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Data sharing in learning analytics: how context and group discussion influence the individual willingness to share

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The ethical integration of the data generated by learners into educational practices is of great importance now that data-rich technologies are prevalent in education. Despite the common agreement that learners should have agency in deciding what to do with their data, existing ethical discussions focus on policies or algorithms, with limited attention to participatory learner practices. Participatory practices, particularly around informed consent, can support ethical and meaningful engagement with data sharing decisions. Using a novel experimental methodology, we explored how the decision context influences the perceived acceptability for sharing learning data. We found that participants became more cautious in sharing their data in and after a group discussion. The willingness to share was the lowest when these data were submitted to a government entity and for a collective benefit. Further network analysis of group discussions confirmed the observed attitude shifts: participants consistently discussed different aspects of sharing learning data based on the context such as sharing process vs outcome-related learning data. The results suggest that educational data consent is contextual and that perceptions of privacy in educational technology may differ from those in health contexts. The proposed method of interactive consent, therefore, not only contributes to theories explaining privacy and effective data collection but also represents a new way of conceptualising and realising participatory informed consent.

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Introduction

Learner data collected by educational technologies can provide feedback to learners. The process that enables such feedback is known as learning analytics (Siemens, 2013). Learning analytics (LA) has been used for over a decade contributing to educational theory (Reimann, 2021) and improving student outcomes (Brooks et al. 2021; Ferguson et al. 2016; Knoop-van Campen et al. 2023; Sclater, 2017). Despite the widespread use, concerns about the ethics associated with learner data remain (Wollny et al. 2023; Gaševic et al. 2022). To alleviate these concerns, LA researchers developed numerous policies, frameworks (Liu and Khalil, 2023) and privacy-preserving algorithms (Joksimovic et al. 2022). Despite progress in policy and technical solutions related to ethics in LA, other important aspects like the involvement of learners in learning data practices received less attention. Notably, the contextual factors and the situational nature of learner decisions around learning data remain under-explored. To address this gap, we propose an intervention designed to enhance learner participation in data-sharing decisions and to investigate how different scenarios affect privacy perceptions, aiming to offer empirical insights into the contextual nature of these decisions and to strengthen learner autonomy.

Researchers in LA generally agree on the need for student voice, agency, and data transparency within the ethical frameworks guiding LA (Drachsler and Greller, 2016; Pardo and Siemens, 2014; Slade and Prinsloo, 2013). Studies show that students expect transparency about data access and analysis and want a say in decisions about their data - both in Europe (Ifenthaler and Schumacher, 2016, 2019; Engstrom et al. 2022; Whitelock-Wainwright et al. 2021; Wollny et al. 2023) and in the UK and US (Jones et al. 2020; Sun et al. 2019; Kumi-Yeboah et al. 2023). In reality, however, data collection outpaces the regulatory and governance processes, where students are perceived as passive 'data objects' and mere beneficiaries. While students are sometimes involved as co-designers of technologies that can collect data, their participation is rarely continuous and is often limited to one-time input during tool design. This disconnect highlights the need for innovations that enable participatory practices around learner data-sharing decisions to meet student expectations and align with policy framings.

Top-down approaches where a student opts in or out across contexts are prevalent. However, educational situations involving data-related decisions are nuanced (Kitto and Knight, 2019), and consent may need to be negotiated on a case-by-case basis. In contrast, consent as disclosure, a top-down option currently available to students, is a product of strict privacy laws, requiring learners to blindly agree or disagree, without considering the specific factors shaping their decisions. Therefore, scholars have questioned if top-down privacy regulations and rigid IRB protocols are suited to address situational nuances (Solove, 2013). At the same time, our understanding of learner attitudes towards specific learning analytics situations is limited. Scarce empirical work explored contextual perceptions (Ifenthaler and Schumacher, 2019; Korir et al. 2023), and non-experimental case study nature of these studies only provides a starting point to understanding the actual effect of situational differences in learner decisions.

In this paper, we propose and evaluate an intervention designed to enable learners to engage meaningfully in making data-sharing decisions. The study addresses three research questions. (1) *Can an unstructured group discussion serve as a participatory practice that influences students' decisions about their data-sharing preference held prior to this discussion?* We address this question by drawing on decision-making literature around the wisdom of crowds and interactive groups (Bahrami et al. 2010; Dezecache et al. 2022; Herzog and Hertwig, 2014a; Navajas et al. 2018; Niella et al. 2016), to conduct an in-person experiment that evaluated the effect of group decision on the previously made individual decision to share learner data. (2) *How situational factors, such as the data type, the purpose for sharing or even the data-collecting agent, influence the perceived acceptability of sharing learning data?* To address this question, we examined situational differences in data sharing attitudes, drawing on privacy as contextual integrity theory (Nissenbaum, 2004, 2009) that emphasizes that data-sharing decisions depend on contextual norms rather than individual control. Using contrastive vignettes (Burstin et al. 1980), we investigated the effect of situational factors, such as learning data type, data recipient, and data purpose, on the willingness to share learning data. (3) *Do group discussions that reflect the process of participatory practice vary in content for situations that differ in data type, purpose of sharing, and data collecting agent?* We investigated this question by analysing the content of discussions in different data sharing scenarios and comparing them across different contextual factors.

Addressing these questions helps to understand how student consent attitudes are shaped by differences across learning situations and provide evidence for a further development of a bottom-up, student-centric informed consent practice. Our findings establish a solid foundation for further empirical work examining contextual differences in ethical decisions around learner data. Our fundings also have implications for the future research aimed at identifying learner biases in the consent process. Finally, we offer valuable evidence for design-based research in the learning sciences that can be used to implement meaningful, classroom-based participatory practices.

Literature review

Devising participatory practices for informed consent in education using wisdom of crowds. Consent is at the center of participatory decisions to share data in education, yet its implementation faces significant challenges. In general, people rarely read privacy statements or user agreements (Coles-Kemp and Kani-Zabihi, 2010), and similarly, students often remember little from consent forms (Beardsley et al. 2020) and miss key details (Knepp, 2018). In classroom settings, in-person consent processes can embed power imbalances—particularly when teachers request consent (Clark et al. 2022)—and are further complicated by the lack of the basic information needed to make a data sharing decision (David et al. 2001). LA policies, such as DELICATE, call for active student participation in data decisions (Drachsler and Greller, 2016; Slade and Prinsloo, 2013), but current practices rely on top-down privacy laws that apply across a variety of situations where data could be shared. Some scholars question whether rigid protocols from ethical boards can capture the nuanced, context-specific situations that shape consent decisions (Kitto and Knight, 2019; Luger and Rodden, 2013; Solove, 2012). Hence, an intervention that is student-focused and enables participatory decision-making is needed.

