity of the data source before using the system. As providing evidence as to the accuracy of data sources for AI can increase trust for users [12], this recommendation should result in both increased perceived trust and helpfulness of the system, and therefore increased system satisfaction.

7.4.3.2 Creating an Adaptive and Intelligent Explanation System

An interesting trend, though not significant in the model, was the interaction effect between *occurrence - during disclosure* and *occurrence - during recommendations*. Specifically, there was a trend to improve system perceptions when explanations were provided both during disclosure and during recommendations. This can be seen in Figure 7.6 as the conditions that provided explanations at both times resulted in the highest perceived helpfulness (for both algorithmic and benefit explanations) and can be seen in Figure 7.4 as the condition that provided benefit explanations at both times resulted in the lowest perceived privacy concerns.

Based on this trend, a reactionary design recommendation would be to provide both benefit and algorithmic recommendations at both times for every disclosure and every recommendation for an information-sharing recommender system. However, prior research has emphasized the importance of providing the right content and level of detail depending on the goals of the explanation and the type of user [264]. This is likely due to designers needing to consider the cognitive overload or confusion that is possible when providing too much information or no the right type of information [123, 199, 413]. With this in mind, recent research has suggested making personalized explanations and explanations with different level of detail depending on the user [61].

Therefore, I suggest for this context creating an adaptive and intelligent user interface to provide explanations. In this design, both benefit and algorithmic explanations will always be available to users if they interact with the user interface to request an explanation. Furthermore, the system could be adaptive to specific users to provide explanations when items are more important to disclose or adapt to user profiles to proactively give benefit-related explanations to users who are more likely to have privacy concerns. In such a system, the recommender system will give the right explanation at the right time for the appropriate user.

7.4.4 Limitations and Future Work

As described in Section 7.4.1, there are numerous considerations when studying or designing explanations for an information-sharing recommender system. As such, this study serves as a useful foundational study for investigating occurrence and content for explanations in this context. However, two limitations provide an opportunity for future research. First, like in Study 3, vignettes served as a means to convey the work and technology context that participants responded to. Future research would benefit from utilizing actual temporary teams. Using actual teams would likely create greater and more realistic disclosure behavior as participants would actually be disclosing information to their unknown colleagues. Second, a study such as this is fully dependent on how the variable of *explanation content* is operationalized. Future studies would benefit from investigating multiple types of both algorithmic and benefit explanations to discern how multiple facets of these classifications might influence disclosure and system perceptions.

Chapter 8

Conclusion

Temporary teams are of growing importance as the modern workforce is increasingly shifting toward using them due to their flexible and dynamic nature to meet the needs of complex and specific tasks [362]. Meanwhile the construct of TMMs has and continues to be a cornerstone of teamwork research which seeks to understand the cognitive aspects of teaming and how to best develop and support teamwork [91]. Importantly, supporting TMMs on temporary teams, particularly *teammate* TMMs, is understudied which limits these teams who stand to gain more from quickly developing TMMs due to their short lifespan and working in novel environments [238]. Prior research has suggested supporting such teams through technology-mediated personal information-sharing [118, 394]; however, little research has investigated how to best share such information to support team outcomes in a way that users feel is appropriate.

This dissertation focused on understanding how recommender system technology can be designed and used to support personal information sharing on temporary teams. Specifically, this dissertation aimed to understand what information to share and how to share such information to promote *teammate* TMMs while limiting privacy concerns. In four studies, I investigated how users perceive information sharing on temporary teams and how users perceive and interact with an information-sharing recommender system. In each study significant research contributions are made which culminate in a multidimensional understanding of what information to use, how to present the information, and how factors such as group context, individual differences, and explanations contribute to disclosure behavior and system perceptions.

This chapter serves as a final discussion to conclude the dissertation. First, I revisit the research questions that were formulated and presented in Chapter 1 and their answers. Second, I describe the contributions made by this dissertation. Third, I discuss opportunities for future work based on this dissertation. And finally, I make closing remarks.

8.1 Revisiting Research Questions

In Chapter 1, I defined an umbrella goal for the dissertation which was to **understand how a teammate information-sharing recommender system can be designed to promote *teammate* TMMs while limiting privacy concerns**. To achieve this goal and to close the research gaps outlined in Chapter 1, I defined four dissertation-level research questions which guided the experimental design and study-level research questions. Through the four studies, I answered each of these research questions. Specific answers to these research questions will be outlined in the following subsections.

8.1.1 RQ1: What teammate information should be used/shared to promote *teammate* TMMs while limiting privacy concerns on temporary teams?

Two studies specifically addressed RQ1 in this dissertation including Study 1 and Study 3 (see Figure 8.1. Using both qualitative and quantitative data, Study 1 took an exploratory approach by using a basic information-sharing system with actual temporary teams to better understand what types of information users perceived as helpful and why they had privacy concerns sharing information. Study 3 investigated users who interacted with an information-sharing recommender system to investigate helpfulness and disclosure preferences at an item level.

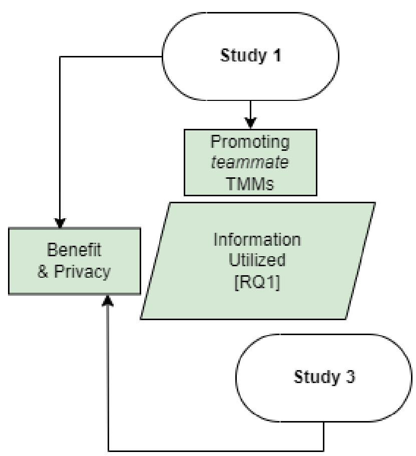


Figure 8.1: Study Connections to RQ1

Study 1 revealed that overall users perceive both Big Five personality assessments to be accurate and that sharing these results was helpful. However, users had mixed perception on the appropriateness of sharing. Comparatively users perceived sharing conflict management data as more helpful and appropriate. Regarding RQ1, qualitative data suggested that individuals have strongly differing opinions on what type of information is helpful and appropriate to share. Importantly, this study also highlighted that users are particularly interested in receiving information related to task skills, conflict management styles, and reliability in order to support their *teammate* TMMs.

