Crowdsourced, Actionable and Verifiable Contextual Informational Norms

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Abstract

There is often a fundamental mismatch between programmable privacy frameworks, on the one hand, and the ever shifting privacy expectations of computer system users, on the other hand. Based on the theory of contextual integrity (CI) [24], our paper addresses this problem by proposing a privacy framework that translates users’ privacy expectations (norms) into a set of actionable privacy rules that are rooted in the language of CI. These norms are then encoded using Datalog logic specification to develop an information system that is able to verify whether information flows are appropriate and the privacy of users thus preserved. A particular benefit of our framework is that it can automatically adapt as users’ privacy expectations evolve over time.

To evaluate our proposed framework, we conducted an extensive survey involving more than 450 participants and 1400 questions to derive a set of privacy norms in the educational context. Based on the crowdsourced responses, we demonstrate that our framework can derive a compact Datalog encoding of the privacy norms which can in principle be directly used for enforcing privacy of information flows within this context. In addition, our framework can automatically detect logical inconsistencies between individual users’ privacy expectations and the derived privacy logic.

1 Introduction

Incorporating privacy expectations into real world systems remains an important research challenge. For the privacy-by-design initiative [1] this calls for more than technical rigor; it calls for the adoption of a socially meaningful conception of privacy, namely, one that meets people’s expectations, and is ethically and legally legitimate. In the case of online information platforms, where privacy must be maintained amidst complicated flows among participants, and between the participants and the platform, the challenge is particularly acute [26,20,7]. In this regard, the account of privacy [23] as contextual integrity has been promising, inspiring work on formal expression of contextual informational norms, on detection of infractions, and on approaches to accountability and enforcement [9,8,10]. These, and other similar efforts [14] have made extensive contributions to the technical field — generating machine-readable access rules and implementing complex constraints that map given rules. Building on this body of work, our project incorporates an additional component, namely, the discovery, articulation and verification of norms.

The framework we are developing, based on the theory of contextual integrity, offers designers a comprehensive form of this functionality centered on contextual informational norms. This framework not only provides tools to implement privacy rules based on social norms, but also to continuously update those rules according to the fluid and ongoing evolution of privacy expectations, as is characteristic of social norms more generally. In cases
where the discovery of norms may not be possible, and in systems where privacy rules are based on legal and policy documents as well as professional codes, our framework meets the remaining challenge faced by designers and requirements engineers alike, namely expressing privacy norms and implementing them as privacy rules on the one hand, and ensuring their consistency and overall compliance with privacy expectations, on the other hand.

The theory of contextual integrity informs the structure of our privacy rules, and our project embeds these in a logic framework which encompasses a system for learning norms as well as the ability to enforce them in a system that is built on these norms. Further, these norms are formally expressed and verified to safeguard from privacy violations that may result from a semantic gap between privacy norms and mechanisms that enforce the privacy norms. The need for such functionalities is reflected in Figure 1, depicting Facebook’s privacy check-up utility. Our system offers the ability to automate such check-ups. The framework continuously functions in the background and can track the evolution of norms.

In summary, our privacy framework makes the following key contributions:

1. **Formal expression based on the theory of privacy as CI.** Our framework uses the theory to contextual integrity to formalize informational norms as logical rules using three key parameters: a) actors (senders, subjects and receivers of information, usually people or organizations); b) attributes (information types); and c) transmission principles. (See Section 2 for further explanation.)

2. **A methodology for discovering informational (privacy) norms through crowdsourcing** We have developed an approach to identifying contextual privacy norms based on the “wisdom of the crowds,” in this case, the collective input from system users/participants.

3. **Converting crowd-sourced responses to a corresponding privacy logic.** To derive a functional privacy logic, our system encodes structured informational norms discovered through the crowdsourcing methodology using the Datalog declarative language.

4. **Verification of privacy norms.** Our framework is designed to support formal verification of the derived privacy logic. Specifically, we were able to verify for consistency of flows described by the logic including checking the consistency of transitive flows.

The paper is organized as follows: Next section provides a brief overview of the CI theoretical framework. Section 2 describes our framework design. Section 4 discusses how we represent and evaluate CI norms in Datalog, while verifying additional high-level properties using the theorem prover Z3 [11]. We also describe our crowdsourcing methods in this section. We provide details on the evaluation in Section 5 and reflect on our results in Section 6. Finally, in Sections 7 and 8, we describe related works and then conclude the paper.

## 2 Contextual Integrity Primer

The theory of contextual integrity (CI) postulates that informational privacy is not all about secrecy (blocking information) [25] or control [33] but about the appropriateness of information flow within a particular context. Appropriateness of flow means flow that is compliant with contextual norms governing informational flows. To express an informational norm one must specify key parameters: actors (senders, recipients and subjects), attributes (the type of information at hand) and transmission principles (the constraints imposed on a particular information flow). Taken together, these components constitute context-relative informational norms. For instance, in the health context, the patient, acting in his capacity as both the sender and subject of an information flow, could be telling his doctor, the recipient, about his health issues, the attribute. The information flow would be constrained by the transmission principle of confidentiality, which restricts the onward flow of this information to other parties. Exchange the doctor for a friend, and the transmission principle might be reciprocity instead, since friends tend to expect to hear about each other’s problems. A patient, by contrast, does not expect to hear about the health issues of his doctor. This is because the context of health and the context of friendship have different overarching goals: the doctor is there to promote the patient’s health; friends are there to support each other. An informational norm is breached when an action or practice disrupts the actors, attributes, or transmission principles within a given information flow. Contextual integrity “is preserved when informational norms are respected and violated when informational norms are breached” [22]. In legal deliberations about privacy, the same intuition is captured by the concept of “reasonable expectation of privacy” [30].