Engaging learners in participatory process where individual decisions are aided by a group discussion is one possibility, as evidenced by the research on the wisdom of crowds. Rooted in social psychology, this research suggests that collective judgement can surpass individual judgement when diverse perspectives are maintained, but independence of opinion is preserved. This effect has been widely demonstrated, including when groups are deliberating general knowledge or estimating probability, by showing that the average of multiple independent opinions often outperforms individual guesses. Research shows that both inner crowds, i.e. time-spaced repeated self-generated opinions (Herzog and Hertwig, 2014a), and outer crowds, i.e. group-based discussion (Bahrami et al. 2010), can enhance accuracy. Group discussion, in particular, adds belief diversity and social exchange (Bahrami et al. 2010; Dezecache et al. 2022; Navajas et al. 2018; Niella et al. 2016). People generally overweight their own opinion compared to the advice from others (see Bonaccio and Dalal, 2006; Larrick et al. 2024, for a review). Integrating advice from others generally improves task accuracy (Bazazi et al. 2019; Farrell, 2011), individual decision confidence (Bonaccio and Dalal; 2006; Pescetelli et al. 2021; Soll et al. 2020), and normative judgements (Franklin and Guerber, 2020; Ta et al. 2023). Therefore, based on the accuracy enhancing effect of social settings (Hertwig, 2017; Herzog and Hertwig, 2009; Jayles et al. 2017), *we can expect that the group discussion about data sharing will influence the perceived acceptability of sharing learning data (H1)*, although the directionality of this effect remains unknown.

Examining contextual differences in data sharing in education using contextual integrity theory. Despite agreement about contextuality of educational scenarios where data can be shared, little is known about the specific effect of these contextual factors on learner decisions. In education, 'context' is a vague term (Salomon, 1991; Tabak, 2004, Poquet et al. 2021). Researchers commonly distinguished between endogenous, such as student attitudes and characteristics, and exogenous contextual factors, such as characteristics of the situations where data-sharing decisions occur (Tabak, 2004). LA research thus far has examined endogenous contextual factors related to ethics, relying on survey instruments that measure generic attitudes toward data sharing in universities. For instance, a validated instrument SELAQ (Whitelock-Wainwright et al. 2019) measures general expectations of privacy and ethics in LA in universities. Another validated instrument, SPICE (Mutimukwe et al. 2022), in contrast, differentiates privacy concerns from general expectations by assessing constructs such as trust, disclosure, and personal control. Studies show that SELAQ-based expectations in LA are similar across European universities (Wollny et al. 2023). However, privacy concerns as measured by SPICE have been shown to differ by gender (Kizilcec et al. 2023) and culture (Viberg et al. 2024). Further, other individual differences exist, Ifenthaler and Schumacher (2019) show that students' willingness to share learner data increases with study years, internet use, awareness of data control, and higher expected benefits.

Only few studies have examined the effect of exogeneous contextual factors on data-sharing acceptability. Korir et al. (2023) conducted a case study with two vignettes comparing data-sharing with a company versus a university. Students discussed these vignettes and were more comfortable sharing anonymized data in educational environments than in commercial ones, identifying trust and clear control over data as key decision factors. Bourgeous et al. (2024) explored the causal effect of decision context on data sharing, specifically for wearable technologies in education. They found that data type, its intended purpose, and the identity of the data sender significantly affect data-sharing appropriateness. Similarly, data used for research or functionality development and shared under user control was more acceptable than data used for advertising. Both studies built on an existing paradigm of studies that examine data sharing using Nissenbaum's (2004, 2009) contextual integrity framework. This framework has been applied for understanding situations that shape data sharing in health, social media, and energy, but less so in education. Nascent evidence suggests that situational factors shape data-sharing decisions in education, though the precise impact of contextual factors on learner perspectives needs to be further investigated.

Privacy as contextual integrity. Privacy as contextual integrity (CI) is a theoretical framework applied in experimental research examining situational differences in how individuals share data (Nissenbaum, 2004, 2009). The concept of CI emphasizes that privacy is not a static condition but is deeply embedded in the norms and expectations of particular contexts, which determine the appropriateness of what information can be shared, with whom, and under what circumstances. Nissenbaum defines privacy in terms of the appropriateness of information flows within specific social contexts. Conceptually, here contexts are defined as abstract representations of social structures that are characterized by canonical activities, roles, relationships, power structures, norms (or rules), and internal values (goals, ends, purposes) (Nissenbaum, 2009). The CI framework is increasingly applied across various domains to address privacy concerns in socio-technical systems. For instance, in the realm of human-computer interaction (HCI) and social computing, CI serves as both a conceptual and analytical tool to evaluate privacy attitudes and behaviours, guiding researchers in understanding how new information flows introduced by technology can violate privacy norms (Kumar et al. 2024). Empirical work further supports that context-relative informational norms capture normative prescriptions that for a given context, type of information, involved parties, and the transmission principles state what ought to be done (see Martin and Nissenbaum (2017), Silber et al. (2022), Gerdon et al. (2020), Longin and Deroy (2024), Longin et al. (2023) for empirical studies). Overall, privacy as contextual integrity offers a suitable lens for analysing contexts that shape perceptions about appropriate information flows and social norms governing them.

Our overarching hypothesis was that *contextual differences in data sharing scenarios will impact learner decisions to share (H2)*. Although some evidence points at higher levels of trust in companies than governments (see Edelman Trust Institute 2025), which can drive the perceived acceptability of sharing data (Heldman and Enste, 2018; Rickert, 2016), we expected that learners will be more willing to share their data with public governments than private companies (Deruelle et al. 2023; Gerdon, 2024; Gerdon et al. 2020; Kim et al. 2015). This expectation was in line with similar empirical results around contextual factors of sharing health-related data. Hence, we expected that *participants will find sharing data with public authorities generally more acceptable than with private companies (H2a)*. We also expected participants' general trust levels to be a good predictor for their perceived acceptability of sharing learning data (Hutchings et al. 2021; Pickering, 2021; Waind, 2020). Moreover, empirical work on health-related data found that participants reported being more likely to share health data for a collective than for personal benefit (Cascini et al. 2024; Johnston et al. 2024; McDonald et al. 2023). Therefore, we also expected that *participants will rate sharing data for a collective benefit as more acceptable than sharing data for an individual benefit (H2b)*. Lastly, given the findings of Bourgeous et al. (2024), *we expected that willingness to share data types will differ (H2c)*, but no directionality of effect was hypothesized given that Bourgeous et al. examined very specific data types rather than student grades (outcome data) versus process logs (process data) that are typically used in learning management systems.

Summary of hypotheses

Given the literature on potential impact of group discussion on data sharing and potential effect of contextual factors operationalized through the CI framework, we expected that *(1) students would revise their independent initial judgement of the acceptability of a data sharing situation after a group discussion*;

and that *(2) contextual factors, such as data type, purpose of sharing, and the data collecting agent would have different effects on student acceptability of data sharing*. In addition, we expected that *(3) the process of discussion, i.e. how participants would arrive to a group decision, would be different across the situations varying data type, purpose of sharing and data-collecting agent*. No prior work has examined differences in discussion processes but the role of information influences during the discussions is evident and well theorized in the early literature on how cognitive factors within the group discussion can generate more or better-structured arguments than individuals might consider alone (Myers and Lamm, 1976).