Meanwhile Study 3 provided valuable insights regarding what categories users are more likely to disclose which can be related to the categories they have higher privacy concerns with. For instance, users were most willing to unconditionally share items in the Big Five categories of Agreeableness, Conscientiousness, and Extraversion and least likely to disclose information in the categories of Emotionality and Openness, with Conflict Management information somewhat in between regarding amount disclosed. At an item level, when user results are considered sensitive (e.g., rating high on anxiety or low on intellect) they are less likely to disclose such information.

Notably these studies present somewhat conflicting yet reconcilable results. Study 1 highlighted how users perceive sharing Conflict Management data to be more appropriate, yet Study 3 showed the Conflict Management category to be moderate in terms of disclosure behavior. It is likely that participants considered the most sensitive items of personality (e.g., Emotionality items) when comparing the appropriateness of sharing to Conflict Management which resulted in Conflict Management being considered more appropriate to share as a whole.

Further synthesis of these two studies with regard to RQ1 results in several key answers to the research question. First, information pertaining to task skills, conflict management styles, and reliability are important to consider for sharing to support *teammate* TMMs on temporary teams. Second, the Big Five personality assessment and Conflict Management data are viable options for sharing as they address both conflict management styles and reliability (although do not address task skills) and they are overall perceived as accurate and helpful to share. Third, users are less likely to disclose information in certain categories (i.e., Emotionality and Openness). And fourth, individual differences and how users rate in certain categories relate to how sensitive items are perceived and how willing they are to disclose (see more in Section 8.1.4.

8.1.2 RQ2: How can teammate information recommendations be presented to promote *teammate* TMMs on temporary teams and positive system perceptions?

To better understand how to present teammate information recommendations, Study 1, Study 2, and Study 4 were designed to approach this research question from different angles (see Figure 8.2). Study 1 took an exploratory approach to answer this question at a high level to see what contents should be included. Next, Study 2 investigated the use of anonymity and explanations to see what effects these presentation aspects had on team outcomes and system perceptions. Last, Study 4 specifically looked at when and what to explain to promote positive system perceptions.

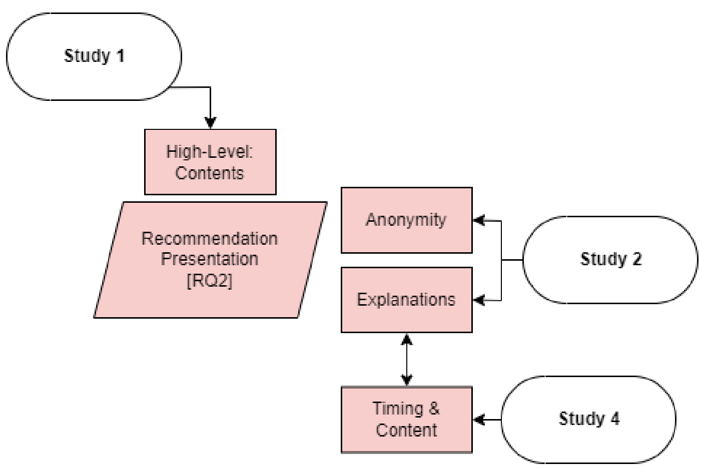


Figure 8.2: Study Connections to RQ2

In Study 1, qualitative data revealed that designers should show restraint regarding how much information is shared with teammates as 35 attributes for each teammate was perceived as overwhelming. These findings also highlighted the need for context and insights to be shared with the information to help users understand what to do with the information. These findings inspired the development of the information-sharing recommender system used in later studies which was designed to selectively share a few recommendations and contextualized these recommendations with information pertaining to how users compared and what that information could mean for teamwork.

Study 2 utilized a real temporary team setting and explored anonymizing recommendations and providing explanations with recommendations. Counter to expectations, results showed that identifying recommendations (compared to anonymized ones) did not increase privacy concerns. Also surprisingly, providing explanations with recommendations did not increase trust. In this study, providing identified recommendations with no explanations produced the best results for system-satisfaction in the long term. This study also highlighted the importance of identifying recommendations in that anonymized recommendations resulted in worse team outcomes including team satisfaction, team cohesion, team psychological safety, and perceived team effectiveness. Qualitative results helped to explain these findings by highlighting how participants perceived anonymous recommendations to result in incorrect assumptions about their teammates and recommendations not being as actionable.

Study 4 was in part an intentional follow-up to Study 2 by exploring why explanations did not increase trust. By investigating both the content and timing/occurrence of explanations, this study revealed that providing explanations during recommendations can improve perceived trust competence in the system which can partially mediate the relationship between occurrence during recommendation and both perceived helpfulness and system satisfaction. Further, providing benefit-related explanations can reduce privacy concern, which can partially mediate the relationship between benefit-related explanations and perceived helpfulness and system satisfaction. In exploring how content and occurrence of explanations interact, results show that algorithmic explanations provided during disclosure can reduce trust competence and benefit-related explanations provided during recommendations can increase perceived helpfulness.

