To Share or Not to Share

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To Share or Not to Share: Understanding and Modeling Individual Disclosure Preferences in Recommender Systems for the Workplace

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Newly-formed teams often encounter the challenge of members coming together to collaborate on a project without prior knowledge of each other's working and communication styles. This lack of familiarity can lead to conflicts and misunderstandings, hindering effective teamwork. Derived from research in social recommender systems, team recommender systems have shown the ability to address this challenge by providing personality-derived recommendations that help individuals interact with teammates with differing personalities. However, such an approach raises privacy concerns as to whether teammates would be willing to disclose such personal information with their team. Using a vignette survey conducted via a research platform that hosts a team recommender system, this study found that context and individual differences significantly impact disclosure preferences related to team recommender systems. Specifically, when working in interdependent teams where success required collective performance, participants were more likely to disclose personality information related to Emotionality and Extraversion unconditionally. Drawing on these findings, this study created and evaluated a machine learning model to predict disclosure preferences based on group context and individual differences, which can help tailor privacy considerations in team recommender systems prior to interaction.

CCS Concepts: • **Human-centered computing** → **Empirical studies in HCI**.

Additional Key Words and Phrases: Group recommender systems, Individual difference, Teamwork, Privacy

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1 INTRODUCTION

A group of individuals who come together or are chosen based on their skills and expertise for a specific purpose and/or task for a short period of time is often referred to as an ad-hoc team

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[30, 92, 136]. Some forms of ad-hoc teams include project teams [94], task forces [51], and student teams [120]. Ad-hoc teams are increasingly popular in organizations and are typically disbanded once the task or project is completed, and their members return to their regular roles within the organization [55]. A key challenge of ad-hoc teams is that members may have different working styles, personalities, and communication preferences, which are often unknown to one another [66]. This lack of knowledge of each other's perspectives can lead to conflict and misunderstandings if team members do not have sufficient time to establish norms and expectations for working together [34]. Prior work has attempted to address this challenge by proposing a team recommender system that provides unique recommendations to individuals on how to accommodate their specific teammate's work and communication style based on said teammate's personality [101].

Similar to that of a social recommender system, this team recommender system requires the disclosure and sharing of personal information with others, which can create privacy concerns [4]. While research has improved the privacy awareness of social recommender systems and shown the benefits of this awareness to system use and satisfaction [156], team recommender systems present three unique considerations that challenge disclosure practices. First, social recommender systems often establish new relationships with content and other people [113], but team recommender systems work to improve existing relationships. Second, team recommender systems require users to directly disclose information to the recommender system, while disclosure to social recommender systems is often encapsulated within disclosure to a social media platform [25]. Finally, the goals and contexts of team recommender systems are uniquely placed in workplace settings, while social recommender systems often exist within leisure settings [27]. In turn, these three aspects change the structure of both disclosure and privacy within team recommender systems, and understanding these factors will help provide a fundamental understanding of the privacy perceptions surrounding team recommender systems.

Outside of team recommender systems, privacy concerns and awareness in single-user recommender systems have been extensively investigated and theorized. For instance, the privacy calculus theory has emerged as one of the prominent frameworks in information privacy research [33, 36, 61]. This theory examines information disclosure as a decision involving a trade-off between risks and benefits. It considers the perceived privacy risk associated with the release of personal information and the context-specific benefits individuals expect in exchange for the information they provide. Additionally, research has explored individual differences in privacy concern and its impact on information disclosure decisions within single-user recommender systems[73]. These explorations have yielded an understanding that privacy-aware recommender systems are not static, as privacy awareness has to be modified and tailored to accommodate differences among users, contexts, and recommendation content (e.g., [70, 72]).

These frameworks provide a starting point for enabling future privacy awareness in team recommender systems. For example, some group members may be more hesitant to disclose personal information during team collaboration [66], as there is a risk of losing one's presented self-image if unbecoming information is disclosed to teammates [107]. Furthermore, members' privacy concerns and curation behaviors may differ for various types of groups (e.g., varying levels of interdependence), as the perceived benefits of disclosing personal information may increase as interdependence increases. For example, members may see the increased level of collaboration associated with higher interdependence as benefiting from personal information disclosure [88]; yet, this benefit also carries a risk to it as unbecoming information would likely be more impactful in teams with this greater frequency in collaboration and interaction [14]. In empirically exploring these and other trade-offs to understand privacy awareness in team recommender systems, the following research questions have been identified:

RQ1: How does group context (especially interdependence) relate to disclosure behavior in a team recommender system?

RQ2: How do individual differences relate to disclosure behavior in a team recommender system?

These RQs are further motivated by the knowledge that a recommender system's compatibility with a user's privacy preferences improves system perception, which is why adequate privacy awareness requires consideration of an individual's personal policy [72]. In turn, identifying and predicting a user's privacy and potential disclosure preferences prior to system interaction would help tailor system design to user preference and improve perception and experience. As such, the additional following research question is motivated by the need to tailor future team recommender systems to individuals' privacy preferences:

RQ3: How can we predict users' disclosure decision with the above-mentioned factors?

Answering these research questions is critical to understanding the factors influencing individuals' privacy preferences and disclosure behavior in workgroup contexts, as they will inform the human-centered design of recommender systems for ad-hoc teams. To do this, we conducted a vignette survey that manipulated group context as a between-subjects factor: 1) members assessed fully based on individual performance (individual-assessed), 2) members' assessment is half dependent on individual and half on team performance (mixed-assessed), 3) members assessed fully based on team performance (team-assessed), in which 152 participants took personality and conflict management style assessments and indicated whether and how they wanted to disclose their results with their hypothetical teammates. Results suggested that participants were more likely to unconditionally disclose their personality information in a highly interdependent team-assessed team than in mixed-assessed or individual-assessed teams, and that individuals scoring high on Openness attribute significantly increase their likelihood to disclose. This study makes a number of contributions to the GROUP and CSCW communities. First, it provides the first empirical analysis that examines individuals' privacy concern and curation behavior in a social recommender system in work group contexts, while prior work in this area has almost exclusively focused on leisure groups [102, 103, 105]. Second, this work advances the understanding of how group context and individual differences in personality contribute to people's disclosure preferences both individually and jointly. Third, it provides insights into how social recommender systems can be more thoughtfully designed to account for the use of personal information, the goals and composition of groups, and the differences of individuals to create privacy-aware recommendations that also benefit team outcomes.