Methods

Participants. We targeted and recruited 12 groups of five participants via the Munich Experimental Laboratory for Economic and Social Sciences (Melessa). We targeted uneven participant numbers per group to ensure a clear group consensus. 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 to mitigate any possible gender effects (Boring, 2017; Centra and Gaubatz, 2000; Koch et al. 2015; Mitchell and Martin, 2018; Stroebe et al. 2017). We targeted groups of five as it has been shown the groups of four to five adequately predict generalisable attitudes (Mannes et al. 2014; Palley and Soll, 2019; Soll and Mannes, 2011; Soll et al. 2015). Our total sample size estimation followed similar experiments (Keshmirian et al. 2022; Longin and Deroy, 2024; Longin et al. 2023; Myers and Kaplan, 1976) as well as previous pilot data.

Each experimental session lasted approximately 60 minutes involving one group of five participants. There were no minimal educational requirements for participants except being fluent in speaking and reading English. Out of 60 participants, 27 participants reported a university entrance qualification (general or subject-related university entrance qualification/Abitur [high school or EOS]), while 20 participants held an additional bachelor degree. The mean age of participants was 23.92 ± 3.85 SD years old. Variance in age composition across groups was relatively low and stable (min $SD = 0.45$ at a mean age of 24.2 years old; max $SD = 9.34$ at a mean age of 26.2 years old).

Design. We used an in-person within-subject experimental design to test the impact of contextual factors on the perceived acceptability of sharing learning data with and without social influence. To test the impact of contextual factors on perceived learning data acceptability, we follow the contextual integrity literature on data sharing which has successfully shown that the willingness to share depends on contextual factors (see literature review on contextual integrity above). We varied three main factors with two levels each: data type (process vs outcome learning data), data recipient (private company vs public government), and data collection purpose (individual vs collective benefit) (see Fig. 1B). Combining the experimental factors yields eight possible experimental conditions. We used contrastive vignettes to compare participants' attitudes across conditions (Burstin et al. 1980; see supplementary for detailed vignettes). Each vignette was designed with a unique background story to minimise any transfer effects (Grossman and Salas, 2011; Ford and Weissbein, 1997; Simons, 1999).

To test the role of social influence, we conducted a multi-phase experimental design (see Fig. 1A), adapted from the wisdom of crowds and collective decision-making literature (see above for details; notably Bahrami et al. 2010; Dezecache et al. 2022; Herzog and Hertwig, 2014a, b; Longin and Deroy, 2024; Longin et al. 2023; Myers and Kaplan, 1976; Navajas et al. 2018; van Dolder and van den Assem, 2018). The main experiment consisted of four sequential decisions-making phases. While participants rated the acceptability of sharing data individually in the first, second and forth phases, they were asked to form a group consensus in the third phase. Comparing ratings for the same condition in the first phase with ratings from the second phase allowed us to test the effect of internal deliberation. Comparing ratings from the first phase with ratings from the fourth phase tested the effect of external, group-induced deliberation. The difference between ratings of the second and forth phase allowed us to test the effect of social influence on individual ratings. To ensure a balanced comparison of experimental conditions across decision phases, each vignettes has two versions varying only in their background story. All versions and vignettes were rated individually in the first phase. However, while one version was rated in the second phase, the other version was rated in the third and fourth phases. The version allocation was randomised and counter-balanced. This experimental design, much like in the aforementioned wisdom of crowds literature, was designed to measure the impact of social influence while mitigating the possible confounds of learning and transfer effects as much as possible.

Measures. To measure the perceived acceptability of data-sharing, we asked: 'How acceptable is it to use data for this reason?'. Responses were collected on a 7-point Likert scale ranging from 1 (not at all acceptable) to 4 (neutral) and 7 (completely acceptable). The measure was the same across all four decisions phases and all vignettes, differing only in how participants arrived at their answer. In the first, second, and fourth phases, participants were instructed to rate the presented vignettes by themselves. In the third phase, participants were instructed to discuss with their fellow participants and arrive at a group consensus. No further structure or information was provided. With a full consent of the participants, we recorded and transcribed the audio of the group discussions.

Procedure. Throughout the experiment, participants were seated in a U-shaped seating arrangement, facing each other and the wall where the experimental instructions and vignettes were projected for everyone to see. After having been shown experimental instructions and a practice scenario, participants started the main experiment. Presented with one vignette at a time, participants had one minute to rate each vignette in the first phase, half a minute in the second and fourth phase, and two and a half minutes in the third phase. The specific time estimates are based on work by Keshmirian et al. (2022) and have been validated by previous pilot data and discussions with focus groups. Participants noted down their ratings on sheets of paper which were replaced with new ones after each experimental phase. After completing the fourth and final phase of the main experiment, participants were given a final sheet with demographic questions.

Research instruments

Vignettes. The study utilized a series of vignettes to explore participants' perceived acceptability of sharing learning data in various contexts. Each vignette described a specific data-sharing scenario that systematically varied along three contextual factors: data type (process vs outcome learning data), data recipient (private company vs public government), and data collection purpose (individual vs collective benefit) (see Fig. 1B and design above; supplementary material for a full list of all vignettes). Responses were collected on a 7-point Likert scale ranging from 1 (not at all acceptable) to 4 (neutral) and 7 (completely acceptable).

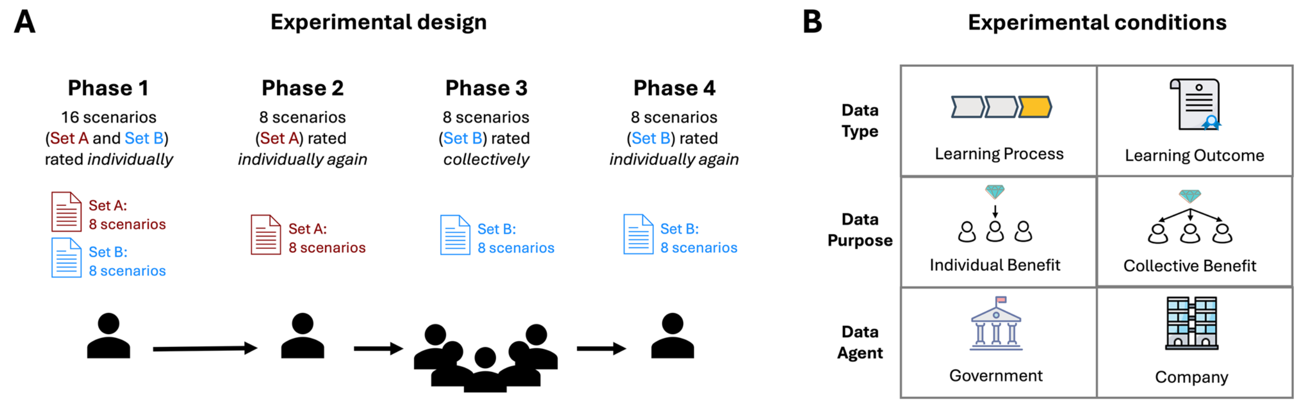

Fig. 1 Experimental design and conditions. A We tested participants' perceived acceptability of sharing learning using contrasting vignettes in a sequential multi-phase experimental design. Participants rated the vignettes alone in phases 1, 2, and 3. In phase 3, participants rated the vignettes after a group discussion. Sets of vignettes A and B included all experimental conditions. The sets differed only in their background stories. **B** Vignettes varied across three factors with two levels each: data type (process vs outcome), data agent (government vs company), and data purpose (individual vs collective benefit). Each vignette combines one level of each factor, resulting in eight unique vignette variations.

