Critical Argumentation about Data from Educational Technology Influences Subsequent Data-Sharing Decisions

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Abstract

Learning analytics frameworks are equivocal that learners should be active in deciding what to do with their data in educational technologies. However, learners do not engage meaningfully with data sharing decisions that are at the core of informed consent. Recent research shows that discussions with others boost learner engagement with data sharing decisions. According to emerging research, discussions where individuals exchange opinions about data sharing resulted in more cautious decision choices afterwards. It remains unclear whether the quality of these discussions contributed to this effect. To further understand the effect of the discussion quality, we analysed how students made arguments about data-sharing, using 96 short discussions from 12 groups. By combining content analysis, clustering, and linear mixed-effects modelling, we examined if a particular way of argumentation in a group affected subsequent individual data-sharing decisions. We found that data-sharing discussions were characterised by assertions and supportive statements, but that overall evidence-based reasoning was limited. Three argumentation patterns were observed: critical argumentation, high engagement argumentation, and low engagement argumentation. Discussions where learners critically argued their data sharing positions showed a negative effect on their data sharing decisions after the discussion. These findings suggest that participatory practices for data sharing such as interactive consent require scaffolds to support argumentation quality and improve decision-making.

Keywords: Argumentation, learner data, learning analytics, data-sharing, informed consent, participatory consent, group deliberation

1. Introduction

The growing integration of data about learners and their processes into higher education offers new opportunities for teaching, learning, and institutional decision-making. This integration rests upon the affordance of educational technologies to record, store, and analyse digital traces and linked data about students. These data are increasingly presented to individuals to inform their activities and are potentially relevant to learners, teachers, researchers, educational policy makers, and managers (Knight & Buckingham Shum, 2017). However, the growing use of learner data has raised ethical concerns around student privacy and agency in data governance (Heath, 2014; Prinsloo & Slade, 2018; Slade & Prinsloo, 2013). These concerns are more pertinent with the rapid roll-out of generative AI applications that utilise extensive learner data.

Data about behaviour, performance or student experience may include information students do not want to share. Research shows that students hold high ethical standards and expectations for learning analytics across European systems, in Germany (Ifenthaler & Schumacher, 2016, 2019), Sweden (Engstrom et al., 2022), Spain, the Netherlands (Whitelock-Wainwright et al., 2021; Wollny et al., 2023), and in English-speaking countries (Jones et al., 2020; Kumi-Yeboah et al., 2023; Sun et al., 2019). However, research shows that when it comes to consent to data sharing, students skim disclosure texts and ignore privacy statements (Coles-Kemp & Kani-Zabihi, 2010). This limited engagement may either indicate learned helplessness, i.e. students think their choice cannot be meaningful to start with, or be the result of a well-known privacy paradox where individuals opt into data sharing for the benefits, at times against own privacy concerns (Barth & De Jong, 2017).

Learner consent to share their data or opt out of sharing is central to how individuals enact their privacy decisions. Current consent practices in educational technologies can vary from *simple notice-and-disclosure* forms in situations of certainty, to *informed consent* where risks and benefits must be presented, to *active consent* that requires shared decision-making when the outcomes are uncertain (Whitney et al., 2004). In higher education, consent remains embedded in a top-down formality at the start of a university or technology use, often structured as a one-time, blanket agreement (Prinsloo & Slade, 2018). This legitimises data collection rather than offers opportunities to engage.

To help students become more engaged in their privacy-related decisions, alternative approaches to consent, such as group-based or interactive formats, have been proposed. Blinded (2025) operationalised an interactive consent approach and showed that a group discussion reduced students' willingness to share data across various learning situations. In their study, discussion was treated as a single, undifferentiated intervention, and the mechanisms that drove the change in student privacy decisions remain under-explored. To better understand these potential mechanisms, we examined if the quality of argumentation, i.e. *how* students formulated claims, offered evidence or counter-positions, influenced individual decisions that followed a group discussion.

Examination of argumentation quality when individuals decide on consent to manage their privacy is novel. From a practical perspective, it opens a question of how to support better data sharing decisions. It is also interesting from a theoretical perspective. Blinded (2025) examined data sharing decisions through the lens of Contextual Integrity (CI) framework (Nissenbaum, 2004). In contrast to dominant approaches to privacy, CI theorises it as entrenched norms of appropriateness for information flow specific to each context. Contexts are defined according to several parameters, such as who sends or receives the data, among others. Notably, CI does not theorise that these contextual norms might be negotiated in situ. To examine the quality of argumentation during data sharing decisions, we redefine this conceptualization. Instead, we use the notion of *appropriateness judgement* that can be negotiated, drawing on Lazega's micro-sociological *information elaboration* theory (Lazega, 1992). Due to this re-conceptualization, our study seeks to understand if a process view of how individuals articulate their privacy views before consent decisions extend CI theory.

The aim of this study is two-fold: (1) it describes data sharing discussions from the perspective of argumentation quality, and (2) it determines if the argumentation quality affected subsequent individual decisions, in addition to CI differences. To address these aims, we used Clark and Sampson's (2008) framework to analyse argumentation quality in 96 transcripts representing discussions in 12 groups from Blinded (2025). Content analysis codes were aggregated and clustered via k-means clustering, yielding three discussion profiles (RQ1). Further, linear mixed-effects models were used to identify if argumentation quality explained post-discussion decisions, beyond the contextual factors manipulated in the data-sharing scenarios (RQ2). Our findings show that judgements around privacy are affected by *how* a group of individuals elaborates their decisions. This finding has important theoretical and practical implications.