2 BACKGROUND

This study aims to inform the privacy awareness of a team recommender system that uses social recommender system principles to improve the collaboration of teammates. First this section presents theories surrounding the practices of privacy and disclosure, which guide and frame this work. Then, this section discusses what we do and do not know about privacy in team recommender systems based on our understanding of their closest counterpart, social recommender systems. Finally, this section concludes that examining the additional factors that are likely to impact privacy preferences surrounding team recommender systems, which will help inform the design of this empirical work.

2.1 Privacy Calculus and User-Tailored Privacy

Recommendations, especially those that involve recommending social factors, often share one user's personal data with another to help facilitate a connection, and this sharing requires user disclosure. However, this disclosure presents a trade-off, as disclosing one's personal information can be challenging and uncomfortable, but disclosure may yield higher quality recommendations, leading to greater system satisfaction [77]. To understand users' decision-making regarding the disclosure of personal information, it is essential to consider the concept of privacy calculus, which examines how individuals weigh anticipated benefits against perceived risks [32, 82, 137]. This decision-making process involves considering the factors of privacy risk and disclosure benefits [105].

Privacy encompasses various dimensions, including being left alone [142], secrecy, control over personal information, personhood, and intimacy [128]. However, in online contexts, privacy is often focused on controlling personal information, including its disclosure, storage, and use [48, 61, 137, 146, 148]. Privacy concern, in this context, refers to individuals' concerns about potential privacy loss through sharing personal information with external entities such as technology or companies [36, 151, 152]. In the context of relationship-focused social recommender systems, privacy concerns often go beyond sharing personal information with a computational system and also have to consider the sharing of this information to other users [87, 102]. Increased privacy risk or concern often leads to decreased willingness to share personal information and accept a technology [65, 91, 93, 109].

Conversely, users also consider the benefits of self-disclosure, which pertain to context-specific gains resulting from sharing personal information during online activities [61]. Previous studies have explored perceived benefits such as monetary rewards from location-based services [153], social benefits from blogging [83], image curation on personal websites [59], and personalized experiences in online shopping [22, 107]. When users perceive benefits, they may be willing to trade off a certain level of their privacy [26, 69, 150].

However, it is worth noting that some researchers question the completeness of decision theories like privacy calculus, as they may overemphasize the rationality of users and their decision-making processes [47, 63, 64, 125]. In response, recent research has proposed the concept of tailored privacy solutions, which involves predicting users' privacy preferences and behaviors, and providing adaptive nudges, such as automatic initial default settings [72]. This approach aims to alleviate the burden on users to calculate risks and benefits by considering factors like user characteristics, decision history, and context [72].

Importantly, when designing user-tailored privacy solutions, algorithm decisions should consider numerous factors. Subsequent subsections will delve into these factors and explore the relevant research conducted in the context of group recommender systems.

2.2 Disclosure in Team Recommender Systems and Its Relationship to Social Recommender Systems

Among the various types of recommender systems, team recommender systems have been recently conceptualized and proposed within the domain, and this novel recommender system works to improve team interaction through social recommendations that improve collaborations [101]. While team recommender systems are a newly introduced technology, they share a number of functional aspects with social recommender systems, especially in terms of disclosure functionalities. In particular, social recommender systems often operate on top of social interactions and data, and their recommendations are derived from these data [50, 84, 144, 154]. Further, these systems often facilitate sharing personal information between users [3, 124]. For example, a social recommender system on a dating application can recommend a potential partner, which is accompanied by various personal information that the prospective partner previously disclosed [1, 117, 149]. In turn, disclosure can happen at two stages of both social and team recommender systems: when the user discloses information to the system and when the system discloses said information to other users through recommendations and accompanying explanations.

Within social recommender systems, this similarity to human-human interaction often leads disclosure habits to be partially governed by the disclosure and privacy concerns users have in the general social media platform [25, 157]. In turn, the factors that often inform privacy in social interaction, such as trust [54] and social context [28, 126], also inform privacy preferneces surrounding social recommender systems. Similarly, team recommender systems operate in proximity to team member interactions, which means disclosure practices and preferences may already exist within these interactions [38, 90]. In turn, the potential disclosure of information to another teammate is likely dictated by one's interpersonal privacy preferences, with factors like trust and context also becoming relevant to this novel system [133, 143]. Additionally, for both team and social recommender systems, the actual individuals within a group can also be an important contributor to a disclosure decision and recommendation [3, 134].

However, team recommender systems are still distinct from common social recommender systems for three reasons: their goals, interaction method, and context. Traditionally, social recommender systems aim to recommend and establish new social connections. Indeed, whether it be a new romantic partner or new social media content, social recommender systems are often working to gain and retain users to a platform through relevant recommendations and explanations [114, 138] On the other hand, team recommender systems aim to improve an already established team. Due to this, the rationale and explanations behind recommendations will likely differ, as team recommender systems need to provide a recommendation that benefits the existing team and maybe not a singular individual [46, 155], which also makes these systems similar to group recommender systems [106]. Additionally, the proximity of these recommender systems to their target populations is also different, as social recommender systems are often integrated within the social interaction they facilitate [123, 124]; meanwhile, team recommender systems exist outside of team interaction and provide guidance to an established team. Due to this difference, users' interaction with this system is often more explicit, as teammates directly disclose information to the recommender system rather than an existing social media platform, and their disclosure habits may be more heavily dictated by privacy considerations related to human-AI interaction rather than social media disclosure [20, 39, 61]. Lastly, while social recommender systems can recommendations to teams in workplace environments, such as in the case of expertise recommenders [96], team recommender systems create pairwise recommendations between individuals, not whole teams. In sum, while a number of conclusions can be made about the privacy preferences users will have for team recommender systems, these core differences require additional exploration to create a holistic understanding.

2.3 Factors Influencing Privacy and Disclosure to Recommender Systems

Due to the more explicit disclosure requirements of team recommender systems, factors beyond those explored in social recommender systems are likely impactful. Indeed, exploring the factors that generally impact disclosure to recommender systems will be pivotal in understanding privacy in team recommender systems due to their unique differences. In turn, the following subsection details the most prevalent factors identified by research within the broader recommender system community, which this study will use to explore privacy concerns within team recommender systems.

2.3.1 Individual Differences. First, individual differences are an important factor in predicting a user's privacy concerns when it comes to disclosing personal information [71, 74]. These differences are often assessed using personality models such as the Big Five, which consists of five factors: extraversion, emotionality (or neuroticism), conscientiousness, agreeableness, and openness [31].