Demographic questionnaire. Participants completed a demographic questionnaire at the end of the main experiment. The questionnaire collected information about participants' age (open text box), gender (ticking either male, female, or other), highest completed educational degree (ticking either 'lower educational certificate', 'Abitur (or equivalent qualification', 'bachelor degree', 'master degree', or 'doctoral degree'), general trust in public authorities and private companies (both collected on 10-point Likert scale ranging from 1 (do not trust at all) to 10 (trust completely), general privacy concerns and towards specific data types (collected on 4-point Likert scale: 'not at all concerned', 'little concerned', 'quite concerned', and 'very concerned'), a validated 11-item social conformity questionnaire (Mehrabian and Stefl, 1995; each item collected on 7-point Likert scale ranging from 1 (does not apply to me at all) to 4 (neutral), and 7 (applies to me completely)), and), five items to capture the social experience during the group discussion (Aron et al. 1992; Sprecher, 2021; Sun et al. 2020; involving four 7-point Likert scales ranging from 1 (not at all), to 4 (neural), and 7 (a great deal) as well as ticking the most suitable Venn-Diagram representation of self vs other), and an open-text box for feedback.

Discussion analysis

Content analysis. Content analysis of discussion transcripts was implemented using a coding framework derived from contextual integrity theory. The group discussions were recorded, transcribed, and analysed using a coding scheme grounded in contextual integrity theory (Nissenbaum, 2004, 2009). The coding scheme (available in the supplementary material) categorized participants' perceptions of information sharing into five key themes: actors involved in the data-sharing process; data attributes; transmission principles, focusing on norms like anonymization, security; and purpose, identifying the beneficiaries of or concerns around data sharing. Using a coding scheme, these categories were iteratively coded by the second and the third author, in several rounds until sufficient agreement was reached.

Epistemic network analysis. Labelled data were analysed via ordered epistemic network analysis (Shaffer et al. 2016; Tan et al. 2022) - a widely adopted methodology well-suited for content analysis of discourse. This method enables us to compare if the discussions about different situations were statistically different. Epistemic network analysis (ENA) aggregates categories derived from content analysis within a selected unit of analysis and transforms them into networks, based on the co-occurrence of categories within this unit. This method bridges qualitative and quantitative data analysis (Shaffer, 2017; Shaffer et al. 2016; Siebert-Evenstone et al. 2017). It combines content analysis with network analysis to examine co-occurrence of the thematic codes as a network. In such a network, content analysis codes are network nodes, and their co-occurrences are network ties. To compare multiple networks comprised of the same set of codes, the utilised ENA tool projects each network graph into the same space, using single value decomposition. For instance, for each discussion, a graph represents co-occurrences of CI codes brought up by each group. Since these graphs are projected into the same space, they can be described in relation to each other and compared them statistically and visually. A Mann-Whitney test is a common method to compare the structures of co-occurrence between different groups to establish if these structures are statistically different (see supplementary material for details around ENA, and Shaffer et al. 2016 for a series of studies explaining the basics of the method).

Therefore, we analysed differences between the co-occurrence of contextual integrity codes across in different group discussions. We applied ordered network analysis (Tan et al. 2022) to the coded transcript data using the epistemic network analysis web tool (ENA, version 1.7.0) (Marquart et al. 2018). Using this technique, we compared 96 networks of contextual integrity themes at the level of a vignette conversation within each group (eight conversations per group), i.e. 'group-vignette' thematic networks (Fig. 4A). We also statistically compared 18 networks of contextual integrity themes at the level of each vignette, with themes aggregated across all groups (Fig. 4B). These structures were compared statistically between experimental conditions and for vignettes rated with the highest and the lowest acceptability. Details of the content and epistemic network analysis are presented in the supplementary material, including sensitivity analysis to select the unit of aggregation.

Results

Acceptability of sharing learning data decreases in and after group discussion

Acceptability ratings. Participants rated all items individually in the first phase, half of them again individually in the second phase, discussed the other half openly in the group in the third phase, and rated the discussed items again individually in the fourth phase. To analyse a general effect of group discussion, we fitted a linear mixed model to predict acceptability ratings of sharing learning data with decision phases as a fixed effect. The

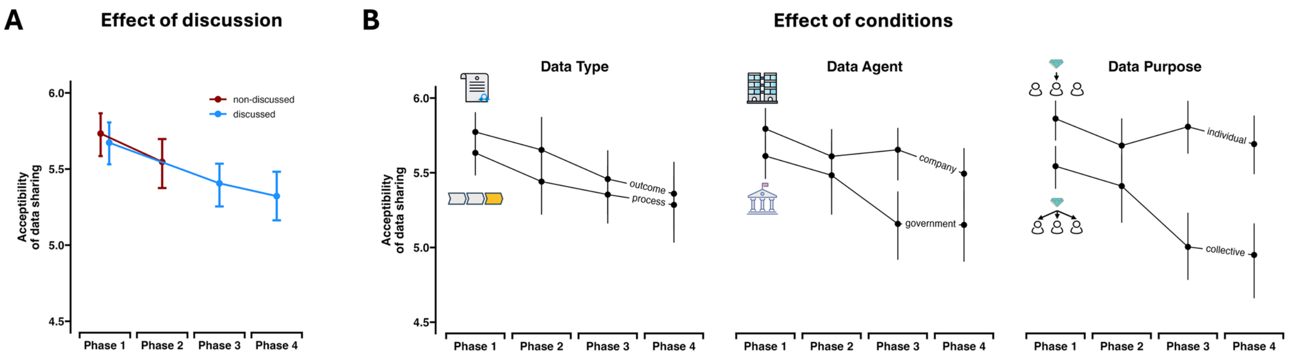

Fig. 2 Effects of discussion overall and of conditions through decision phases. A Progressing through each phase, participants overall find data sharing slightly less acceptable. **B** Data Sharing with governments and for collective benefit are the main drivers for the decrease in data sharing acceptability in and after group discussion. **A**, **B** Plotted are mean values and 95% confidence intervals obtained from resampling the collected data across individual acceptability ratings using the bias-corrected and accelerated (bca) bootstrap method (Canty, 2002).

experimental setup consists of four decision phases (see methods). The model included the unique participant ID and associated group ID as random effects (formula: rating ~phase + (1 | group/participant)).

Participants on average found sharing learning data less acceptable in and after a group discussion compared to their initial, individual ratings (see Fig. 2A). The average rating on a 7-point scale for the group discussion in phase three is by 0.3 points significantly lower (95% CI [−0.45, −0.14], $p < 0.001$) compared to the initial individual ratings in phase one. Similarly, the average rating in phase four is by 0.38 points significantly lower (95% CI [−0.53, −0.23], $p < 0.001$) than the initial ratings in phase 1. Notably, ratings in phase two were non-significantly different from those in phase one (b = −0.14, 95% CI [−0.30, 0.01], $p = 0.06$). The impact of group discussion becomes further evident when comparing individual ratings before (phase two) and after (phase four) group discussion. Here, the average rating was by 0.23 points significantly lower (95% CI [−0.46, 0], $p = 0.05$) in phase four compared to phase two.