The combination of these findings provide meaningful answers to RQ2. First, an information-sharing recommender system should share information in a way that prevents unwanted sharing while selectively sharing the most helpful information in a way that is contextualized where users can understand and use the information to promote teamwork. Second, the presentation feature of anonymity should not be used (at least with small team sizes) as it does not decrease privacy concerns and results in worse team outcomes. As this feature did not decrease privacy concerns and noting that Study 2 revealed vastly different privacy concerns between different individuals, other privacy-mitigating features must be explored (e.g., allowing for disclosure settings - see Studies 3 and 4). Third, benefit-related explanations are especially useful in a system of this nature for reducing privacy concern and not decreasing trust competence.

8.1.3 RQ3: How does a temporary teaming environment mediate disclosure behavior and privacy concerns in an information-sharing recommender system?

As an information-sharing recommender system will have inherent privacy concerns for some, it is important to understand how the temporary teaming environment might mitigate these concerns and encourage disclosure (see Figure 8.3). Study 2 collected qualitative data to understand how users perceive the balance of privacy concern to the teaming benefits in using such a system. Meanwhile Study 3 used various group/team conditions to better understand how the teaming context might influence privacy concerns and disclosure.

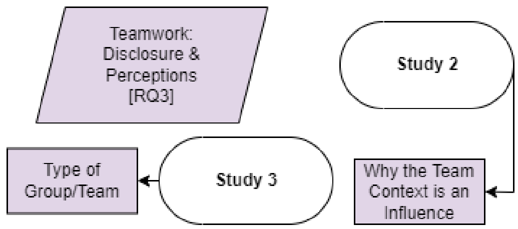


Figure 8.3: Study Connections to RQ3

Study 2 utilized actual temporary teams and concluded by collecting qualitative data to assist in answering RQ3. Among numerous stated benefits, participants found that the sharing of information through the system was beneficial in creating an awareness of their teammates and not being surprised by their behavior. Further, participants perceived that they were able to organize and communicate better with their teammates by understanding their differences. Users were aware of the short time frame and the benefits of forming more accurate *teammate* TMMs from the start of the project. Interestingly, the balance between benefits and privacy concerns were vastly different between participants as polar views existed regarding privacy concerns which was likely due to individual differences.

Study 3 took a quantitative perspective in answering RQ3 by comparing three conditions who differed by how they would be hypothetically assessed as a group (i.e., individually, mixed, or as a team). Although there were no significant effect of group context on either system perceptions or total amount disclosed, there was a significant effect of group context on unconditional disclosure behavior (i.e., disclosing without the reciprocity setting). Participants whose grades were fully dependent on the team's success were more likely to disclose information in certain personality categories compared to the other two categories (i.e., individual and mixed assessments).

Synthesizing the results of this study provide answers to this research question in the dimensions of *why*, *what*, and *how*. **Why**. Users are likely to perceive less privacy concerns and disclose more information as the teaming environment mediates the relationship to disclosure benefit. Teaming benefits related to an accelerated development of *teammate* TMMs include improved awareness, organization, communication, and less surprises. **What**. Being fully assessed as a team can have an effect on increased disclosure in the personality categories of Emotionality and Extraversion. **How**. The teaming environment can influence *how* users are willing to disclose. Specifically, users that are fully assessed as a team might be more likely to unconditionally disclose their personal information.

8.1.4 RQ4: How do other factors (e.g., individual differences, explanations) influence disclosure behavior and privacy concerns?

Influences that can affect disclosure behavior and privacy concerns are numerous; therefore, this dissertation utilized three studies, Studies 1, 3, and 4, to better understand these influences for this context (see Figure 8.4). Study 1 investigated the influence of experience with a sharing system, Study 3 explored individual differences, and Study 4 investigated the timing/occurrence and content of explanations.

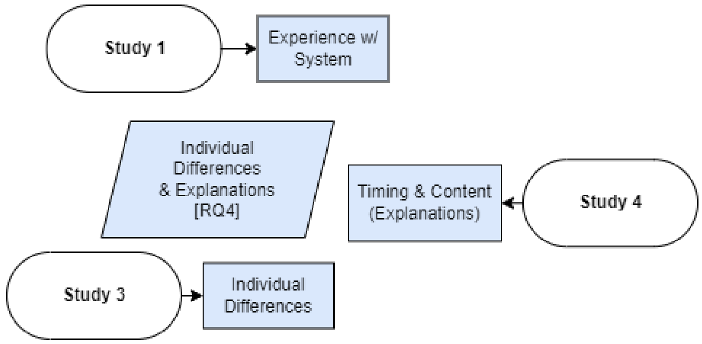


Figure 8.4: Study Connections to RQ4

Study 1 revealed one of the first findings of this dissertation regarding what can influence privacy concerns. In this study, users who were in the sharing condition were more likely to perceive sharing personality and conflict management data as helpful and sharing conflict management data as appropriate. Therefore, it is likely that giving users experience with an information-sharing recommender system might decrease their privacy concerns and increase their disclosure in future uses of the system.

For individual differences, results from Study 3 showed that the personality category of Openness can have a significant positive effect on unconditional disclosure for items in certain personality categories. Further, when users rate on certain attributes in a way that is considered sensitive, there is a negative effect on disclosure. This means that individual differences define how users score on certain attributes which in turn can influence how willing they are to disclose that information.

Study 4 results are valuable in knowing when and what to explain in an information-sharing recommender system to increase disclosure and decrease privacy concerns. In this study, providing explanations during disclosure had a positive effect on the amount that users disclosed. For explanation content, providing benefit-related explanations had a significant effect on reducing privacy concerns and can be associated with an increase in disclosure (not significant). An additional finding from Study 4 revealed that the individual difference of having higher trust propensity can also decrease privacy concerns in using the system.