Studies have explored the relationship between personality factors and privacy concerns in various online contexts [111]. Higher levels of agreeableness and neuroticism, along with lower levels of extraversion (in certain contexts), have been associated with increased privacy concerns [7]. In the context of location-based services, agreeableness, conscientiousness, and openness to experience were found to be linked to higher levels of privacy concern [62]. Similarly, agreeableness was identified as a significant factor influencing privacy concerns in a survey study on information privacy [78]. Additionally, Dinev et al. [36] focused on the e-commerce context and found that trust propensity, a sub-facet of agreeableness, played a role in facilitating information disclosure.

These findings suggest that factors like personality and conflict management styles are valuable predictors for understanding privacy and explanation preferences in group recommender systems. However, there are inconsistencies in how personality relates to privacy concerns, likely due to the specific context in which information is shared (e.g., comparing [7] with [105]). For example, a collaborative context may moderate the relationship between agreeableness and users' willingness to share information in order to reach a group decision [105].

2.3.2 Context and Relationships. Second, the context in which information is shared plays a crucial role in privacy concerns and disclosure. In online environments, the sensitivity of the context, such as finance, e-commerce, or health, can significantly impact individuals' privacy concerns and their willingness to disclose information [7, 74]. Within the field of group and social recommender systems, the group type and user relationships can have demonstrable impacts on the function of the system and disclosure habits of individuals [40, 49, 56, 97, 124, 147]. For example, Mehdy et al. [97] found that the user's relationship with the recipient (e.g., family, friend, colleague, or stranger) had a significant impact on the intention to disclose information, with closer relationships leading to more positive attitudes towards information disclosure.

Similarly, Najafian et al. [102] discovered that loosely coupled groups often see greater privacy concerns when compared to tightly coupled groups using recommender systems. Another study by Prasad [118] identified that explanation preference (complete information vs. privacy-preserving) was directly related to their conflict handling practices in combination with the type of group they operated in. Furthermore, researchers have examined how task design can influence information disclosure, such as comparing users instructed to convince others of their opinions to those aiming to reach a group consensus [103, 105]. The results indicated that framing the context as competitive can impact the disclosure of emotion-related information [103] and mediate the relationship between privacy risk and information disclosure [105]. Therefore, contextual factors such as the relationships among group members and the framing of the task (competitive vs. collaborative) have an influence on privacy concerns and information disclosure in group recommender systems.

2.3.3 Information Type. Third, the type of information plays a significant role in privacy concerns and individuals' willingness to disclose it. Private information encompasses various categories such as location, medical data, emotions, personal details, and associations [19]. Previous research has demonstrated that both the specific type of information, such as health, finance, or relationship-related [74, 97], and the level of detail associated with it can influence individuals' disclosure behavior [29].

In group settings, negative impressions and conformity may also be a point of consideration when crafting users' privacy concerns. Studies conducted in different online contexts have identified strategies employed by users to withhold personal information that they believe may create a negative perception among others (e.g., [15, 112, 139]). In domains like corporate communications and personal websites, individuals tend to curate their self-presentation, emphasizing positive aspects while refraining from disclosing information they perceive as negative [17, 59].

Research has also found information type to be a critical component when conformity is a potential consideration. For instance, in music recommender systems, users in groups tend to utilize more privacy options in scenarios where there is low consensus among group members [104].

Factor Type	Specific Factor	Description of Known Impact
Individual Differences	Trust Propensity	Shown to significantly impact disclosure [36]
	Personality	Sub-facets of personality, such as agreeableness and extraversion, significantly correlate to disclosure behaviors [7]
Context & Relationships	Group Type	Loosely coupled groups see greater privacy concerns and less disclosure [118]
	Team Context	The collaborative nature of a task context can moderate the impact of individual differences [105]

Table 1. List of factors to be explored in a team recommender system and their known impact in other recommender system types.

This behavior may be attributed to individuals' inclination to align their preferences with the group and match the majority, reflecting the phenomenon of conformity [6, 42, 95]. Furthermore, studies conducted in tourism group recommender systems have revealed that having a minority preference within a group is associated with higher privacy concerns [105], particularly regarding emotion-related information [102].

2.4 Considerations Surrounding AI in the Workplace

Additionally, while team recommender systems can directly relate to social recommender systems, their placement within the workplace means that concerns unique to workplaces are likely relevent as well. In particular, the growing prevalence of AI within the workforce has led people to form personal opinions surrounding AI technologies, and these perceptions are not always positive [99]. Prior work on HCI and the workplace highlight how labor itself needs to be a central concern of design [43]. Further, as AI technologies have been introduced, it is this labor component that has been relatively ignored [12]. In turn, as team recommender systems, which will likely leverage AI, workers, labor, and impacts on said labor need to be a predominant consideration. For example, the implementation of team recommender systems that leverage AI will likely need to be cognizant of the presentation of these systems [41], the literacy people have for them [21], and identified goals of these systems as they relate to labor [108]. Without these considerations, the actual privacy preferences humans form may be unintentionally restrictive.

2.5 Summary

This literature on team recommender systems highlights that a basic understanding of privacy and disclosure can be derived from social recommender systems research. However, the unique qualities that separate team recommender systems merit further explorations of the factors that directly impact privacy and disclosure. In turn, a selection of these factors (Shown in Table 1) will be empirically explored within this team recommender system. Further, bringing these factors out of leisure contexts and into a social workplace context is also needed to understand how workplace environments can impact privacy preferences and disclosure habits.

3 METHODOLOGY

3.1 Study Design

To answer the research questions of how group context (RQ1) and individual differences (RQ2) impact disclosure behavior for a personalized team recommender system, we conducted a vignette survey study. We manipulated group context as a 3-level between-subjects factor, with the conditions denoting a group scenario with either loose (low interdependence), partial (medium interdependence), or tight (high interdependence) group goals. These conditions were operationalized as how members would be assessed (i.e., graded only as individuals, graded half as individuals and half dependent on team performance, or graded fully as a team). The prompts used for each of the three conditions is shown in Table 2.

Individual difference was a within-subjects repeated measure. It was operationalized as individual scores in 30 personality facets categorized into 5 personality categories, and that in conflict management style, which were inherently measured by the team recommender system research platform (see 3.4 for details), as each participant took the Big Five personality and conflict management style assessments for the platform to generate recommendations.

To answer RQ3 (How can we predict users' disclosure decision?), we created and evaluated machine learning models with inputs of group context, individual differences in five personality categories and in conflict management styles, as well as covariates such as system perception and trust propensity, to predict disclosure preferences.