2. Literature Review

2.1 Contemporary approaches to privacy and consent.

Providing meaningful informed consent in learning analytics requires that students understand what is of value to them when it comes to privacy in an educational setting. It also requires that they think of the consequences of a data-sharing trade-off. Existing ways of consenting are not well-suited to supporting engagement with these decisions, as current consent formats largely stem from the views of privacy as a regulation of control and access. Recently, researchers have been proposing other views of privacy and arguing towards alternative approaches to what consent may look like (Bourgeois and Vandercruysse, 2024).

For many decades, regulators have been enforcing a control-first model of privacy, whereas researchers have started to have shifted towards contextual approaches and shared decision making

(Bourgeois and Vandercruysse, 2024). Control-first approaches define privacy as either control or access of personal information (Smith et al., 2011; Wisniewski & Page, 2022). First, privacy as control is shaped by Westin's definition of privacy as individuals right "to determine for themselves when, how, and to what extent information about them is communicated to others" (1969, p. 7). Second, privacy as access refers to inaccessibility or restricted access to personal information (Altman, 1975; Gavison, 1980; Margulis, 2011; Petronio, 2002). Both views paved the way for privacy-as-commodity, where customers exchange personal data for perceived value in a service (Bennett, 1995). In such exchanges, consumers may accept future risks for immediate benefits, even though they may have privacy concerns, a well-studied trade-off known as privacy paradox (Barth & De Jong, 2017).

Newer approaches have emerged more recently, such as contextual integrity (CI) framework (Nissenbaum, 2010). CI stands in contrast to control-first approaches to privacy. Control-first approaches are based on controlling the boundary between the public and private. Nissenbaum, however, finds these boundaries ill-defined and unhelpful. Instead, Nissenbaum argues that privacy is contextual. Context is defined through the subject, sender, receiver, attributes of the information shared, and transmission principles (i.e., norms governing how information flows from a sender to the receiver). From this perspective privacy is what individuals find appropriate for how data flows in specific contexts; privacy reflects entrenched social norms of this appropriateness.

A more contextual view of privacy aligns well with many calls to stop designing consent as a top-down notice-and-disclosure models, as voices by researchers in technological (Luger & Rodden, 2013), legal (Solove, 2023; Bourgeois and Vandercruysse, 2024), and educational (Kitto & Knight, 2019) communities. In contrast to traditional consent models, contextualised approaches do not assume that individuals easily understand and evaluate privacy trade-offs for each unique context, just when they encounter the terms of data sharing (Bourgeois and Vandercruysse, 2024).

2.2 Empirical work on privacy and consent in learning analytics

In learning analytics (LA), a domain focused on the use of student data, the question of privacy is seldom treated as context specific. Scholarship is largely normative, foregrounding learner agency and voice and calling for meaningful engagement of learners in data decisions. Empirical work, by contrast, concentrates on algorithmic fairness and broad ethical frameworks, with only occasional attention to the practicalities of consent (Pargman & McGrath, 2021). Studies typically frame privacy as access or control (Viberg et al., 2022) and, following information-systems traditions, rely on instruments such as SPICE (Mutimukwe et al., 2022) to measure privacy concerns across sub-populations rather than to examine privacy in situ. Theories such as CI are not used though noted as relevant (e.g. Drachsler & Greller, 2016; Heath, 2014). This contrasts arguments on privacy-related decisions in LA (e.g. Kitto & Knight, 2019) that highlight their contextual and nuanced nature, in line with the long-standing propositions from ubiquitous computing (Luger & Rodden, 2013).

Only recently has learning analytics research begun to apply CI. Studies, such as Korir et al. (2023), Bourgeois et al. (2024), and Blinded, show that context variables shape data-sharing choices. Korir et al. found that students were more willing to share educational data in academic than in commercial settings. Bourgeois et al. examined the appropriateness of wearable technologies in education. Both followed earlier CI research examining sharing energy, location, and health data (Gerdon et al., 2021; Silber et al., 2022, 2024), where vignettes were used to systematically vary contextual characteristics, such as receiver or data type. Blinded extended contextual investigations of data sharing by including a discussion between peers as a precursor to final individual decisions. They found that the discussion significantly decreased the final individual data sharing acceptability across contexts. These results are worth contrasting against a similarly designed study where groups decided individually after a discussion about moral dilemmas, such as the trolley problem (Keshmirian et al., 2022). In the case of moral dilemmas, the discussion did not alter subsequent individual scores. This implies that privacy in context as appropriateness of data flows is something that may be, at least in part, constructed in relation to the context.

2.3 Exploring Argumentation Quality to Understand Appropriateness Judgements.

To understand if consent-related decisions result from the process of discussion, we examine argumentation quality of the discussions from the Blinded study. This examination needs to be conceptually adapted to suit CI framework. Nissenbaum describes privacy as appropriateness of data flow in each context, but these norms of appropriateness are conceived as entrenched. To allow for process-related examination, we draw on the micro-sociological theory of informed decisions (Lazega, 1992). Lazega defined informed decision as an *appropriateness judgement* which is socially situated and decoupled from the information on which the judgment is based. This appropriateness judgement is the result of a social process of *information elaboration* that helps individuals espouse *the definition of a situation* they find themselves in. Lazega positions *information elaboration process* as communication of various knowledge claims related to this information. Viewing appropriateness of data flow in context (*privacy*) as a judgement towards an informed decision (*consent decision*) enables us to take an interactionist perspective focused on the content of interactions exchanged in the process of information elaboration. This grounding of information elaboration in knowledge claims allows us to draw on argumentation literature to operationalize the analysis of argumentation quality.