Sharing process vs outcome learning data makes no difference to the perceived data-sharing acceptability

Acceptability ratings. We compared two kinds of learning data: outcome-related learning data (final performance measures like grades) and process-related learning data (behaviour during learning process like sequence of clicks). To find out whether participants' perceived acceptability of sharing learning data depends on the presented data type, we fitted two linear mixed models to predict acceptability ratings of sharing learning data by *learning data types*: a general model only predicting an overall difference in learning data type (formula: rating ~type + (1 | group/participant)), and a more specific model including an interaction term with the decision phases (formula: rating ~type*phase + (1 | group/participant)). While the first, general model tests for a main effect of data type assuming the effect of data type on acceptability ratings is consistent across all decision phases, the second, more complex model tests whether the effect of data type varies across decision phases. The second model highlights possible phase-specific effects that would be missed in the general model. Both models included the unique participant ID and associated group ID as random effects to account for within-subject and within-group variability.

Overall, we find that participants rated the sharing of process-related learning data significantly less acceptable than outcome-related learning data ($b = -0.14$, 95% CI [−0.25, −0.02], $p = 0.017$; see Fig. 3A1). However, when including decision phases as an interaction term in the second model, the general effect of data type breaks down (see Fig. 3A2). Participants found the sharing of process learning data as acceptable as outcome-related learning data. Process-data ratings are on average 0.07 points non-significantly lower than outcome-data ratings in phase 1 (95% CI [−0.17, −0.03], $p = 0.11$), 0.11 points lower in phase 2 (95% CI [−0.25, −0.04], $p = 0.1$), 0.05 points lower in phase 3 (95% CI [−0.19, 0.09], $p = 0.41$), and 0.04 points lower in phase 4 (95% CI [−0.18, 0.1], $p = 0.55$). These findings suggest that the decision phases influence the perceived acceptability of data sharing, such that the overall trend observed in the general model does not hold consistently across all decision phases (see Fig. 2B). In other words, data type alone is not a strong predictor of acceptability ratings when phase-specific factors are taken into account.

Discussion structure. 'Group-vignette' thematic networks (Fig. 4A3) were compared across discussions focused on sharing process learning data versus outcome learning data. A Mann-Whitney test showed that they were statistically different along the x-axis (Mdn = 0.06, $N = 48$, $U = 706.00$, $p = 0.00$, r = 0.39), explaining 6% of network structure variance. Vignette-level thematic networks (Fig. 4B3) were also statistically significantly different along the x-axis (Mdn = −0.12, $N = 8$, $U = 9.00$, $p = 0.01$, $r = 0.72$), explaining 14% of network structure variance.

Surprisingly, participants discussed the relationship between outcome data, who receives it and what benefit would that offer in ways where they questioned the utility of this common data from learning environments. For process data, the focus on transmission norms were more prominent. Yet, some participants were both positive and negative about these two data types, using other context information to make sense of their decision. With outcome data, they could be concerned that this outcome would be misused and known to others. For process data, they often failed to see its relationship to learning, e.g.: "I don't know about the timing of clicks and sequence of language exercises (*data attribute, utility*). I think it depends on each person. It has nothing to do with [learning]". The nature of discussions suggests that while LA researchers consider performance (outcome) data and learning (process) data as different types, learners potentially make sense of the data types in other ways, more so as "what are these data a proxy for". If learning outcome data are a proxy for failure or aptitude, there may be a risk, despite these data perhaps being the most commonly used in educational applications."

Sharing learning data for an individual rather than collective benefit is more acceptable

Acceptability ratings. Learning data can either be shared for a collective or an individual benefit. Sharing for a collective benefit

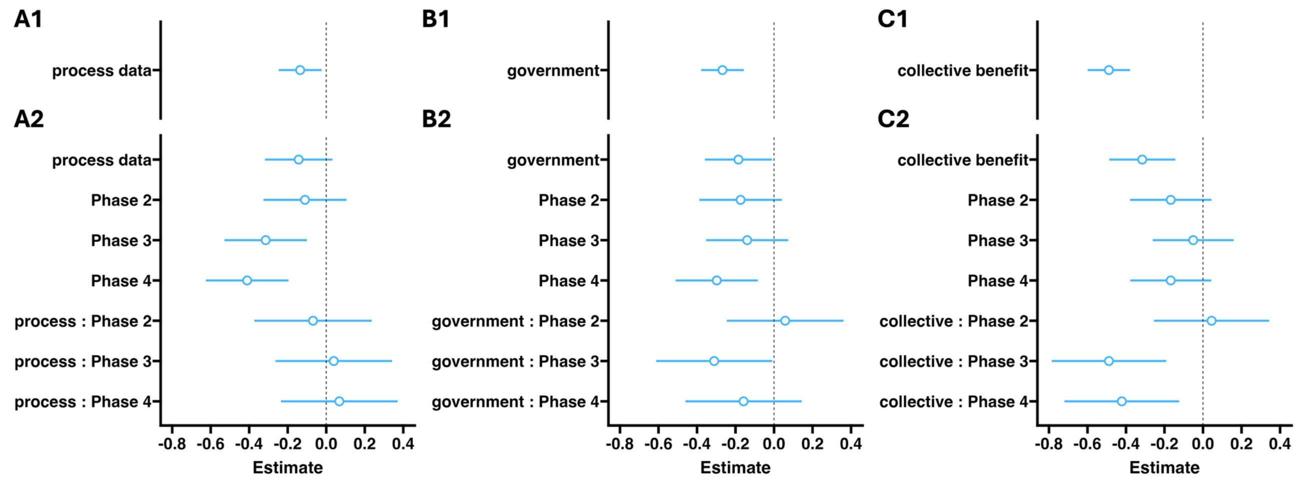

Fig. 3 Plotted regression summaries of lmer regression coefficients. A1 Overall effect of learning data type: process-related learning data was rated on average lower than outcome-related learning data. **A2** Effect of learning data type by decision phases: comparing data types by decision phases reveals no difference in data types. **B1** Overall effect of data recipient/agent: sharing learning data with governments was rated less acceptable than with companies on average. **B2** Effect of data recipient by decision phases: sharing learning data with governments was rated less acceptable overall as well as in phases one and three. **C1** Overall effect of data sharing purpose: sharing learning data for a collective benefit was rated less acceptable than sharing for a individual benefit. **C2** Effect of data purpose by decision phases: sharing learning data for a collective rather than individual benefit was rated less acceptable overall as well as in decision phases three and four.