Table 2. Group Context Conditions Prompts

Condition #	Interdependence and assessment	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**.

3.2 Participants

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. Undergraduate students are a suitable population to study privacy in group context because 1) they often need to work in ad-hoc teams for group projects, 2) such teamwork can often benefit from personality and conflict management-based advice, and 3) they care about their reputation and self-presentation in front of their peers such that privacy can become a concern. Participants received the standard credit associated with participating for 45 minutes which was the anticipated length of the study. Participants were randomly assigned to one of the group context between-subjects conditions.

A power analysis was performed to determine the number of participants required for a between-subjects ANOVA with three conditions. This analysis determined that 159 participants were required to reach a power of 0.80 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.

3.3 Individual Difference Assessments and Recommendations

The purpose of the recommender system created was to solicit participants' Big Five personality traits and their management styles, then provide them with recommendations for how they should interact and manage their team to best utilize these traits. In turn, this data serves a functional purpose in the recommender system, but it can also serve as a potential variable in predicting participant disclosure.

3.3.1 Big Five personality assessment. Personality assessment results provide a high-level overview of how an individual works and interacts with others on a team (e.g., tendencies, preferences, etc.). The Big 5 personality assessment was selected as it is the most frequently used personality theoretical model and assessment in teamwork and psychology research [9, 18, 68, 100, 116, 141]. This model gives users insight regarding how their personality fits onto five factors including extraversion, emotionality (or neuroticism), conscientiousness, agreeableness, and openness [8]. Prior research has shown that the Big Five is stable on temporary learning teams [132] and that team members on these teams are able to better assess the personality of their team members over time [131]. 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) [31] is often utilized as it provides more granular information and is better able to predict behavior compared to the broad five categories alone [115]. A list of the 30 facets and the Big Five trait they are associated with can be found in Table 3. Each facet was measured using 4 items resulting in a total of 120 items [60].

Table 3. Big Five Personality and 30 Facets

Big Five Traits	Facets	Scale Reliability (Cronbach's alpha)
Extraversion	Activity Level, Assertiveness, Cheerfulness, Excitement-Seeking, Friendliness, Gregariousness	0.784
Emotionality	Anxiety, Frustration, Immoderation, Melancholic, Self-Consciousness, Vulnerability	0.793
Conscientiousness	Achievement-Striving, Cautiousness, Dependability, Orderliness, Self-Efficacy, Self-Discipline	0.770
Agreeableness	Altruism, Cooperation, Modesty, Morality, Sympathy, Trust	0.645
Openness	Adventurousness, Artistic Interests, Imagination, Intellect, Liberalism, Sentimentality	0.629

3.3.2 Conflict Management Styles. Conflict management styles refer to how individuals deal with and handle interpersonal conflicts [119]. 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' [119]. Prior research has shown that individuals understanding their own and teammates manage conflict styles can assist in essential team processes such as communication and decision making [110], and can improve collaboration on teams [10, 13, 16, 23].

3.3.3 Recommendations. Recommendations were created and validated along the lines of ITP metrics [57] that was created by The Individual and Team Performance Lab. It 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 [58, 127, 140]. ITP metrics generates *individual* recommendations after a user takes the assessments, provides their 'percentile' and a category (i.e., low, moderate, or high) based on their raw score for each attribute (e.g., Compromising - High - 93%) compared against a "normative sample" (i.e., compared to 20,000 respondents for ITP metrics) [57]. An example of an individual recommendation can be found in Figure 1.

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.

Fig. 1. Platform Individual Results Page

Each participant received one of three recommendations (depending on their percentile category) for each of the 30 personality facets and the 5 conflict management facets. The 35 x 3 = 105 recommendation options 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 that has gone into their development points to an acceptable validity for use as a starting point in fostering an understanding of individual differences for team members.

3.4 Research Platform and Procedure

The research platform took the form of an in-house developed website that participants could visit through a link. The backend for the application was made by an undergraduate research assistant using a Python framework called Django. The front-end uses Bootstrap for styling and JavaScript for interactive elements.

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 2). 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 then directed to the assessment page where they completed multiple individual difference assessments. Subsequently, participants navigated to the results page where they were given a break-down of their personality and conflict management styles. Following each result, participants were able to indicate which of their results they would be willing to share with hypothetical teammates given the context. After recording disclosure for each result, participants received the full 35 recommendations. 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.

3.5 Measurements

The measurements for this study include personal assessments as independent variables measuring individual differences, disclosure selections as dependent variables measuring disclosure preferences, as well as system perception measures and trust propensity as covariates.

3.5.1 Personal Assessment Measures. As described earlier, participants took a Big Five Personality assessment [60] and Conflict Management Styles assessment [119], so the system could generate user-tailored recommendations. 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 and each of the five conflict management styles were collected. The relationships between each of these facets and disclosure behaviors will be a core focus of the results.

3.5.2 Trust propensity. Trust Propensity was collected as a covariate that measured how likely an individual is to trust a person or thing, which was found by prior studies (e.g., [105]) to mediate the effect of privacy concerns on disclosure behavior. This was a 4-item 5-point Likert-scale adapted from [44]. Items included "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", and "Trusting someone or something is difficult for me" (reverse coded). They were averaged to form a reliable scale (Cronbach's alpha = 0.87).

3.5.3 Disclosure Selection. For each attribute of Big Five and Conflict Management Style, a disclosure decision followed. 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 a reciprocity setting where participants can choose only to share if their group member was also willing to share the attribute. The last option implies a sharing decision that is unconditional. As a dependent variable, disclosure selection was collected for each personality and conflict management facet, and the results of this work will explore how the experimental manipulations and other personality factors can predict this selection.

3.5.4 System Perception Measures. Once they finished using the system, participants took two final surveys measuring their *system-specific privacy concern* [76] and their *satisfaction with the system* [73]. System-specific privacy concern assessment is a 3-item 5-point Likert scale with the following items: "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-coded). They were averaged to form a reliable scale (Crohbach's alpha = .89). Satisfaction with the system uses an 11-item 5-point Likert scale. Example items for satisfaction with the system included "The system has no real benefit to me" (reverse-coded) and "I would use this system if it were available". The 11 items were averaged to form a reliable scale (Crohbach's alpha = .79).