Argumentation is a process of constructing, defending, and critiquing claims using evidence and reasoning, making an assertion reasonable to others (Toulmin, 2008). Argumentation has been recognized among key mechanisms for knowledge construction (Leitão, 2000). In collaborative learning, high-quality argumentation has been shown to improve conceptual understanding and reasoning (Clark & Sampson, 2008; Stegmann et al., 2007, 2012; Von Aufschnaiter et al., 2008). In individual assignments, students with better argumentation quality demonstrated stronger conceptual understanding (Clark & Sampson, 2008; De La Paz et al., 2012). Moreover, prompting students to state claims, provide evidence, and respond to counterarguments enhanced both the quantity and quality of arguments, leading to greater conceptual learning gains (Stegmann et al., 2007).

Assessing the quality of argumentation is well-studied studied in learning sciences (e.g. Clark & Sampson, 2008; Jin et al., 2021; Wachsmuth et al., 2017), to address the issue that students do not always engage in quality argumentation and may struggle to reason deeply or integrate evidence (Noroozi et al., 2012). Many frameworks have been developed to assess argumentation (e.g. Fancourt & Guilfoyle, 2022; Jin et al., 2021; Kim et al., 2024; Wachsmuth et al., 2017). None of these frameworks have been applied to a setting like the one in BLINDED and not all of them are well-suited to examining argumentation quality in such a specific context.

Clark and Sampson (2008) offer a structured approach to assess how well students justify their decisions and integrate evidence in a group setting. Because it was created to analyse online dialogue known to facilitate deeper cognitive engagement, this framework has a strong focus on the structure of the argument through elements such as claims, grounds, and warrants. The framework is suited to assess the form of arguments and their quality in a setting like data sharing discussion. It captures forms of arguments, but also engagement levels and social elements of the discussion. At the same time, these social elements are not as intense as would be expected in situations where students know each other and therefore also translate well to the brief data sharing discussions. In addition to describing forms of individual arguments, it includes group-related statements, such as organizational and off-topic talk.

We draw on argumentation quality, such as articulating claims, weighing evidence, and addressing counterarguments, with an assumption that it may help groups refine their data sharing judgments. Research highlights that elements of argumentation, such as discourse moves (e.g., claims, rebuttals), the use of evidence, and perspective-taking are key indicators of high-quality argumentation (Clark & Sampson, 2008; Fancourt & Guilfoyle, 2022; Stegmann et al., 2012). Using clustering techniques to profile discussions with these argumentation quality categories is, therefore, a promising approach to detect argumentation patterns in data sharing discussions.

3. Research Questions

To date, no study has examined whether *how* individuals articulate their privacy views to explain data-sharing decisions beyond the contextual factors that define privacy for that context. To examine this, we take an argumentation quality perspective to analyse data-sharing discussions between students. The study poses two research questions:

RQ1: What argumentation patterns emerge in students' discussions about data sharing?
RQ2: How do argumentation patterns influence students' individual subsequent decisions about data sharing?

4. Methods

4.1 Data and Experiment

We briefly report details related to data collection, for further detail please refer to the BLINDED. The sample consisted of 60 individuals enrolled in the study; they did not know each other prior. The gender distribution was balanced (30 female). Mean age was 23.91 years; range 18–42. 45% of participants had a high school diploma (*n* = 27), 33.3% had a bachelor's (*n* = 20), 20% had a master's degree (*n* = 12), and 1.6% had a lower education certificate (*n* = 1). Participants were assigned to the groups of five, a total of 12 groups. Each group was gender balanced with either three males to two females or vice-versa resulting in six male-dominant and six female-dominant groups.

During the study, participants were presented with vignettes describing different data sharing scenarios based on the CI framework. Each of the following elements was integrated in the vignettes describing an educational technology: (1) receiver, i.e. vignettes varied the entity receiving the data as private company or a public institution; (2) beneficiary, i.e. vignettes varied personalized benefits or collective benefits; (3) data type, i.e. vignettes varied if the data collected by the learning technology was behavioural, such as logs, clicks, or timestamps, or performance, such as grades, error rates; (4) transmission principle, i.e. how information was transmission, this was not manipulated, stating the data was collected anonymously and protected from misuse; (5) sender, i.e. in all of the vignettes the person sharing their data was a university student. A final set of 16 vignettes were used for the study.

Each group participated in an experimental session divided into four phases. In the first phase, students rated the acceptability of 16 vignettes individually. In the second set A of vignettes was presented and rated individually; in the third phase set B was discussed in a group and participants were asked to reach a consensus decision; in the fourth phase, the vignettes of set B were rated individually. Set A and B were consistent in conditions (CI elements) but varied background stories. Outcome variables were individual and group ratings of acceptability of data sharing in each vignette, rated with a 7-item Likert scale. Audio recordings were made during the discussions, and later transcribed. There was *no* linkage between individual's statements during the discussion and their data sharing acceptability scores.

4.2 Data Analysis

Transcripts of the group discussions were analysed using content analysis. K-means clustering was applied to group discussions using the counts of codes of argumentation quality, derived from the content analysis. Clustering profiles were then used as a fixed effect in linear mixed effect models predicting final participant ratings, to identify the effect of the argumentation quality.