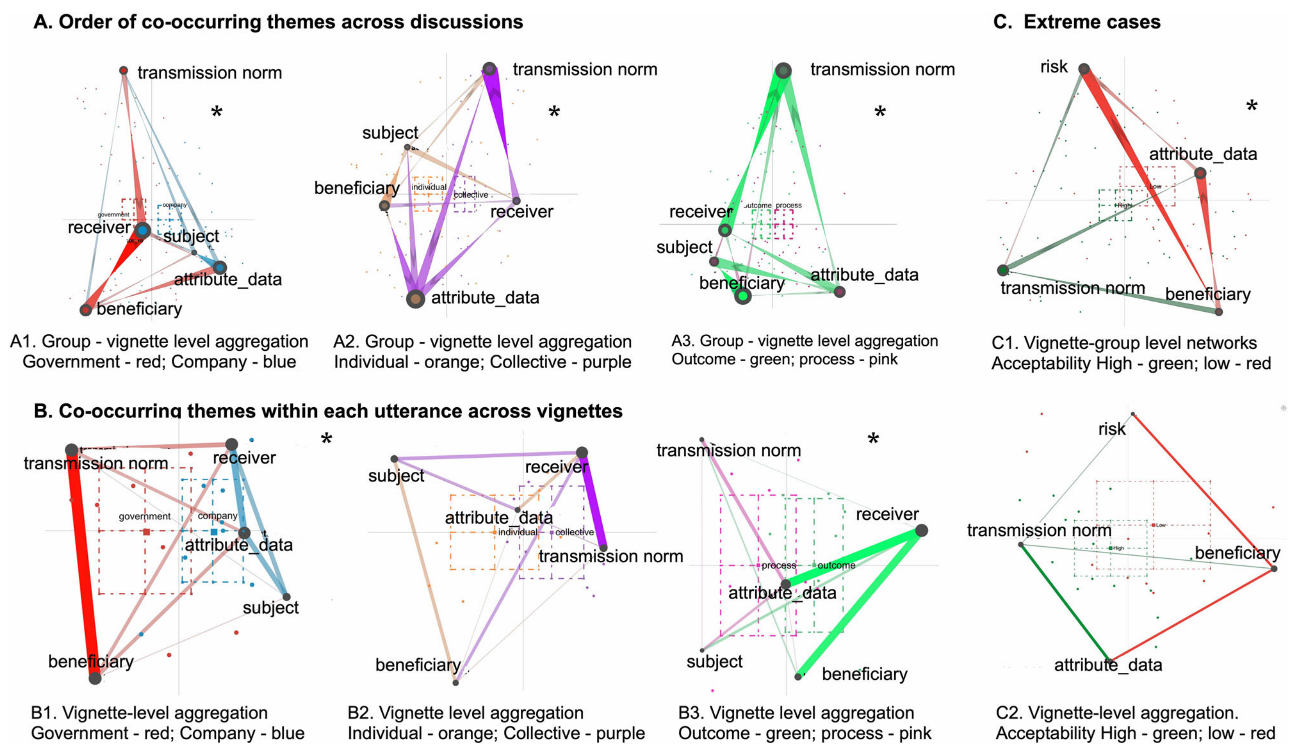

Fig. 4 Subtracted plots of co-occurring discussion themes. Nodes represent contextual integrity themes assigned to each participant's utterance; the size of a node represents if a theme auto recurred. If two contextual integrity themes co-occurred in a discussion, they share an edge projected in the two-dimensional space. Edges are directional, with thicker edges and error directions representing the sequence of co-occurrence. Subtraction plots only show edges that differed across two juxtaposed contextual integrity conditions. Plotted networks were averaged across all networks within the same condition. **A** Subtracted ordered network plot per condition aggregated at the level of a group and vignette. **B** Subtracted ordered network plots per condition aggregated at the level of vignette across groups. **C** Sample of subtracted co-occurrence networks. (1) ordered at the level of the group and vignette for cases when vignettes were rated extremely low ($n = 26$) and high ($n = 58$). (2) Unordered co-occurrence networks at the level of vignette across groups, for vignettes rated extremely low ($n = 11$) and for vignettes rated extremely high ($n = 16$).

includes cases of developing global teaching best practices, whereas sharing for an individual benefit capture cases of personalised learning recommendations. We find that participants rated the data sharing acceptability for an individual benefit consistently higher than for a collective benefit. We fitted two linear mixed models to predict acceptability ratings of sharing learning data by *sharing purpose*: a general model only predicting a difference in sharing purpose (formula: rating ~purpose + (1 |

group/participant)), and a more specific model including an interaction term with the decision phases (formula: rating ~purpose*phase + (1 | group/participant)). Both models included the unique participant ID and associated group ID as random effects.

Overall, participants rated sharing learning data for a collective benefit by 0.49 points as significantly less acceptable than sharing learning data for an individual benefit (95% CI [−0.60, −0.38], $p < 0.001$; see Fig. 3C1). The overall effect holds when including the decision phases as an interaction term within the more specific model (see Fig. 3C2). Already in the first phase, participants rated sharing learning data for a collective benefit by 0.32 points as significantly less acceptable than sharing for an individual benefit (95% CI [−0.49, −0.14], $p < 0.001$). While the effect was non-significant in the second phase ($b = 0.04$, 95% CI [−0.25, 0.34], $p = 0.771$), it was significant again in the third ($b = -0.49$, 95% CI [−0.79, −0.19], $p = 0.001$) and fourth phase ($b = -0.42$, 95% CI [−0.72, −0.12], $p = 0.006$). The effect of the data purpose on the acceptability of sharing data is hence strongest in the group discussion (see Fig. 2B). Notably, the general decrease of data sharing acceptability of phases three and four compared to phases one and two are non-significant in the larger model.

Discussion structure. 'Group-vignette' networks (Fig. 4A2) were compared across discussions focused on sharing data for individual and collective benefit. A Mann-Whitney test showed that discussion around sharing benefits were statistically different along the x-axis (Mdn = 0.08, N = 48 U = 618.00, p = 0.00, r = 0.46)), explaining 8% of network structure variance. Vignette-level thematic networks (Fig. 4B2) were not statistically significantly different. In vignettes with data sharing for individual benefit participants focused on the benefit elements against transmission norms.

In contrast, in data sharing for collective benefit, participants tended to focus on transmission norms governing the collective sharing of their data and sensitivities surrounding data they are submitting. One may speculate that their risk perceptions was less associated with the entity receiving the data, more so on the others who will have access to these data, despite it being de-identified and anonymised. As exemplified here: "I think anonymised is a problem because you are recorded, they hear your voice or maybe see you (*data attribute*), so not very anonymous (*transmission norm*)", with another participant responding: "Yeah, but it depends on how they use the data of yourself (*data attribute*), because anonymised to me means that the video of myself (*data attribute*) won't be shown anywhere else. But maybe the contents of what I'm doing and how I performed will be used for continuously improve the website." Exception to these were the data used to teach medical emergency skills where participants were open to collective data sharing, as the quotes shows: "It's surgery and medical students (*data subject*), so it's important. For sure, it's a seven."

Sharing learning data with companies is more acceptable than sharing data with governments

Acceptability ratings. Learning data can be shared with different institutions. Comparing participants' acceptability ratings of sharing data with private companies versus public governments revealed that participants found sharing learning data with companies more acceptable than sharing learning data with governments. We fitted two linear mixed models to predict acceptability ratings of sharing learning data by *data recipient*: a general model only predicting a difference in sharing purpose (formula: rating ~agent + (1 + group/participant)), and a more specific model including an interaction term with the decision phases (formula: rating ~agent*phase + (1 + group/participant)). Both models included the unique participant ID and associated group ID as random effects.