As a whole, these studies answered this research question in four ways. First, having experience using an information-sharing recommender system might reduce privacy concerns and increase disclosure. Second, having greater trust propensity can decrease privacy concern and rating higher in the personality category of Openness can increase disclosure. Third, when users rate on certain attributes in a way that is considered sensitive, there is a negative effect on disclosure. Finally, providing benefit-related explanations during disclosure can increase disclosure and decrease privacy concerns.

8.2 Overall Dissertation Contributions

This dissertation brings together four studies that result in a confluence of four main contributions that are relevant to both research communities and recommender system practitioners. First, this dissertation contributes the conceptualization, development, and research of an entirely new form of recommender system, an information-sharing recommender system. Second, the findings contribute to a better understanding of how *teammate* TMMs can be supported on temporary teams which is an important topic that has been understudied in the teamwork literature. Third, this dissertation contributes to the established field of group recommender systems pertaining to understanding factors related to disclosure in a group setting. Finally, the findings of this dissertation provide important preliminary design recommendations that can be applied to creating an information-sharing recommender system which aims to support *teammate* TMMs while promoting positive system perceptions.

8.2.1 The Conceptualization and Development of a Novel Recommender System

As discussed in Chapter 3, this dissertation contributes the conceptualization, development, and research of an entirely new recommender system called an information-sharing recommender system. Although this novel system is similar to an established form of recommender systems, group recommender systems, the conceptualization of this new system has numerous differences from prior recommender systems regarding how recommendations are generated, the purpose of recommendations, and how recommendations are distributed to users (outlined in Figure 3.1. In addition to this conceptualization, this dissertation contributes to this new field by providing the actual implementation and development of such a system. This took the form of an actual website that users could create accounts, take surveys, and receive recommendations based on an expert system about their teammates. This development was essential for researching the novel system as the website had admin features which allowed for creating conditions and editing parameters specific to each study. Although the field of information-sharing recommender systems is nascent, the foundational conceptual, development, and research contributions of this dissertation pave the way for future research on teammate information-sharing recommender systems or numerous other contexts. For instance, future information-sharing recommender systems could be used in contexts including dating applications, relationship counseling, onboarding new employees, and accelerating student-teacher understanding to name a few. Any field that could benefit from intelligent personal information sharing is a potential context for this novel technology.

8.2.2 Understanding Supporting TMMs Through Information Sharing on Temporary Teams

The work of this dissertation makes contributions to the cognitive teamwork research community (e.g., research on team cognition and TMMs). As discussed in previous chapters, temporary teams are being heavily utilized due to their dynamic and agile nature as they are able to form based on the skill/personnel requirements for a specific task. Intersecting with the context of temporary teams is the need to support these teams with TMM development. Although prior literature is prevalent pertaining to how the development of *task*, *equipment*, and *team interaction* TMMs can be supported, there is a dearth of empirical evidence for how *teammate* TMMs can be supported on temporary teams. This dissertation contributes to closing this research gap by providing evidence for how personal information can be shared to promote *teammate* TMMs on temporary teams. The findings of this dissertation reveal what type of information temporary team members perceive as beneficial for supporting their *teammate* TMMs and why these members perceive the sharing of such information as beneficial. Further, findings provide empirical evidence that reveal how sharing personal information the right way can provide team outcomes associated with TMMs. The culmination of this dissertation, an understanding of how a teammate information-sharing recommender system should be designed to promote *teammate* TMMs, is of great importance to future temporary teams that elect to utilize such a system. These teams will benefit from the accelerated development of their *teammate* TMMs which are known to benefit both team processes and team outcomes.

Importantly, an information-sharing recommender system provides a human-centered approach to utilizing AI to support *teammate* TMMs on temporary teams.

Previous approaches have suggested using AI to select which team members are selected for temporary team composition in order for members to naturally have more similar TMMs [377]. In contrast, this dissertation pushes back on such technology determinism by emphasizing humans still making decisions with information being suggested to teammates by an AI (i.e., a recommender system) rather than the AI choosing the teammates. This approach puts humans in the active role, a human-centered computing solution, rather than the AI being in control.

8.2.3 Contributions to Group Recommender System Research

This dissertation focuses on a novel type of recommender system that can be used for information sharing. Although most of the contributions of this dissertation relate specifically to information-sharing recommender systems, many of these findings can also be used and applied to other types of recommender systems, particularly group recommender systems). Thus, this body of work contributes to the design of future group recommender systems and group recommender system research as a whole. First and foremost, group recommender system research has yet to investigate the team context and has primarily investigated casual groups (e.g., travel groups). Therefore group recommender system research benefits by this dissertation's improved understanding of how and why the group/team context can influence disclosure behavior and privacy concerns which are important concepts in group recommender system research. Second, as group recommender systems can often provide improved recommendations when the system receives increased levels of disclosure, this dissertation contributes to understanding what other factors can contribute to disclosure. Prior research in group recommender systems has highlighted how individual differences can influence disclosure. This dissertation provides additional insights for how such individual differences influence disclosure. Furthermore, the findings of this research investigate an unexplored avenue in group recommender system research, designing explanations to influence disclosure behavior.

8.2.4 Developing Design Recommendations

As an information-sharing recommender system is a novel technology, design recommendations are essential for pioneer developers, practitioners, and researchers. Because of this, this dissertation provides practical and foundational design recommendations in each of the study chapters based on their associated findings. Study 1 provides recommendations pertaining to what types of content should be included in recommendations to promote *teammate* TMMs, how recommendations should be presented to team members, and ways to mitigate privacy concerns while sharing. Study 2 includes recommendations for how to use anonymity for such a system more effectively as well as opportunities for more beneficial recommendations. In Study 3, recommendations are provided on how disclosure preferences could be predicted by the system (i.e., user-tailored privacy) and how to design privacy settings in consideration of how they might influence user disclosure. Finally Study 4 recommends ways to improve trust in the system (e.g., improving trust in the information source used by the system) and how to design an adaptive and intelligent explanation system within the recommender system that can suggest the right recommendation type to use at the right time for the right user. Each of these recommendations has implications for the design of a different aspect of the system. Therefore, this dissertation contributes by offering design recommendations that are crucial for implementing such a novel system.