4.2.1 Content analysis.

To analyse argumentation about data sharing positions within student transcripts, we developed a coding framework following operationalizations proposed by Clark and Sampson (2008). Alternative coding frameworks exist and were carefully reviewed, particularly in relation to the context where our data were collected. For instance, analysis of argumentation by Stegmann et al. (2007, 2012) rests on capturing formal argumentation quality, particularly counterarguments and integration. However, their framework relies on constructing grounded claims and meaningful counterarguments, which were not observed too often in our unstructured face-to-face discussions. In contrast, Clark and Sampson (2008) emphasized collaborative argumentation and its role in collaborative knowledge building, assessing structural, conceptual, and evidential quality of discourse, connecting structure and content. We found that their framework has flexibility to apply to many instances in our data, yet also indicators differentiating types of knowledge discourse and quality.

Clark and Sampson's (2008) framework on collaborative argumentation comprised three categories: discourse moves; grounds quality, and conceptual quality. For this study, we only used *discourse moves* and *grounds quality*. The *conceptual quality* category that describes the quality of how students use concepts in their arguments was excluded since it was inapplicable to data sharing discussions. Definitions of the codes were tailored for face-to face conversations (see Appendix A with a full coding framework):

- *Discourse moves* are defined as utterances at the level of the entire statement by one person at a given time, around its intentions. Discourse moves included the following categories: claim, change of claim, rebuttal, clarification, support, query, organizational comments, off-task comments.
- *Grounds quality* defined the level of evidence provided in each statement to justify a claim, with the ordinal levels of reasoning quality as follows: no reasons (level 0), explanation only (level 1), evidence only (level 2), and evidence and explanation or coordination of multiple pieces of evidence (level 3).
- Some codes from the original framework were excluded due to the ambiguity of identifying them during the coding process, e.g. counterclaim, rebuttal against ground and rebuttal against thesis, clarification in response to a rebuttal, clarification of meaning. This allowed for clear boundaries between all the coded categories.

Utterances were coded at the level of each statement by a distinct speaker during a distinct turn. The codes were aggregated at the level of a vignette discussed in a group, 96 vignette discussions, a total of eight vignette discussions per group. Two coders applied the framework to four groups transcripts, analysed in three rounds. For inter-rated reliability, a Cohen's Kappa was calculated after every round, with final scores 0.82 for discourse moves and 0.72 for grounds quality.

4.2.2 Clustering.

To identify argumentation patterns in students' discussions on data sharing, a k-means cluster analysis was used. Cluster analysis is an oft-used profiling approach for identifying subgroups. Examples include identification of patterns in interactions with automated feedback systems (Zhu et al., 2020), argumentation patterns in chemistry (Martin et al., 2024), and student communication profiles (Dowell et al., 2018). Frequencies of each category were calculated at the level of vignette-bounded discussion and normalized. Variance-inflation factors were low (M = 1.67, range = 1.30–2.25), with all values well below the recommended threshold of 7. Ground level 0 had 0.6 correlation with off-task utterances count but was retained due to its important theoretical value. Upon the evaluation of the elbow plot, two-cluster and three-cluster solutions were both possible and were evaluated further. Relative to two clusters, the three-cluster solution reduced the total within-cluster sum of squares and increased the proportion of variance explained between clusters from 21% to 29%. Internal-validity indices between the two solutions were comparable: the Dunn index changed from 0.216 to 0.237. Mean bootstrapped Jaccard similarity fell from 0.96 to 0.62 but within the acceptable 0.60 threshold. Cluster connectivity worsened (41.9 vs 50.3) for the three-cluster solution, reflecting the finer partitioning introduced by the extra cluster. The three-cluster solution yielded three groups of 56, 28, and 12 discussions and revealed an additional distinct discussion profile described by higher levels of *organisation*, *rebuttal*, and *change* codes that would have been absorbed in the two-cluster partition. Considering comparable and explainable separability measures and gain in compactness, combined with clearer interpretability, we opted for a three-cluster solution.

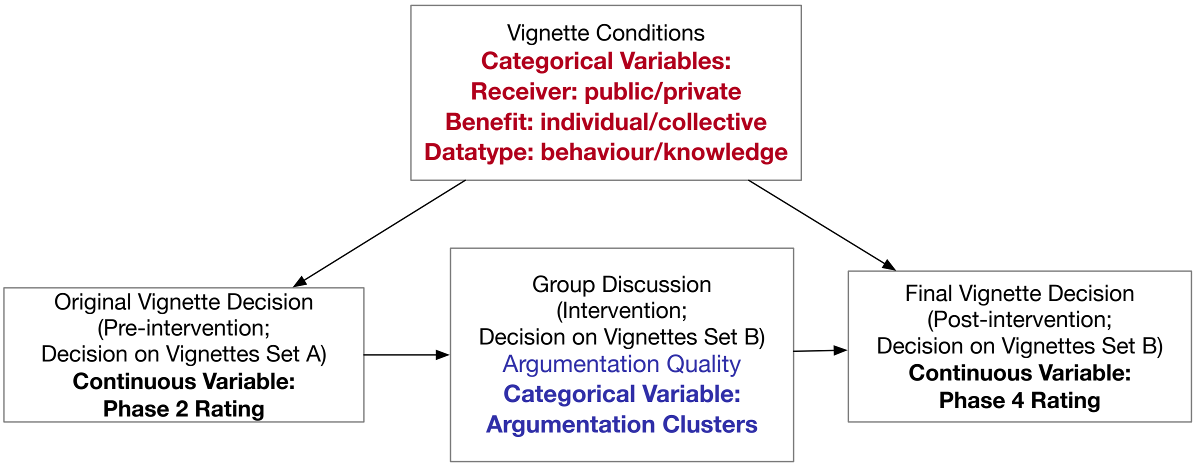

Figure 1. Overview of modelling framework

4.2.3 Mixed effect modelling

Mixed-effects models are well suited for hierarchically structured data, where within- and between-group variability can be accounted for. They are often applied to analyse complex learning phenomena, such as student dropout rates, course-specific effects, and learner characteristics (Fontana et al., 2021; Linck & Cunnings, 2015). Our data was nested within a group, with multiple decisions in the same group (namely eight) and multiple decisions per individual at various times.