4 RESULTS

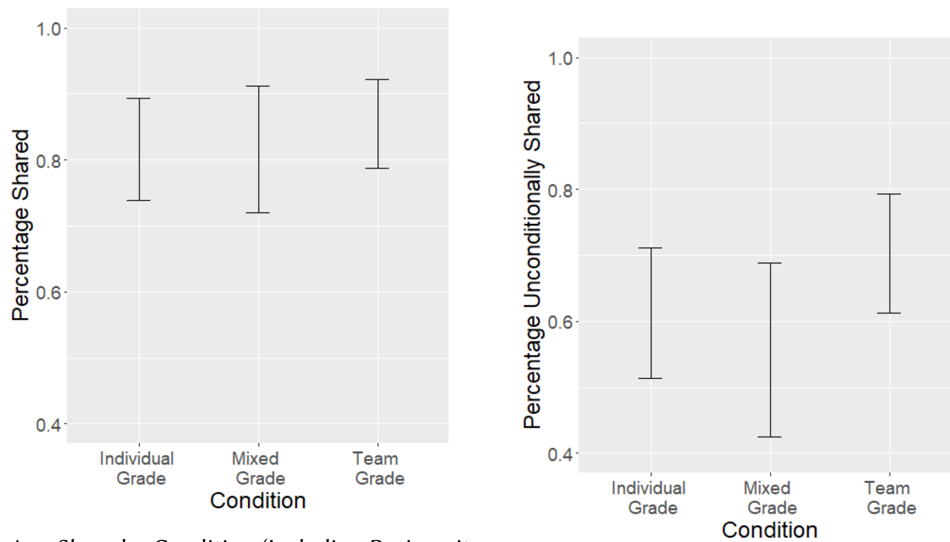
We divide the results into two main segments. First, we present results from statistical testing of the effect of group context and individual differences on participants' disclosure preferences. Second, driven by the user-tailored privacy concept and guidelines [72], we detail Machine learning (ML) based regression models that serve to predict participants' disclosure preferences based on factors of interest such as group context, individual differences in personality and conflict management styles. These predictions will lend insights into potential real-world versions of the team recommender system that can automatically personalize default sharing decisions based on an individual member's personality and conflict management type, as well as the group context, such that users will no longer need to make 35 decisions.

4.1 Effect of Group Context and Individual Differences on Disclosure Tendency

To explore the effect of group context on disclosure tendency, we first created visualizations and exploratory statistics. As seen in Figure 2a, there was no significant difference between conditions regarding *how much* personal information participants were willing to disclose (operationalized by calculating the percentage of "Any Share" that combines both Reciprocity share and Unconditional share). However, upon visual inspection of Figure 2b, 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 more than those in the *mixed grade* condition. Based on this trend, we focused on unconditional sharing in the analysis.

Next, we tested whether a participant's willingness to unconditionally allow the system to disclose information to other teammates differed based on the personality or conflict management attribute being disclosed. Using the Emotionality category as a baseline, analysis revealed that participants were more likely to share the following categories of information with the other group member unconditionally: **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**, $t(5129) = 0.77$, $p = .441$. A visualization of unconditional sharing by attribute category can be seen in Figure 3a.

To test the effects of group context (condition) on unconditional disclosure behavior, we ran a generalized linear mixed-effects regression model (glmer) with a random intercept for each of the attribute categories (Emotionality, Agreeableness, Conflict Management, Conscientiousness, Extraversion, and Openness). We used the independent variable of group context (Individual vs.



(a) Any Share by Condition (Including Reciprocity Share)

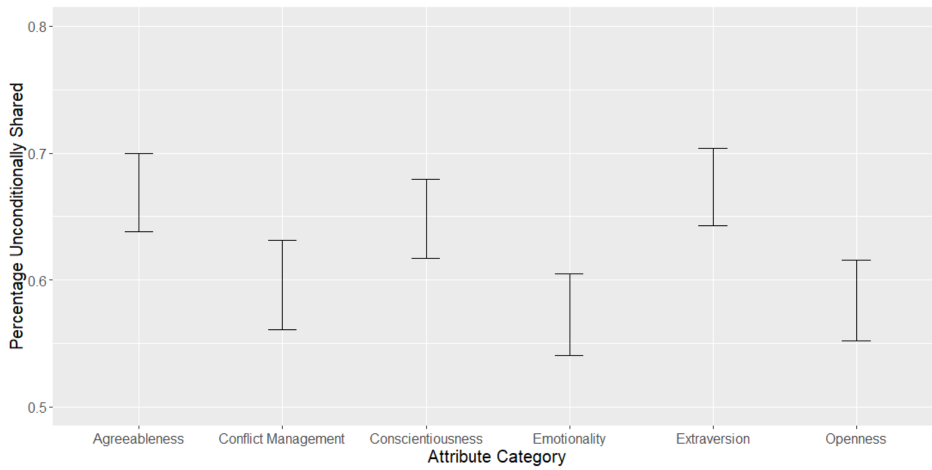
(b) Unconditional Share by Condition

Fig. 2. Sharing Pattern by Condition Category

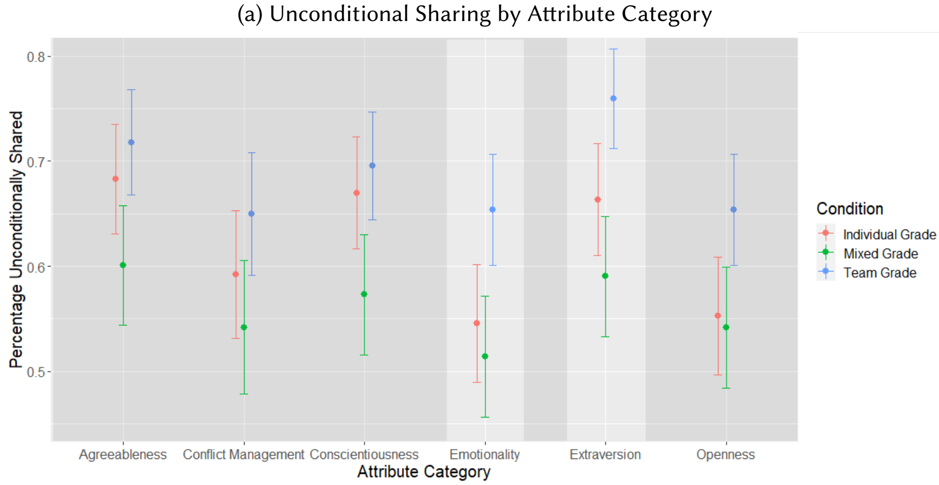
Mixed vs. Team Grade) as well as System-Specific Privacy Concern and participants' raw openness score as predictors in the glmer. We found that context significantly impacted the unconditional disclosure of participants for two personality attributes: Emotionality and Extraversion (highlighted in Figure 3b). Effects of condition were not significant in the other 4 models (Agreeableness, CM, Conscientiousness, and Openness).