Overall, participants rated the acceptability of sharing learning data with the government significantly lower than sharing learning data with companies ($b = -0.27$, 95% CI [−0.38, −0.16], $p < 0.001$; see Fig. 3B1). When including the decision phases as a regressor in the second model, the average decrease in acceptability for sharing learning data with governments rather than companies remains significant for the first ($b = -0.18$, 95% CI [−0.36, −0.01], $p = 0.037$; see Fig. 3B2), and the third phase ($b = -0.31$, 95% CI [−0.61, −0.001], $p = 0.043$). However, the difference between sharing learning data with governments and companies was non-significant in the second ($b = 0.06$, 95% CI [−0.25, 0.36], $p = 0.709$) and fourth decision phases ($b = -0.16$, 95% CI [−0.46, 0.14], $p = 0.304$).

Discussion structure. A Mann-Whitney test showed that group-vignette networks compared between government versus company-oriented scenarios were statistically different along the x-axis (Mdn=0.07, N = 48 U = 629.00, p = 0.00), explaining 7% of network structure variance. As per Mann-Whitney test comparing vignette thematic networks (Fig. 4B1), discussions of government versus company-oriented scenarios were statistically significantly different along the x-axis (Mdn=0.12, N = 8 U = 54.00, p = 0.02, r = −0.69), explaining 29% of network structure variance.

When talking about data sharing with governments, groups discussed government and regulations or intentions to process and use the data. The risk of a particular data type owned by the government was prominent, as demonstrated in this quote: "It's a public authority (data receiver) [offering] driving education for everyone in the world (beneficiary). How does that data get to everyone in the world (*transmission norm; beneficiary*)? Is it sold?". In contrast, the purpose of transmission norms was less prominent in discussions with company as data receiver. In company-related scenarios, participants focused on data types, reflecting on their utility, for example: "It's also like for personalized recommendations (*beneficiary*) so yeah it's really helpful although it's a company (*data receiver*). Timing of clicks and sequences is good to get recommendations and individual support (*attribute data*)".

Discussions differ between scenarios with high and low acceptability. Although thematic networks differed across conditions, the same themes co-occurred within multiple conditions. The results, therefore, are limited in clarifying the relationship between the differences in discussions and levels of acceptability. To identify if particular thematic patterns were associated with more or less acceptability, we constructed thematic networks at the vignette-group and vignette levels (Fig. 4C1 and C2) only for scenarios rated extremely low (four or less) and extremely high (seven). Low acceptability of four was not only descriptive of the lower end of the distribution but also reflective of the participants' attitudes to these numbers as more negative, as gleaned from the transcripts. Differences across group-vignette networks were statistically significantly different on x-axis component, explaining 20% variability in structures representative of groups and vignettes (Mdn = 0.00, $N = 58$, $U = 530.50$, $p = 0.03$, $r = 0.3$). Vignette networks were not statistically significantly different.

High acceptability scenarios were more likely to contain co-occurring themes of risk, transmission norm, and attribute data, whereas low acceptability scenarios were more likely to contain co-occurring themes of attribute data, risk, and beneficiary. Higher acceptability appeared in contexts interpreted as safe for this specific data to be transferred under these conditions and reasonable for the utility suggested. In contrast, if participants interpreted the context as a setting where the data they were asked to share could indicate something about them that they may not want others to know, they were less likely to find this acceptable. The same low acceptability would apply to contexts where the participants did not understand the benefit, even if evidence unknown to them would indicate that submitting these data may positively impact their outcomes. These suggest that context characteristics defined by contextual integrity theory may be interpreted in relation to the larger themes of risk and utility, which were dominant codes connected to other themes.

General trust levels predict data sharing attitudes. After completing the main experiment, participants answered demographic questions, including age, gender, highest completed educational degree, general trust in public authorities and private companies, general privacy concerns, sensitivity of learning data, a social conformity questionnaire, and five items to capture the social connectedness during the group discussion (Aron et al. 1992; Sprecher, 2021; Sun et al. 2020). To analyse demographics effects, we fitted multiple linear mixed models. We find that neither age, nor gender, nor education made a considerable impact on average data acceptability ratings (see supplementary results for a full breakdown of all demographic effects). Male participants rated the acceptability of data sharing non-significantly lower on average than females ($b = -0.34$, 95% CI [−0.71, 0.03], $p = 0.072$). Being older had no significant influence on the average data sharing ratings ($b = -0.03$, 95% CI [−0.09, 0.02], $p = 0.192$). Similarly, having obtained an university entrance qualification ($b = 1.18$, 95% CI [−0.28, 2.64], $p = 0.113$), a bachelor degree ($b = 1.05$, 95% CI [−0.46, 2.55], $p = 0.173$), or a master degree ($b = 0.43$, 95% CI [−1.07, 1.92], $p = 0.574$) had no significant influence on the average data sharing rating compared to the participants without a completed educational degree.

Examining general trust levels, however, revealed an expected effect: participants with higher trust levels in companies found data sharing with companies on average significantly more acceptable ($b = 0.14$, 95% CI [0.01, 0.28], $p = 0.034$), while participants with higher trust levels in governments found data sharing with governments on average significantly more acceptable ($b = 0.12$, 95% CI [0.005, 0.23], $p = 0.04$). Notably, general trust levels in companies reliably predicted only higher data sharing acceptability with companies, not with governments. Likewise, general trust levels in governments reliably predicted only higher data sharing acceptability with governments, not with companies. Both general trust levels correlate positively ($r = 0.55$, $t = 4.99$, $p < 0.001$). The effects of reported general trust ratings on data sharing acceptability are further validated by the effect of general privacy concerns on data sharing acceptability. We find that participants who were more concerned with privacy in general had on average significantly lower data sharing acceptability ratings ($b = -0.39$, 95% CI [−0.66, −0.13], $p = 0.003$).

Discussion

Ethical integration of the data generated by learners into educational practices is of great importance now that data-rich technologies are prevalent in education. Despite the common agreement that learners should have agency and autonomy in deciding what to do with their data, existing ethical discussions focus on policies or algorithms. A review of literature shows that attention has been mostly focused on developing ethical frameworks and policies as well as devising privacy-preserving and less biased algorithms (Liu and Khali, 2023). Less attention has been given to practices that enable learners to meaningfully participate in their data sharing decisions. Participatory practices, particularly around informed consent, can support ethical and meaningful engagement with data sharing decisions. However, designing participatory practices within educational technologies is non-trivial. On the one hand, learners do not meaningfully engage in decisions in their data. On the other hand, decisions about sharing learner data are context-specific, whereas existing consent practices are top-down and apply across contexts. Yet, the evidence that explains how situations affect learner decisions is limited.

This paper proposed and evaluated the intervention where learners can meaningfully engage in making a data sharing decision through a group discussion. The intervention also examined how contextual differences in data sharing vignettes affect the learner's willingness to share data. In designing this intervention, we combined research from social decision-making (Bahrami et al. 2010; Dezecache et al. 2022; Herzog and Hertwig, 2014a; Navajas et al. 2018; Niella et al. 2016) with work on contextual integrity (Nissenbaum, 2004, 2009). The resulting experiment consisted of four sequential decision-making phases during which participants, individually and in a group, rated the acceptability of sharing learning data in different learning contexts, that varied learning data type, data recipient, and data purpose.

We found that (1) unstructured group discussion can serve as a participatory practice since it influences initial student decisions; (2) the willingness to share learning data depends on the context, as participants favoured sharing data for the individual over the collective benefit and sharing data with companies over governments while being agnostic to the learning data type; and (3) processes of group discussions differed alongside the contexts they were discussing.