Due to the complexity of the experiment, Figure 1 outlines the major structure of the research design, highlighting the variables used for modelling. Linear mixed effect model predicting final post-discussion data sharing acceptability rating (1-7 Likert scale) was fitted iteratively, with random effect of the group and the participant. Fixed effects included: vignette conditions that were decided upon (three categorical variables), initial individual rating (phase 2, 1-7 Likert scale, acceptability of data sharing), and categorical variable of a cluster denoting argumentation quality (three categorical variables). We first fitted a null model without fixed effects (Null Model), then a model with a fixed effect of conditions only (Conditions Model), then the effect of argumentation quality (Argumentation Model) to observe different contributions of these elements to explainability of the outcome. The main effect model included the initial acceptability rating, argumentation quality, and conditions. Interaction model is also reported, capturing interactions between argumentation quality and initial score, although its increased model complexity does improve explainability by much.

5. Results

5.1 Describing argumentation patterns

The discussions analysed contained a total of 1,304 utterances. An utterance was defined as a single speaking turn that could include few words or few sentences before the next speaker talks, i.e. the same participant could contribute multiple utterances within a single discussion. After applying the coding scheme, 17 utterances were removed due to being too short or ambiguous, leaving a final dataset of 1,287 utterances. These were grouped by conversation per group, with each of the 12 groups discussing eight different vignettes, resulting in 96 units of analysis. The average number of utterances per vignette was of 13.4 (SD = 5.87). Different vignettes elicited varying length of discussions; length of discussions also varied across the groups.

Across all group discussions, we observed the dominance of discourse moves, such as *claims* and *support*, with little justification or deeper reasoning. The analysis of discourse moves revealed that students primarily engaged in making claims (37.19%) and providing support for those claims (25.92%).

Discourse moves associated with deeper reasoning, such as rebuttals (8.36%) and clarifications (5.29%), were less frequent. This suggests that participants tended to reinforce each other's perspectives rather than critically challenge them. The quality of justification also reflected this tendency, with 69.17% of utterances classified as *Level 0*, i.e. they lacked justification, and only 3.99% reaching *Level 3*, where multiple sources of evidence were integrated. In summary, even though they engaged in discussions, the participants rarely supported their claims with reasoning, relying on intuitive judgments or shared group consensus.

Figure 2 presents the distributions of the different *Grounds Quality* levels in every discourse move. Claims were the most frequent discourse move, with 485 occurrences and were predominantly associated with Level 0 grounds quality, indicating that students often made assertions without providing substantial justification, with a smaller proportion of claims being of higher grounds quality. For example, one student simply stated, "I think it's fine" (*gr8u63*), offering no justification for the claim (Level 0). In contrast, a more developed claim from another student included, "I find just the, like, the relation between, like, timing of clicks and the private company. Like, we all know Facebook, who collected private information and sold it. That's why I find, like, something, like, bad intention of collecting these kinds of things that does have nothing with learning" (*gr8u72*). This claim provides more substantial reasoning, demonstrating a Level 3 justification.

Support moves followed a similar pattern, accounting for 338 of all utterances. Like claims, support moves were predominantly rated at Level 0, reinforcing the tendency for students to provide arguments without extensive reasoning. A smaller proportion of support moves demonstrated higher grounds quality reasoning, indicating that even if students attempted to justify their positions, in-depth explanations were relatively rare. For example, a student offered a basic justification (Level 1) with, "I think the reason is to provide personalized recommendations that support individual learners" (*gr8u41*), but did not provide additional reasoning or evidence.

In contrast, the levels of grounds quality were more distributed in rebuttals. This suggests that when students did engage in counterarguments, they were more likely to provide some level of reasoning compared to other discourse moves. For instance, one rebuttal included, "But I think the most important thing is, like, are they relevant to each other? And how do they provide personalized support?" (*gr8u54*), engaging with the reasoning behind the data sharing and offering a counterpoint that was more developed than basic disagreement (Level 2).