For unconditional disclosure of attributes in the **Emotionality** category (see Table 4), 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 **system-specific privacy concern** for users, there is a 1.56-fold decrease in the odds that they will disclose items unconditionally ($p = 0.004$). Further, when users had a 1-point increase in there **Openess** score, there is a 8.97-fold increase in the odds that they will disclose items in the emotionality attribute unconditionally ($p = 0.021$). The full summary of the glmer model for emotionality can be seen in Table 4.

For unconditional disclosure of attributes in the **Extraversion** category (see Table 5), 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 **system-specific privacy concern** for users, there is a 1.54-fold decrease in the odds that they will disclose items unconditionally ($p = 0.007$). Further, a 1-point increase in a user's **Openness** score saw a 7.15-fold increase in the



(a) Unconditional Sharing by Attribute Category



(b) Unconditional Sharing by Condition and Attribute Category

Fig. 3. Attribute Categories and Unconditional Sharing

odds they would disclose items in the extraversion attribute unconditionally ($p = 0.051$). The full summary of the glmer model for extraversion can be seen in Table 5.

4.2 ML-based prediction

A supervised machine learning approach to determine if participants' personality attributes could be used to predict their disclosure habits. In what follows, we highlight the architecture of the models built, the workflow used to run these models, and their results.

Model setup and architecture. The model architecture was designed to be representative of the defining attributes observed during this study, including context, individual differences, and system perceptions. Thus, independent variables used as the prediction set include: *Condition (group context), the big five personality assessments, conflict management styles, trust propensity, and system satisfaction.* While system satisfaction was measured post-disclosure, the system design could have

Table 4. Generalized Linear Mixed-Effects Regression Model Results for Unconditional Disclosure - Emotionality Category

Emotionality Disclosure	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
System-specific Privacy Concern	0.64	(0.47, 0.87)	0.005
Openness	8.97	(1.39, 58.07)	0.021

Table 5. Generalized Linear Mixed-Effects Regression Model Results for Unconditional Disclosure of Extraversion Attribute Information

Extraversion Disclosure	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
System-specific Privacy Concern	0.65	(0.47, 0.89)	0.007
Openness	7.15	(0.99, 51.64)	0.051

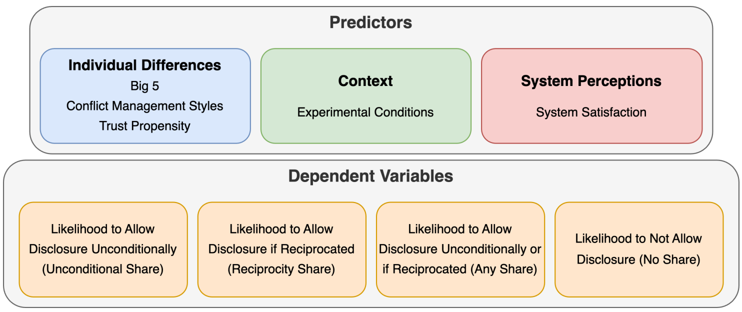


Fig. 4. Variables used in the ML architecture.

influenced participants' ability to disclose and other associated decision-making attributes. This combination was selected to probe for latent assimilation of these factors and understand how different attributes act in unison to impact disclosure trends and gain a composite view of other variables that might affect disclosure patterns. For dependent variables, four different models were run, one for each of the possible sharing patterns selected (Section 3.5.3). All of these variables have been graphically summarized for clarity in Figure 4.

ML model workflow. The following details the ML model workflow, which has also been graphically abstracted into Figure 5. We used a support vector machine regression approach to conduct the ML-based analysis drawing on prior research that elicits its robustness compared to other ML regression models [122]. For implementing the SVM model, an RBF (Radial Basis Function) kernel was used, given that it has been shown to adapt well to non-linear datasets and is capable of accounting for latent complexities in the dataset that can throttle the computational performance of SVM models [145]. To validate the model, an 80-20 train/test split was used [122]. To further optimize the performance, following best practices, a hyperparameter tuning methodology using grid search and five-fold cross-validation was employed [2]. Hyperparameter tuning can help to refine ML models and can also help counter overfitting issues and other potential threats to model validity [81]. Key model parameters (the regularization parameter (C) and the margin of tolerance (ϵ) were varied as part of this hyperparameter tuning approach [52]. All models were implemented using the scikit-learn python package [79]. The R^2 metric was used to understand model performance, following best practices in empirical studies that employ SVM regression models [122].

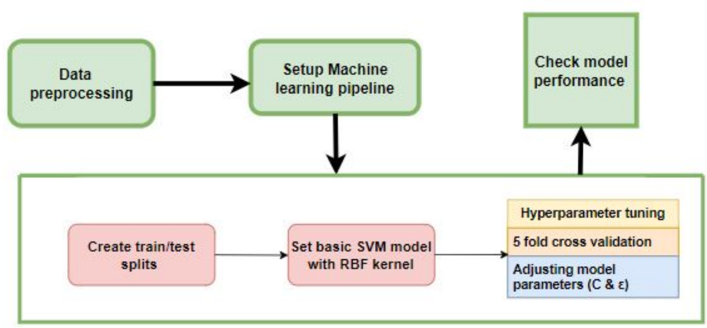
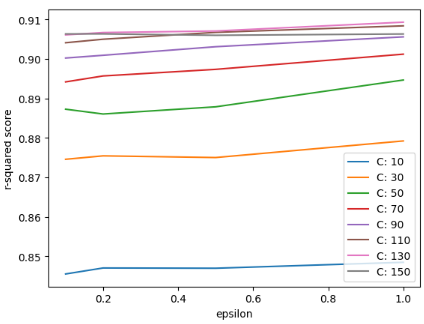


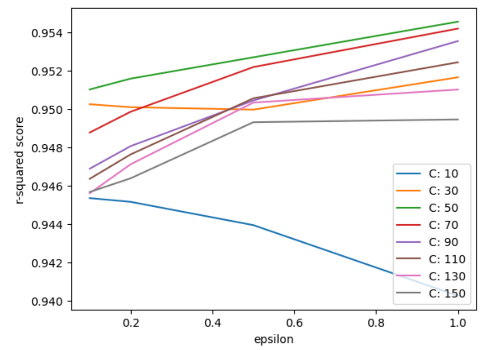
Fig. 5. Different stages of the ML workflow

ML Model Results. Figure 6 depicts the model performance (optimization outputs across the different parameters of the SVM model). Table 6 shows the performance associated with the best-performing model found from the model optimization routines outlined in figure 6. While in all cases, we see that the model pipeline achieves high performance (as indicated by the R^2 values), but reciprocity share has a lower overall performance. Interestingly, with only the individual difference attributes, the R^2 value for the reciprocity share significantly increases, achieving a value of *0.85*. These inferences highlight that individual factors are more astutely at play in governing the sharing patterns observed in the case of reciprocity sharing.