Our findings contradict evidence observed in the acceptability of sharing health data, also framed from the contextual integrity theory. Studies on health data sharing found that participants preferred to share for the collective over the individual benefit (Cascini et al. 2024; Johnston et al. 2024; McDonald et al. 2023), as well as with the government over the private company (Deruelle et al. 2023; Gerdon, 2024; Gerdon et al. 2020; Kim et al. 2015). We found the opposite for both effects. A reason for this difference could be the underlying perceptions of responsibility and trust associated with the respective data types and recipients. Health-related data is often perceived as highly sensitive due to its intimate connection with personal privacy and the potential consequences of misuse, such as discrimination or stigmatization (Cascini et al. 2024; Johnston et al. 2024). In this context, collective benefits, such as public health improvements, may outweigh individual concerns, as participants prioritize societal welfare and trust public institutions like governments to handle such data responsibly (Deruelle et al. 2023; Gerdon et al. 2020; Silber et al. 2022). This may contrast sharply with learning data, which potentially may be perceived as more utility driven (Mutimukwe et al. 2022, 2023; Riahi et al. 2013). Hence, learners may prioritize individual benefits, such as personalized learning or academic success, over collective outcomes.

The discrepancy in trust toward data recipients is another likely explanation (Mutimukwe et al. 2022, 2023; Viberg et al. 2024). Governments are traditionally viewed as legitimate stewards of public health (Beller et al. 2023), which may explain the preference for sharing health data with them over private companies. However, in the educational domain, governments are not always perceived as equally competent or innovative in leveraging learning data for immediate, tangible improvements. Private companies, on the other hand, are often associated with advanced technological solutions and personalized services, which may align more closely with participants' expectations for learning data usage. Such an explanation is supported by our findings on the influence of trust on data sharing acceptability. Participants with higher trust in private companies rated data sharing with companies significantly more acceptable, while participants with higher trust in governments rated data sharing with governments significantly more acceptable. Notably, trust in one type of recipient (e.g., companies) did not predict increased acceptability for the other (e.g., governments), suggesting that these trust levels operate independently. Together, these results suggest that trust in the specific recipient, rather than broader demographic factors such as age, gender, or education, plays a pivotal role in shaping participants' data-sharing preferences. In educational contexts, the preference for private companies over governments may therefore reflect a perception of greater competence, innovation, or alignment with individual benefits offered by private entities, the contexts, societal trust in public institutions as protectors of collective welfare may dominate. The importance of trust in sharing learning data underscores the importance of involving students in the design and implementation of learning analytic systems through participatory design approaches (Ifenthaler and Schumacher, 2016; Viberg et al. 2024).

The analysis of the group discussions provides further insight into the role of social decision-making in shaping learners' attitudes towards sharing learning data. The results indicate that the group discussion was a crucial catalyst for learners to become more cautious when sharing learning data, as it was only in and after these discussions that participants consistently distinguished between contextual data types. A closer examination of the discussion dynamics reveals that the kind the data recipient and the purpose of data sharing influenced the focus of the conversations. When discussing data sharing with government, participants emphasized the risks associated with government ownership and regulation of data, whereas discussions centred on companies as data recipients focused on the utility of specific data types.

In scenarios where data sharing was intended for individual benefit, participants prioritised the benefits over transmission norms, whereas collective benefit scenarios led to a focus on transmission norms and sensitivities surrounding specific data. These differences are interesting as they reveal a notable bias in dealing with learning data: just because learners do not discuss transmission norms in the scenarios where data are submitted to the company does not mean that these are inherently safer than the norms they discuss in the government-sharing scenarios. Understanding such cognitive biases is important to provide scaffolds or questions that can a balanced evaluation of data option during a group discussion. Notably, the exception to this pattern was the sharing of data for teaching medical emergency skills, where participants were more open to collective data sharing.

The thematic analysis of the discussions reveals that high acceptability scenarios were characterized by the co-occurrence of themes related to risk, transmission norms, and attribute data, suggesting that learners were more willing to share data in contexts perceived as safe and where the utility of sharing data was clear. In contrast, low acceptability scenarios were marked by the co-occurrence of themes related to attribute data, risk, and beneficiary, indicating that learners were less likely to share data in contexts where the benefits were questionable or where the data could reveal sensitive information about the sender. These findings suggest that learners interpret the context of data sharing through the lens of risk and utility, which are dominant themes connected to other factors such as transmission norms and beneficiary—again aligning with previous work on students' perception of privacy risks in LA practices (Mutimukwe et al. 2022, 2023).

Several important limitations and open questions remain that present useful opportunities for further research. First, this study did not cover the full extent of contextual factors for sharing learning data. While the study compared the influence of private to public institutions, it did not consider certain receivers of learning data that are common in educational settings, such as universities, fellow students, or instructors. Similarly, the study only varied two main data types. It remains unclear whether this lack of differentiation of data types reflects a limited understanding of data attributes or a genuine indifference to the sensitivity of specific types of learning data. Future work should strive to align researcher-driven definitions of learning data with learners' perspectives, ensuring that distinctions between data types are clearly understood and meaningfully addressed in participatory consent frameworks. Second, the relatively homogeneous sample used in this study possibly limits the generalizability of its findings. As participants were recruited in person through a university-governed participant pool (see methods for details), participants might have shared an overall similar cultural and educational background, which may not reflect the diverse perspectives present in global educational contexts. Privacy concerns and data-sharing practices are deeply influenced by cultural norms and values, suggesting that learners from other regions, educational systems, or cultural settings may exhibit different attitudes toward data sharing (Viberg et al. 2024). Future research should replicate and extend this work using larger and more diverse samples, including participants from various cultural contexts, to identify potential cultural or systemic moderators of learners' perceptions.

The results of this paper offer two main contributions to the research and practice around informed consent. First, they provide empirical evidence that learners' acceptability of sharing learning data is highly context-dependent and influenced by factors such as trust in data recipients, perceived risks, and the intended purpose of data sharing. This underscores the importance of tailoring consent processes to reflect these contextual sensitivities. Second, the role of group discussions in increasing learners' awareness and caution highlights the potential for participatory and interactive approaches to informed consent, which could help align learning analytics practices with learners' expectations and preferences. These results also have broader implications for the design of data-sharing frameworks beyond education, suggesting that trust-building strategies and clearer communication of risks and benefits are critical for fostering informed and context-sensitive consent. Furthermore, this research raises questions about the alignment of researcher-driven conceptualizations of learning data with learners' understanding, suggesting the need for an ongoing dialogue and co-design to ensure that learners are empowered stakeholders in the data-sharing and learning process.

Data availability

The underlying data and scripts used for the current study are available in the Zenodo repository, https://doi.org/10.5281/zenodo.15334332.

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Ethical approval
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Informed consent
All participants were recruited via the 'Munich Experimental Laboratory for Economic and Social Sciences'. Before participating in the study, participants provided written informed consent confirming that their participation is voluntary, that they could withdraw from the study at any time without any negative consequences, that their discussions will be recorded, and that their data will be stored and analysed in anonymised form for scientific purposes. The study was conducted throughout March 2024.

Additional information
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