8.3 Future Work

This dissertation which pioneers the conceptualization of a novel technology opens up many different opportunities for future research. At a high level, this dissertation contributes the information-sharing recommender system platform that can be adapted and utilized for future studies. The admin features of the platform allow for manipulating factors such as the information source used, the contents of recommendations, the number of recommendations, the explanations provided, and the number of team members, just to name a few. Such a system could be used by future researchers to investigate numerous factors in the design and implementation of an information-sharing recommender system.

The findings from the studies in this dissertation also provide avenues for future research. First, studies in this dissertation focus on project-based or knowledge-based teams. Future research would benefit from exploring how action-oriented teams interact with and benefit from such a system and how these differences compare depending on the type of temporary team. Second, this body of research would benefit from studying information-sharing recommender system disclosure behavior in an actual teamwork environment. Although Study 1 and 2 utilize actual temporary teams, Study 3 and 4 which investigate disclosure rely on vignettes. In line with this, this dissertation is limited by its reliance on 'WEIRD' (White, Educated, Industrialized, Rich, and Democratic) sampling with Studies 1, 2, and 3 all involving undergraduate participants from a predominantly white institution. Future work would benefit from more inclusive research that involves more diverse participants. Third, Study 3 provided an initial foray into the concept of reciprocity settings and its relationship to disclosure. Although valuable findings from this study revealed how different group contexts are willing to disclose, future research is necessary to understand how simply offering an intermediate setting such as reciprocity in this context can influence disclosure behavior. Finally, future studies should take up the research goals of Study 4 by exploring additional explanation contents. There are numerous ways that explanations can be provided in recommender systems and the investigation of Study 4 simply scratches the surface of how explanations can be worded to increase disclosure behavior and promote positive system perceptions.

8.4 Closing Remarks

Although my motivations for selecting this dissertation topic were numerous, an interesting motivation for me was anecdotal experiences of semi-compulsory personal information sharing in teaming contexts. The common threads that these experiences shared included being on a temporary team, taking some kind of personality assessment, being pressured to share my results with the team, and trying to make some kind of sense out of the results shared with me from my team members. Reflecting on these experiences in the moment and afterward left me with questions such as: *Wait, do I really have to share my information?*; *It would be kind of awkward and unprofessional to refuse, right?*; *What am I supposed to do with ALL of this information?*; and *Does sharing and receiving this information actual help the team?*. This anecdotal evidence as well as the problem and research motivations provided in Chapter 1 motivated the goal of this dissertation: to better understand how a teammate information-sharing recommender system could be designed to promote *teammate* TMMs while limiting privacy concerns. Upon reflection of my work in this dissertation, I am confident that the goal of this dissertation was accomplished.

First from a teamwork perspective, an understanding of how *teammate* TMMs can be supported on temporary teams has been improved. Members join temporary teams with little knowledge of the strengths, weaknesses, tendencies, and temperaments of their new teammates on temporary teams [86]. Although these teams stand to potentially gain more from improved *teammate* TMMs [238], little research has investigated how to support them. Consequently, an improved understanding of how to support *teammate* TMMs on temporary teams including what information to share and why sharing is perceived as beneficial will be a valuable contribution of this dissertation. Importantly, the contribution of this dissertation to supporting *teammate* TMMs should not be utilized in silo. An information-sharing recommender system as a tool should be used alongside and in combination with other established mechanisms for supporting TMMs such as various team training and development practices and tools [263, 342].

Second, recommender systems serve as a valuable technology in supporting the personal information sharing needed to support *teammate* TMMs. This dissertation contributes the conceptualization of a new form of recommender system, an information-sharing recommender system. In doing so, I gained an understanding of the numerous factors that influence disclosure and system perceptions. From considering how the system should elicit personal information to crafting explanations that promote trust, many factors must be meticulously researched and considered. Although much more research needs to be done in this field to better understand how best to promote disclosure and positive perceptions, this dissertation offers a significant foundation for this nascent research field.

Finally, this dissertation took a human-centered approach in investigating how technology can support such personal information sharing. Through this process I learned how vastly different users perceive constructs such as teamwork, privacy, and trust to name a few. From a human perspective, an information-sharing recommender system is vastly complex as it must consider what information unique individuals perceive as sensitive, how the relationship between member personalities might influence what recommendations are helpful, and even how different members might perceive the benefits of various recommendations differently. This dissertation wades, nay, dives head first into the complexities and challenges of designing a human-centered system. I believe that the foundations set by this dissertation will benefit future researchers and practitioners who will inevitably push our understanding of how an information-sharing recommender system can put humans at the center.

Appendices

Appendix A Research Platform

A.1 Big Five Personality

Sources: [174, 132, 81, 292]

Please use the rating scale below to describe how accurately each statement describes you. (5-point Likert, Very Accurate $\Longleftrightarrow$ Very Inaccurate).

Note: the questions have been organized by facet for this appendix but were not grouped as such when presented to users.

(1) Extraversion

Activity Level

Am always busy.

Am always on the go.

Do a lot in my spare time.

Like to take it easy.*

Assertiveness

Take charge.

Try to lead others.

Take control of things.

Wait for others to lead the way.*

Cheerfulness

Radiate joy.

Have a lot of fun.

Love life.

Look at the bright side of life.

Excitement-Seeking

Love excitement.