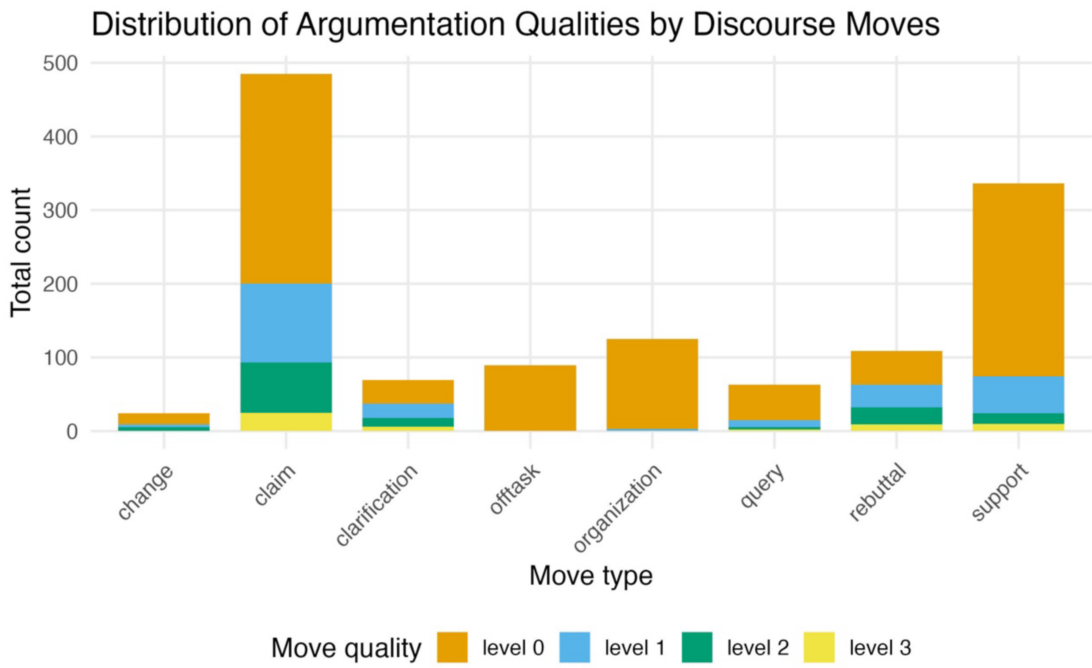

Figure 2. Overview of argumentation quality across all group discussions

5.2 Argumentation Quality Clusters

Using k-means clustering, we have identified three argumentation patterns that describe all discussions. To remind, each pattern describes a vignette-focused conversation, not a group or a participant. These three patterns are visualized in Figure 3.

The first pattern describes *critical engagement* discussions. This cluster consists of 12 discussions that exhibit a unique argumentation pattern. As shown by normalized values of the centroid that is representative of this cluster (Fig.3), these discussions have higher than average counts of organization discourse move, rebuttals, and support utterances. The change code is over two standard deviations higher in count, than in other clusters. This means that participants in these discussions have most often stated that they are considering a change of the initial opinion. Discussions in this cluster also show lower than average presence of claims, indicating that they engage in discussion with structured reasoning rather than simply asserting their views. The relatively low off-task category suggests that in these discussions, students remain focused. The combination of strong argumentation and significant opinion changes suggests that these participants are highly responsive to discussion dynamics and peer input.

The second pattern describes *high engagement* discussions. This cluster, composed of 28 discussions, representing instances of active conversations. This cluster appears highly active. This can be seen through discourse moves of the centroid depicted in Fig. 3 that are all higher than a standard deviation above average and included claims, clarifications, and queries as well as moderately high number of rebuttals and just above average number of support utterances. However, unlike Cluster 1, critically engaged discussions, in this cluster participants almost never stated that they are likely to change an opinion, indicating that they are actively reasoning and debating, although their initial perceptions remain relatively stable. Their moderate levels of off-task talk suggest that though they remain engaged, their discussions occasionally drift away from the main topic. Most statements were of the ground quality levels 0 and 1, denoting a shallow use of evidence and description. Overall, this cluster reflects conversations that are actively involved although shallow in the justifications and less likely to shift student stance during the discussion.

The third pattern describes *low engagement* discussions. With 56 discussions, this is the largest cluster of discussions and is characterized by low engagement with argumentation. Participants in these discussions contributed fewer utterances and rarely engaged in claims, clarifications, queries, or rebuttals. This can be seen through centroid’s discourse moves in Figure 3 that are all below average when compared to the other two clusters. Minimal argumentation of this cluster suggests that participants are either passive or struggle to articulate their reasoning. The "change" variable is also the lowest in this cluster, indicating that these participants' stances remain largely unchanged throughout the discussion. Their low involvement in argumentation suggests that they are less influenced by the discussion process, possibly due to a lack of engagement or strong pre-existing opinions that remain unchallenged.