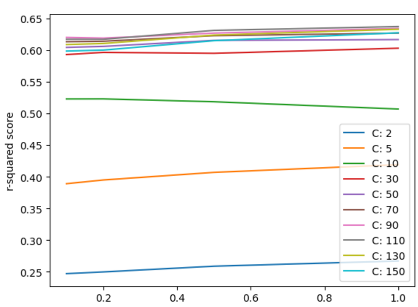
To further unpack these initial insights, we investigated the importance of each feature used in the different ML models to understand better how each factor adds to the model outcome. The permutation importance approach was used to compute feature importance scores, given the non-linear model estimators used to construct the SVM pipeline [53]. Figure 7 highlights feature importance scores (presented in order of importance, with the most dominant feature at the top). The importance of Emotionality in governing any sharing, especially its impact on the decision not to share, is essential to indicate how Emotionality can mediate information-sharing decisions [121]. It is interesting to see that for the sharing behaviors (unconditional or reciprocity sharing), the individual differences metrics (particularly the personality attributes) are most salient. In particular, Extraversion seems to be the most dominant factor. This could be attributed to the fact that extroverts tend to be more prolifically engaged in sharing behaviors[86]. Conflict management style also has high importance for unconditional sharing patterns. This further shows that maintaining camaraderie and a collective orientation to the group initiative can have an important influence on the sharing patterns [5].



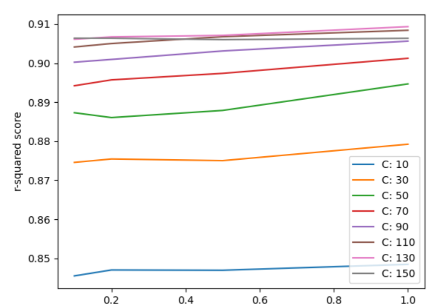
(a) Any share disposition model optimization



(b) Unconditional Share disposition model optimization



(c) Reciprocity share disposition model optimization



(d) No share disposition model optimization

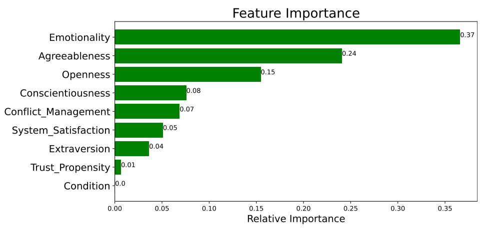
Fig. 6. Disclosure preference SVM model tuning trends

Table 6. Support Vector Machine (SVM) Results

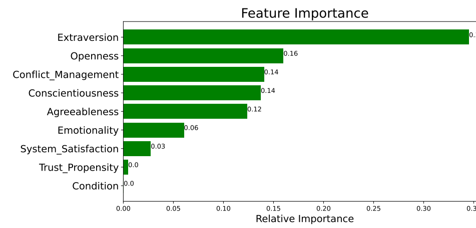
Disclosure type	**R^2 value of best model**
Any share disposition	0.927
Unconditional share disposition	0.945
Reciprocity share disposition	0.659
No share disposition	0.921

5 DISCUSSION

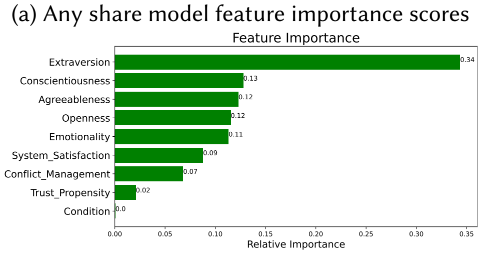
To answer the research questions, we have highlighted how group context and individual differences relate to disclosure behavior in a team recommender system. For **RQ1**, there was a significant effect of group context on unconditional disclosure behavior as individuals whose grades were fully dependent 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



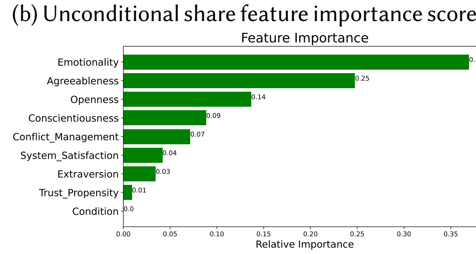
(a) Any share model feature importance scores



(b) Unconditional share feature importance scores



(c) Reciprocity share importance scores



(d) No share importance scores

Fig. 7. Model feature scores across different share patterns

at all dependent on the team's success (**RQ1**). Additionally, individual difference of personality-openness has a significant positive effect on unconditional disclosure of items in the Emotionality and Extraversion categories (**RQ2**). Meanwhile, users are significantly more likely to disclose items in the categories of Agreeableness, Conscientiousness, and Extraversion as compared to the category of Emotionality. Last but not least, we created and evaluated Machine Learning models accompanied with feature importance scores for each factor to successfully predict participants' disclosure preferences (**RQ3**).

In this section, we discuss the importance of the context of teamwork (group interdependence in particular) and how individual differences influence disclosure behavior and what implications these findings have in designing both social recommender systems and team recommender systems.

5.1 The Context of Teamwork for Recommender Systems

A contribution of this study is an improved understanding of how the context of teamwork influences users' disclosure preferences for a team recommender system. Prior privacy research has highlighted how users have a more positive attitude toward information disclosure with increasing levels of relationship closeness (e.g., family compared to colleague) [97]. Within the social recommender system field, one of the core functional capabilities of advanced recommender systems is to distinguish between different types of group relationships based on their closeness [124]. However, this study highlights that the importance of group dynamics also extends into that of work colleagues and privacy concerns, with the evaluation of these ad-hoc teams playing a significant role in disclosure behaviors.