Seek adventure.

Enjoy being reckless.

Act wild and crazy.

Friendliness

Make friends easily.

Feel comfortable around people.

Avoid contacts with others.*

Keep others at a distance.*

Gregariousness

Love large parties.

Talk to a lot of different people at parties.

Prefer to be alone.*

Avoid crowds.*

(2) Emotionality

Anxiety

Worry about things.

Fear for the worst.

Am afraid of many things.

Get stressed out easily.

Frustration

Get angry easily.

Get irritated easily.

Lose my temper.

Am not easily annoyed.*

Immoderation

Go on binges.

Rarely overindulge.*

Easily resist temptations.*

Am able to control my cravings.*

Melancholic

Often feel blue.

Dislike myself.

Am often down in the dumps.

Feel comfortable with myself.*

Self-Consciousness

Find it difficult to approach others.

Am afraid to draw attention to myself.

Only feel comfortable with friends.

Am not bothered by difficult social situations.*

Vulnerability

Panic easily.

Become overwhelmed by events.

Feel that I'm unable to deal with things.

Remain calm under pressure.*

(3) Conscientiousness

Achievement-Striving

Work hard.

Do more than what's expected of me.

Do just enough work to get by.*

Put little time and effort into my work.*

Cautiousness

Jump into things without thinking.*

Make rash decisions.*

Rush into things.*

Act without thinking.*

Dependability

Keep my promises.

Tell the truth.

Break rules.*

Break my promises.*

Orderliness

Like to tidy up.

Often forget to put things back in their proper place.*

Leave a mess in my room.*

Leave my belongings around.*

Self-Efficacy

Complete tasks successfully.

Excel in what I do.

Handle tasks smoothly.

Know how to get things done.

Self-Discipline

Am always prepared.

Carry out my plans.

Waste my time.*

Have difficulty starting tasks.*

(4) Agreeableness

Altruism

Love to help others.

Am concerned about others.

Am indifferent to the feelings of others.*

Take no time for others.*

Cooperation

Love a good fight.*

Yell at people.*

Insult people.*

Get back at others.*

Modesty

Believe that I am better than others.*

Think highly of myself.*

Have a high opinion of myself.*

Boast about my virtues.*

Morality

Use others for my own ends.*

Cheat to get ahead.*

Take advantage of others.*

Obstruct others' plans.*

Sympathy

Sympathize with the homeless.

Feel sympathy for those who are worse off than myself.

Am not interested in other people's problems.*

Try not to think about the needy.*

Trust

Trust others.

Believe that others have good intentions.

Trust what people say.

Distrust people.*

(5) Openness

Adventurousness

Prefer variety to routine.

Prefer to stick with things that I know.*

Dislike changes.*

Am attached to conventional ways.*

Artistic Interests

Believe in the importance of art.

See beauty in things that others might not notice.

Do not like poetry.*

Do not enjoy going to art museums.*

Imagination

Have a vivid imagination.

Enjoy wild flights of fantasy.

Love to daydream.

Like to get lost in thought.

Intellect

Love to read challenging material.

Avoid philosophical discussions.*

Have difficulty understanding abstract ideas.*

Am not interested in theoretical discussions.*

Liberalism

Believe that criminals should receive help rather than punishment.

Believe that there is no absolute right or wrong.

Believe too much tax money goes to support artists.*

Believe that we should be tough on crime.*

Sentimentality

Experience my emotions intensely.

Feel others' emotions.

Rarely notice my emotional reactions.*

Don't understand people who get emotional.*

---

*Reverse scored

Table A.1: Big Five Personality Assessment

A.2 Conflict Management Styles

Sources: [367, 310, 292]

Please use the rating scale below to describe how accurately each statement describes you. (5-point Likert scale, Very Accurate $\Longleftrightarrow$ Very Inaccurate).

Note: the questions have been organized by conflict management style for this appendix but were not grouped as such when presented to users.

Integrating

I try to investigate an issue with others to find a solution acceptable to everyone.

I try to integrate my ideas with others to come up with a decision jointly.

I try to work with others to find solutions to a problem which satisfies everyone's expectations.

I exchange accurate information with others to solve a problem together.

I try to bring everyone's concerns out in the open so that the issue can be resolved in the best possible way.

I collaborate with others to come up with decisions acceptable to everyone.

I try to work with others for a proper understanding of a problem.

Accommodating

I generally try to satisfy the needs of everyone.

I usually accommodate the wishes of others.

I give in to the wishes of others.

I usually allow concessions to others.

I often go along with the suggestions of others.

I try to satisfy the expectations of everyone.

Compromising

I try to find a middle course to resolve an impasse.
I usually propose a middle ground for breaking deadlocks.
I negotiate with my supervisor so that a compromise can be reached.
I use 'give and take' so that a compromise can be made.
Avoiding
I attempt to avoid being 'put on the spot' and try to keep my conflict with others to myself.
I usually avoid open discussion of my differences with others.
I try to stay away from disagreements with others.
I avoid encounters with others.
I try to keep my disagreements with others to myself to avoid hard feelings.
I try to avoid unpleasant exchanges with others.
Dominating
I use my influence to get my ideas accepted.
I use my authority to make a decision in my favor.
I use my expertise to make a decision in my favor.
I am generally firm in pursuing my side of the issue.
I sometimes use my power to win a competitive situation.

Table A.2: Conflict Management Styles

A.3 Study 4 Explanation Examples

This table provides an example explanation for each of the 8 personality traits used in Study 4. These examples are each for the occurrence of *during recommendations* and the content of *benefit*. See Table 7.2 for what the other three explanations types look like for the example of 'Self Efficacy'.