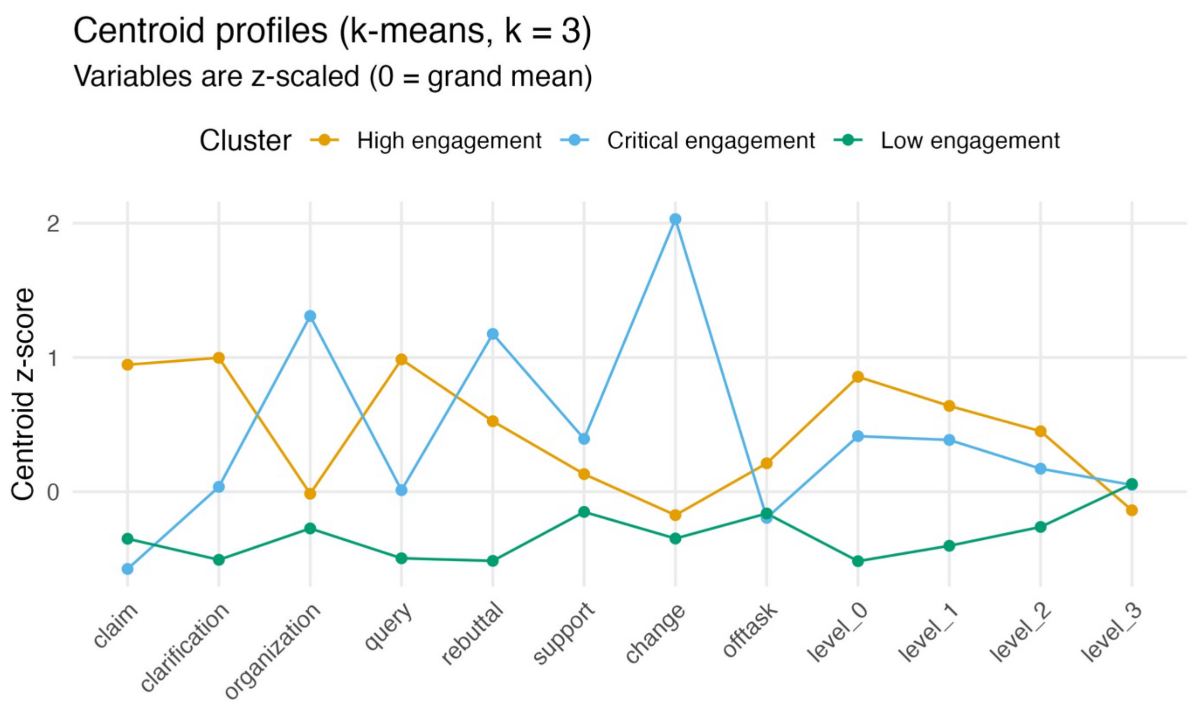

Figure 3. Argumentation quality profiles based on cluster centroids (normalized counts of each argumentation quality feature)

5.3 Effect of Argumentation on Individual Data Sharing Decisions

A likelihood-ratio test confirmed that adding clusters and their interaction with time significantly improved the fit over the simpler model with random effects of a group and an individual. The final model (Main Effect Model, Table 1) examined main effects of conditions, pre-discussion scores, and argumentation quality (high-engagement, critical-engagement; low-engagement as a reference group) on post-discussion acceptability ratings.

In the final main-effects model, the baseline post-discussion rating for a low-engagement discussion was *β = 4.45 (SE = 0.43), p < .001*. Pre-discussion acceptability remained a positive predictor of the final decision *(β = 0.3, SE = 0.06, p = .004).*

Just as reported in Blinded, sharing data with a public receiver lowered acceptability (*β = –0.31, SE = 0.12, p = .007*), whereas the knowledge data type had no detectable effect (*β = 0.03, SE = 0.12, p = .83)*. Scenarios that offered an individual benefit to the participant increased willingness to share (*β = 0.67, SE = 0.12, p < .001*).

The additional contribution, as offered by our analysis, is with the main effect of argumentation quality on data-sharing acceptability. Compared with the low-engagement baseline, high-engagement discussions led to lower final acceptability *(β = –0.43, SE = 0.15, p = .004),* and critical-engagement discussions reduced it still further *(β = –0.84, SE = 0.20, p < .001).*

Main effects model explained 17% of the fixed-effect variance (R^2_Marginal) and 46% when random effects were included (R^2_Conditional), indicating that both contextual features and discussion quality meaningfully contributed to students' data-sharing decisions. Notably, conditions alone explained 5%, whereas argumentation quality explained around additional 3% of variance in data sharing decisions. While the effect of argumentation quality on the final decision is clear, it remains unclear if particular conditions elicited more critical engagement in argumentation.

Table 1. Summary of linear effect modelling

	Null Model		Conditions Model		Argumentation Quality Model		Main Effects		Interactions	
	β (SE)	p	β (SE)	p	β (SE)	p	β (SE)	p	β	p (SE)
Intercept (Final Data Sharing Decision)	5.32 (0.35)	< .001	5.1 (0.37)	<0.001	5.36 (0.36)	< 0.001	**4.45 (0.43)**	**<0.001**	3.66 (0.65)	<0.001
Pre-discussion acceptability										
Initial accepta-bility	--		--		--		**0.3 (0.04)**	**0.001**	0.16 (0.06)	0.004
Contextual factors in data sharing scenarios										
Public receiver	--		−0.34 (0.12)	.006	-0.35 (0.12)	0.006	**-0.31 (0.12)**	**0.007**	-0.31 (0.12)	0.007
Datatype Knowledge	--		0.06 (0.13)	.660	0.08 (0.12)	0.523	0.026 (0.12)	0.825	0.03 (0.12)	0.825
Individual Benefit	--		0.74 (0.13)	< .001	0.70 (0.12)	< 0.001	**0.67 (0.12)**	**<0.001**	0.68 (0.12)	<0.001
Argumentation Quality Profile (low engagement as a reference level)										
High engage-ment	--		--		**-0.49 (0.16)**	**0.002**	**-0.43 (0.15)**	**<0.004**	-2.14 (0.49)	<0.001
Critical engage-ment	--		--		**-0.89 (0.21)**	**<0.001**	**-0.84 (0.20)**	**<0.001**	-2.11 (0.60)	<0.001
Interaction Effects										
Initial acceptability X High Engage-ment	--		--			--	--		0.31 (0.09)	<0.001
Initial acceptability X Critical engage-ment	--		--			--	--		0.232 (0.103)	0.025
AIC	1725		1697		1682		1640		1636.0	
BIC	1741		1726		1720		1681		1685.9	
$R^2_{Marginal}$	0.000		0.05		0.08		0.17		0.184	
$R^2_{Conditional}$	0.39		0.44		0.44		0.46		0.478	

6. Discussion

Data-intensive educational technologies have posed challenges not only for regulators and educators in how to collect and utilise learning data efficiently and ethically, but also for students in how to balance data-sharing risks and benefits. Research on informed consent practices shows that interactive consent, a process during which students discuss their privacy decisions with each other, can be a promising approach to improve engagement with otherwise static notice-and-disclosure statements about data sharing. In a lab study, researchers showed that a brief group discussion about CI-manipulated scenarios shifted students' initial acceptability to share data (Blinded). However, it remained unclear if the discussion alone imposed higher engagement and better decisions, or if something in the discussion process was the trigger for the observed changes in acceptability judgments. This paper explored this question, drawing on the argumentation literature to examine if the quality of argumentation (claims, evidence, rebuttals) can potentially explain the effect of a group discussion. Our overall findings suggest that students predominantly engage in claim-based argumentation, with limited structured rebuttals or critical engagement. Overall, these results suggest that students' discussions may reinforce existing opinions rather than challenge or transform them, unless a quality of argumentation is scaffolded.