In this study, we investigated how the interdependence of a group (operationalized through how members were assessed: individual vs. mixed vs. team) might influence disclosure behavior. This study was able to reveal significant differences between assessment type for the disclosure of certain types of information (attributes) see 5.2. It is possible that the lack of an overall significant effect was 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) [11]. 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 context-related findings in social recommender systems to ad-hoc teams in the workplace that use a team recommender system.

However, contrary to our expectations, we did *not* find that participants in the *mixed grade* condition unconditionally disclosed more than those in the *individual grade* condition. Pulling from other domains, research in group recommender systems may be able to shed light here as competitive contexts can negatively impact disclosure [103, 105]. Further, relationship heterogeneity is known to impact social recommendations [135], and the presence of a *mixed grade* team may provide differing perspectives on what is important to teammates, the team, and the individual. In turn, the *mixed grade* condition might have primed some teammates to have a more individual mindset, which led to an emphasis on reciprocity.

Taking these results holistically with prior work, one can derive practical implications for both the design of team recommender systems and the environment in which they are leveraged. In particular, with past work in group recommender system showing the negative impacts of competition [103, 105], taking a more team-centered approach to team recommender systems, where benefit explanations focus on the team over the individudal may yield a greater outcome in lowering privacy barriers. Additionally, it is not enough for the goals of good teamwork to be used as a justification within a team recommender system. With results showing the importance of assessment type, practical team recommender systems will need to communicate how these recommendations directly relate to the current tasks and goals the team is working toward. In line with work in group recommender systems that show the contextual nature of recommendations [1, 67], the justifications provided by team recommender systems will need to change in tandem with the teams' goals and context. In sum, these practical recommendations provide insight into how a real-world team recommender system would need to operate alongside a living team.

5.2 Considering Individual Differences for Disclosure in Team Recommender Systems

In addition to how the group was assessed, disclosure behavior also differed between participants depending on their individual characteristics. Particularly, 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 [37]. The factor of openness can be described by characteristics such as openness to experiences, feelings, and new ideas [35, 60]. 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. With openness already having a significant relationship with disclosure in social media settings [24, 85], in which social recommender systems are often situated, the results of this study extend this understanding by showing that openness is also a significant predictor in humans' disclosure habits toward a novel recommender system that exists outside but still supports a social context.

Second, we found that disclosure behavior differed depending on the type of information to be disclosed. Figure 3a shows that participants were more likely to share information about their level of agreeableness, conscientiousness, and extraversion being shared more than information about their 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

[15, 112, 139]. This can take the form of users displaying positive information about themselves while not disclosing information they perceive as negative [17, 59]. 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. Importantly, with sensitive personal items already being a critical consideration in the privacy awareness of social recommender systems [80, 98], the results of this study extend this prior work by highlighting how recommender systems in workplace settings that prioritize team benefits still need to be aware of privacy concerns around individuals' sensitive information.

5.3 Design Implications for Personalized Team Recommender System

This results of this study have implications for designing a personalized team recommender system that makes privacy decisions easier for users. 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.

5.3.1 Using 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 [89]. Some of this mismatch can be blamed on the volume of data that online platforms are attempting to categorize for privacy and disclosure settings [89]. To account for this, prior research has explored the possibility of using machine learning algorithms and recommender systems to predict or suggest privacy settings [45, 129].

Social recommender systems, and especially team recommender systems, would benefit from such *smart settings* to assist users in disclosure decisions, especially when they have a large number of disclosure choices. Based on the personality information of a user, social recommender systems would be able to restrict the disclosure of specific data from said user to another by default. At a base level, personality information could be used to identify specific data attributes that users would never want disclosed. In turn, social recommender systems could restrict the disclosure of this information by default, freeing up attention and lowering decision fatigue [130]. This would help users create higher-quality personal privacy policies. Further, based on the machine learning results of this work, social recommender systems could also leverage AI to predict a user-specific privacy policy prior to system interaction, and users would be able to devote their mental bandwidth to fine-tuning this policy within the recommender system to better meet their preferences. These settings would 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 [72]. However, this adjustment would enable user-tailored privacy to be partially formed and modified by users when they first interact with a social recommender system, which would likely include the disclosure of more data attributes within various contexts to various groups and individuals.

5.3.2 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 [75]. They also found that when an 'extreme' option was added, it can cause users to shift their sharing choice toward the added extreme option [75].

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 [75] can be applied to the social and team recommender system context, certain design implications should be considered in future research and development. First, unless a reciprocity disclosure option improves perceived privacy or disclosure habits in a specific context, that context should reduce the disclosure options presented. Second, disclosure could be set based on related attribute characteristics. Within a team recommender system, multiple attributes could be batched together based on semantic and sensitivity relevance, and users could set disclosure settings for each batch at once. Further, a social recommender system could see all posts with a specific tag, a core component to social recommender systems [124], following a preset disclosure setting.

5.4 Limitations and Future Work

This study serves as a useful investigation into how group context and individual difference influence disclosure behavior in a team recommender system. However, three 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. Finally, this study explored the disclosure benefits of ad-hoc teams, which operate within a limited time frame. However, social recommender systems are known to benefit from temporal consideration [124], and team recommender systems are likely the same. In turn, future work should expand this effort into a more traditional team context, which will help explore how temporal considerations, such as historical disclosure preferences, could impact disclosure behaviors toward a team recommender system and the prediction of privacy preferences.

6 CONCLUSION

While we start to see a growing interest in research on privacy in social recommender systems within social media, less focus has been seen on privacy preferences when interacting directly with a social recommender system. In particular, team recommender systems, which make pointed social recommendations directly to individuals through direct interaction with the system are likely to have unique privacy preferences apart from social recommender systems. To address this research gap, this study examined how factors of group context (i.e., interdependence) and individual differences impact group members' privacy concerns and curation behavior in a recommender system for the workplace developed to facilitate communication between teammates by providing recommendations based on individuals' personality and conflict management style data. It was found that group interdependence had a significant impact on users' disclosure of personality information, such that they were more likely to unconditionally disclose personality attributes of Emotionality and Extraversion in a highly interdependent team-assessed team than in mixed-assessed or individual-assessed teams. Further, individuals scoring high on Openness attribute significantly increase their likelihood to disclose their personality data. This study provides the first empirical analysis that examines individuals' privacy concern and curation behavior in a group recommender system in work group contexts, and advances the understanding of how group context, individual differences in personality, and the type of information individually and jointly contribute to people's disclosure preferences. Further, it provides insights into how social recommender systems can be more thoughtfully designed to account for both the use of personal information for facilitating group collaboration, and the support of user-specific privacy curation.

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