Dependability

It is helpful for you to understand how likely members are to meet deadlines in order to calibrate expectations for planning.

Assertiveness

It is helpful for you to understand how likely members are to hold back or express their opinions when planning and making decisions.

Self Efficacy

It is helpful for you to understand how confident members are in their abilities which might influence roles and responsibilities.

Trust

It is helpful for you to understand how trusting members are in order to find a balance between micromanaging and backup behaviors.

Activity Level

It is helpful for you to understand how many projects different members prefer to work on at a time in order to allocate tasks appropriately.

Cautiousness

It is helpful for you to understand how risk adverse or quickly members make decisions when the team is making a collaborative decision.

Anxiety

It is helpful for you to understand how likely or unlikely members are to become stressed out when allocating tasks and discussing tight deadlines.
Self-Consciousness
It is helpful for you to understand how comfortable other members are in new groups or situations as this might influence their confidence and group dynamics.

Table A.3: Study 4 Explanation Examples (Benefit-Related During Recommendations)

Appendix B Demographics and Personal Measures

B.1 Study 1 and 2 Demographic Survey

Course: (options)
Gender: (Male, Female, Non-binary / third gender, Prefer not to say)
Year of Study: (Freshman, Sophomore, Junior, Senior, Grad School - Masters, Grad School - PhD)
Do you have co-op or internship experience? (yes/no)
How many of your teammates did you know before this semester? (numeric entry)
How many of your teammates have you worked on a project with before this semester? (numeric entry)

Table B.4: Study 1 and 2 Demographic Survey

B.2 Study 3 Demographic Survey

Gender: (Male, Female, Non-binary / third gender, Prefer not to say)
Year of Study: (Freshman, Sophomore, Junior, Senior, Grad School - Masters, Grad School - PhD)
Do you have co-op or internship experience? (yes/no)

Table B.5: Study 3 Demographic Survey

B.3 Study 4 Demographic Survey

Age:

What is the highest level of school you have completed or the highest degree you have received? (Less than high school degree, High school graduate (high school diploma or equivalent including GED), Some college but no degree, Associate degree in college (2-year), Bachelor's degree in college (4-year), Master's degree, Doctoral degree, Professional degree (JD, MD))

Choose one or more races that you consider yourself to be: (White, Black or African American, American Indian or Alaska Native, Asian, Native Hawaiian or Pacific Islander, Latino or Hispanic, I prefer not to say, Other [specify])

Is English your native language? (yes/no)

Please specify your identified gender: (Male, Female, Non-binary / third gender, Prefer not to say, Prefer to specify[specify])

Which statement best describes your current employment status? (Working - paid employee, Working - self employed, Not working - temporary layoff from a job, Not working - looking for work, Not working - retired, Not working - disabled, Not working - other [specify], Prefer not to answer

What kind of team experience do you have Professionally in the past 2 years (choose all that apply)? (Ongoing project team - when one project is complete, the team remains the same for the next project; Temporary project team - the team is formed for a specific project and often disbands after completion (e.g., projects that last for weeks or months in a stable environment); Temporary action team - the team is formed for a specific task and often disbands after completion (e.g., emergency response teams, sports teams, military teams, airline crews))

Please provide a description of the type(s) of professional teams you have been on (e.g., I worked on an ongoing marketing team, I worked on temporary software development teams, I was a firefighter, etc.):

Table B.6: Study 4 Demographic Survey

B.4 Trust Propensity

Adapted from Sources: [209, 29, 390]
Please answer the following questions regarding the system that you just used (5-point Likert scale, Strongly Disagree $\Longleftrightarrow$ Strongly Agree (7-point for Study 4)).
It is easy for me to trust a person/thing.
My tendency to trust a person/thing is high.
I tend to trust a person/thing, even though I have little knowledge of it.
Trusting someone or something is difficult for me.*

*Reverse scored

Table B.7: Trust Propensity

Appendix C Assessment Perception Measures

C.1 Assessment Perceptions Survey

No responses will be shared with your instructor or your teammates. Please answer the following questions regarding the personality and conflict management style assessment reports you received (7-point Likert scale, Strongly Disagree $\Longleftrightarrow$ Strongly Agree).
My personality assessment results were accurate.
My conflict management assessment results were accurate.
It is helpful for personality assessment data to be shared with teammates.
It is helpful for conflict management assessment data to be shared with teammates.
It is appropriate for personality assessment data to be shared with teammates.
It is appropriate for conflict management assessment data to be shared with teammates.
For the following questions, please respond in 3-5 sentences (free response):
What information (if any) from the personal reports did you find useful and why?
How could the report be improved so that you would find it more helpful?
What information (if any) from the team reports did you find useful and why?*
How could the report be improved so that you would find it more helpful?*

*Questions only asked to participants in the sharing condition

Table C.8: Assessment Perceptions

Appendix D Team Measures

D.1 Knowledge Elicitation - Information Needed for *Teammate* TMMs

We are seeking to learn how to design a future system that could create interpersonal recommendations to team members at the start of projects to increase teammate understanding and team effectiveness. Consider the next 2 prompts and what type of recommendations you would want a system to make to you when working with team members in the future.
Fill in the blank : I would have worked better with teammate X if I had done ____ differently during this project. Provide multiple responses if necessary.
Fill in the blank : I will work better with teammate X in the future now that I know ____. Provide multiple responses if necessary.
What information would an AI need to know about a teammate in order to make these interpersonal recommendations (previous 2 questions) to future teammates? [Please respond in 3-5 sentences]

Table D.9: Knowledge Elicitation - Information Needed for *Teammate* TMMs

D.2 Team Satisfaction

Source: [382]

These questions are for research purposes only. No responses will be shared with your instructor or your teammates. Please answer the following questions regarding your current project team (5-point Likert scale, Strongly Disagree $\Longleftrightarrow$ Strongly Agree).
I am satisfied with my present colleagues.
I am pleased with the way my colleagues and I work together.
I am very satisfied with working in this team.