Our first research question aimed to describe patterns of argumentation quality in data sharing discussions. The analysis of discourse moves revealed that students primarily engaged in making claims and providing support for them. Deeper reasoning with rebuttals and clarifications was less frequent. The quality of justification reflected this tendency. Just under two-thirds of all discussion statements lacked justification (i.e. Level 0) and only 3.99% of all statements reached Level 3, where multiple sources of evidence were integrated.

Cluster analysis of these characteristics at the level of each short discussion (a total of 96 across 12 groups) identified three discussion profiles: critical engagement discussions, high engagement discussions, and low engagement discussions. These profiles show varying levels of reasoning. Students who participated in critical engagement discussions experienced structured argumentation, incorporating rebuttals, clarifications, and organizational reflections suggestive of meta-cognitive talk about the tasks at hand. Students in highly engaged discussions participated actively but relied mostly on claims and support moves, often reinforcing existing opinions and less so challenging them. Third, students in the low engagement discussions contributed minimally to discussions and showed little evidence of structured reasoning or argument development.

The findings of low presence of argumentation quality in student data sharing discussions aligns with the broader research on argumentation in educational settings (Clark & Sampson, 2008; Leitão, 2000; Noroozi et al., 2012). Existing research shows that students struggle to engage in deep reasoning during group discussions, and without proper scaffolding they may default to agreement-based discourse rather than engaging in critical dialogue (Stegmann et al., 2007). This is appears to be relevant to discussions about privacy and data-sharing, where ethical considerations require a nuanced evaluation of risks and benefits (Slade & Prinsloo, 2013). The lack of counterarguments and queries in data sharing discussions suggests that many of them did not reach shared decision-making imagined in consent frameworks (Whitney et al., 2004).

The second research question inquired about the effect of these various argumentation quality discussion profiles on subsequent individual decisions. We find that students who participated in the critical engagement discussions were most likely to become more cautious in their data sharing decisions. On the other hand, students who participated in the low engagement discussions almost did not change their acceptability ratings after the discussion. High engagement discussion had some negative effect on the ratings. These findings are interesting in relation to the effect of the group discussion as an intervention promoting better decision-making, as they suggest that *on its own* group discussion as an intervention for interactive consent is *not* effective: its effect was limited in most groups where students did not engage actively in discussing, and in some groups where they engaged actively but not critically. Higher levels of argumentation quality within those discussions, however, triggered the change of initial opinion.

The results may suggest that other interventions where individuals are prompted to critically reflect on their decisions could also be effective. However, the results do not fully rule out the effect of socio-cognitive factors on opinion change. The category of ‘change’ that has high presence in critical engagement discussion refers to instances where a person openly states that they are re-considering their earlier stance. This resonates with findings from perspective-taking research (Fancourt & Guilfoyle, 2022; Kim et al., 2024), which emphasize that deliberation involving diverse viewpoints can facilitate cognitive and social growth. Put simply, further investigation is needed to differentiate if social or cognitive factors influence student decision making as this could help design interactive consent intervention that would decrease the embedded biases. In either case, no matter what the cause, argumentation quality appears to play an important role and is of low level.

Notably, the study has some limitations. First, it did not capture social influence measures that would quantify the impact on the social aspects of group discussions on the final acceptability. Second, the study was conducted with a group of students from Blinded country, which limits its generalizability to broader student populations. Finally, being a lab experiment, the study does not address important elements that come into the decision making from within of the educational context, such as complex trade-offs, institutional pressures or instructor influence, and other external incentives that may exist. Examination of the intervention in the more authentic contexts can shed light on what these issues are and how, potentially, they can be designed for and mitigated within the consent practice itself.

The study offers several important implications for research and practice. In relation to privacy research, further elaboration of conceptual categories about how privacy decisions in context come to be is needed. Information elaboration theory (Lazega, 1990) can potentially offer further nuance in how privacy decisions can be understood and enrich contextual integrity framework as well as other group-based views on privacy management (Prinsloo & Slade, 2018) with adjustments for processes underpinning appropriateness judgements. For educational research, our results open several promising directions for future work. First, the importance of argumentation quality suggests that future work should further explore the role of argumentation scaffolds (Valero Haro et al., 2019) to improve data sharing decisions in interactive consent. Second, future research still needs to untangle the effect of cognitive and social forces on data sharing decisions within argumentation quality. They are important to design technology and practices to accompany consent decisions that can scale in an educational setting and address and mitigate potential challenges of engaging with consent in a meaningful manner.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author(s) used gpt model 4.5 to edit selected sub-sections related to literature review and data description for clarity and to remove redundancies. After using this tool, all author(s) further reviewed and edited the content *iteratively* and take full responsibility for the content of the publication.

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