Table D.10: Team Satisfaction

D.3 Team Psychological Safety

Source: [102]
These questions are for research purposes only. No responses will be shared with your instructor or your teammates. Please answer the following questions regarding your current project team (7-point Likert scale, Very Inaccurate $\Longleftrightarrow$ Very Accurate).
If you make a mistake on this team, it is often held against you.*
Members of this team are able to bring up problems and tough issues.
People on this team sometimes reject others for being different.*
It is safe to take a risk on this team.
It is difficult to ask other members of this team for help.*
No one on this team would deliberately act in a way that undermines my efforts.
Working with members of this team, my unique skills and talents are valued and utilized.

*Reverse scored

Table D.11: Team Psychological Safety

D.4 Team Cohesion

Source: [258]
These questions are for research purposes only. No responses will be shared with your instructor or your teammates. Please answer the following questions regarding your current project team (5-point Likert scale, Strongly Disagree $\Longleftrightarrow$ Strongly Agree).
I enjoyed working with my teammates.
I wish I were on a different team.*
The team worked well together.
Everyone contributed to the discussion.
The team wasted a lot of time.*
I trust that my teammates will do their fair share of the work.
*Reverse scored

Table D.12: Team Cohesion

D.5 Perceived Team Effectiveness

Adapted from Source: [315]
These questions are for research purposes only. No responses will be shared with your instructor or your teammates. Please answer the following questions regarding your current project team (7-point Likert scale, Strongly Disagree $\Longleftrightarrow$ Strongly Agree).
Members look forward to team meetings.

Team members 'carry their weight'.
Members are highly committed to the team.
The professor is satisfied with the team's product.
People outside of the team give the team positive feedback about its work.
Team members work better together now than when the team was formed.
Team members are more aware of group dynamics now than when they joined the team.
Being a part of this team helps members appreciate different types of people.

Table D.13: Perceived Team Effectiveness

Appendix E System Perception Measures

E.1 System-Specific Privacy Concern

Source: [205]
Please answer the following questions regarding the system that you just used (5-point Likert scale, Strongly Disagree $\Longleftrightarrow$ Strongly Agree (7-point for Study 4)).
I'm afraid the system discloses private information about me.
The system invades my privacy.
I feel confident that the system respects my privacy.*
*Reverse scored

Table E.14: System-Specific Privacy Concern

E.2 Perceived Over-Sharing Threat

Source: [207]
Please answer the following questions regarding the system that you just used (5-point Likert scale, Strongly Disagree $\Longleftrightarrow$ Strongly Agree (7-point for Study 4)).
I am afraid that due to the system's recommendations, I am sharing my information too freely.
I am comfortable with the amount of information shared about me.*
Due to the recommendations, people will know too much about me.
Nobody gets to see more information about me than I am comfortable with.*
I fear that the system is too liberal in sharing my personal information.

The system is not disclosing too much to anyone.*
*Reverse scored

Table E.15: Perceived Over-Sharing Threat

E.3 Trust Competence

Adapted from Sources: [209, 29, 390]
Please answer the following questions regarding the system that you just used (5-point Likert scale, Strongly Disagree $\Longleftrightarrow$ Strongly Agree (7-point for Study 4)).
This system is like a real expert in assessing teammates.
This system has the expertise to understand my needs for understanding my teammates.
This system has the ability to understand my needs for understanding my teammates.
This system has good knowledge about my teammates.
This system considers my needs and all important attributes of teamwork.

Table E.16: Trust Competence

E.4 Trust Benevolence

Adapted from Sources: [209, 29, 390]
Please answer the following questions regarding the system that you just used (5-point Likert scale, Strongly Disagree $\Longleftrightarrow$ Strongly Agree).
This system puts my needs first.
This system keeps my needs in its mind.

This system wants to understand my needs and preferences.

Table E.17: Trust Benevolence

E.5 Trust Integrity

Adapted from Sources: [209, 29, 390]
Please answer the following questions regarding the system that you just used (5-point Likert scale, Strongly Disagree $\Longleftrightarrow$ Strongly Agree).
This system provides unbiased team recommendations.
This system is honest.
I consider this system to be of integrity.

Table E.18: Trust Integrity

E.6 Satisfaction with the System

Source: [203]
Please answer the following questions regarding the system that you just used (5-point Likert scale, Strongly Disagree $\Longleftrightarrow$ Strongly Agree (7-point for Study 4)).
The system has no real benefit to me.*
Using the system is annoying.*
The system is useful.
Using the system is a pleasant experience.
Using the system makes me happy.

Overall, I am satisfied with the system.
I would recommend the system to others.
I would use this system if it were available.
I would pay $2 to use this system.
I would quickly abandon using this system.*
It would take a lot of convincing for me to use this system.*

*Reverse scored

Table E.19: Satisfaction with the System

E.7 Perceived Accuracy of Personality Results

Please answer the following questions regarding the system that you just used (5-point Likert scale, Very Inaccurate $\Longleftrightarrow$ Very Accurate).
Regarding your personality results (8) that were just displayed to you, how accurate do you think your results were?

Table E.20: Perceived Accuracy of Personality Results

E.8 Perceived Helpfulness of Recommendations

For this hypothetical situation: (5-point Likert scale, Not Helpful at All $\Longleftrightarrow$ Extremely Helpful).

How helpful would it be to receive this recommendation?*

*Displayed 8 times - one for each of the personality facets used

Table E.21: Perceived Helpfulness of Recommendations

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