It is worth emphasizing one of the most fundamental aspects of CI, namely that, in order to determine whether or not information flows respect or violate privacy expectations within a given context, one must address all three parameters: actors, information types, and transmission principles. Omitting any one of them may lead to an inconclusive or ambiguous description. Accordingly, any formal rendering of information flows, for the purpose of assessing their appropriateness, needs to include inde-
Figure 2: Our framework is designed to support several system states. The overall operation consists of 1) generating questions that correspond to information flows, 2) asking the questions, 3) deriving insights from the answers, 4) deciding on which set of actionable privacy rules (APR) to enforce, 5) generating questions from the enforced norms, 6) repeating by returning to step 2.

Dependent variables for these parameters.

CI recognizes that informational norms, like other social norms, are constantly evolving. Sometimes, changes in a sociotechnical environment, such as the ones we are experiencing in this “digital age”, can be quite rapid. Although the theory of CI has a prima facie preference for entrenched informational norms, it also allows for normative transformations when the resultant norms can better promote the values, goals, and ends of a given context. People learn and adopt implicit and explicit informational norms from their families, friends, and communities; by watching how people behave and how they react to other people’s behavior; from educational training, the arts, and cultural activities; from the study of law and policy, and so forth.

Designing a system that translates contextual informational norms into privacy rules must either depend on a range of legitimate external sources of knowledge (e.g. social scientists, ethicists, law, professional codes, etc.), or must incorporate, internally, some form of norm discovery functionality.

Our project has adopted CI as our underlying conception of privacy. There is sufficient regard for it in the privacy community to consider this reasonably uncontroversial. However, readers who are interested in learning about its underlying rationale as well as its policy applications, might wish to consult the relevant literature [22, 31]. In Section 7 we describe related research that pursues similar ends utilizing alternative conceptions.

3 CI-based Privacy Framework

The key components of our CI-based privacy framework is described in Figure 2. Our framework is adaptable to a range of information systems and platforms. We have conceived it as an independent service that can be integrated into the functionality of these respective platforms and systems. Our CI-based framework takes as input a simple state space description of a domain based on the contextual integrity definitions. Specifically, this implies, the input includes the list of actors, subjects, information types and transmission principles that are relevant to the domain of interest. In addition, the domain specific input parameters may also provide information about the importance of specific attributes and subjects that correspond to common information flows in the domain to guide the privacy logic generation process. Given the domain specific input, our framework performs three key steps:

Norm discovery through crowdsourcing. The Question Generation (QG) stage takes as input only the list of parameters associated with a context, including the list of actors, information types, and transmission principles. The QG generates questions from the prevailing set of privacy norms which cover the common information flows. These questions are crowdsourced to a set of users who provide a simple “Yes/No/Irrelevant” response for each question. Based on the users’ collective responses, the framework will derive the corresponding norms.

Learning and Encoding the Privacy logic. At the Learning stage, the answers to the questions are analyzed to learn users’ privacy expectations. Here, we are specifically learning a collective notion of privacy expectation within a domain based on a consensus metric defined on the individual user responses to each question. Next, at the Encoding stage, the norms reflected by the answers to each question are encoded into a set of actionable privacy rules using Datalog: they form the logic behind the users’ privacy expectation. The logic is passed on to the System state which is responsible for privacy norm verification and enforcement based on internal configurations, which may or may not take users’ perception logic into account.

Verification. All of the information flows that form part of the system are governed by privacy rules. Using the Datalog encoding, the system evaluates every information flow against the prevailing set of privacy rules. Furthermore, the system is capable of verifying other meta-assertions for the derived privacy logic, including validating that the enforced norms are consistent and disapproved information flows are impermissible.

In addition, the framework is designed to support learning of constantly evolving norms; as it traverses
through states, new norms are introduced and old ones are re-evaluated.

3.1 An example: the educational context

As a case study, we chose to apply our framework to the educational context, since this is the context with which we have the most familiarity; the discussion, however, can easily be extended to other contexts. We outline a specific example of actors, information types and transmission principles in the educational context below:

Actors (Senders, Recipients, Subjects): Students, Professors, TAs, Registrar, University IT staff, academic advisor

Examples of Attributes: Grades, Transcript, Name, Email address, Address, Record of attendance, Level of participation in class, Photo, Library records, Contents posted on online learning systems (e.g., Blackboard, Classes, etc.), term paper

Example Transmission principles:

Knowledge: If the ⟨ sender ⟩ let the ⟨ subject ⟩ know

Permission: If the ⟨ sender ⟩ asked for the ⟨ subject’s ⟩ permission

Breach of contract: If the ⟨ subject ⟩ is performing below a certain standard

We elaborate upon this example in Section 4.4 in greater detail to show how to automatically design the question generator given a state space description.

4 Verifiable and Actionable Privacy Rules

In this section, we first describe the encoding and verification of the privacy logic and then proceed to describing the procedure behind the crowdsourcing of norms.

4.1 Representation and verified enforcement

We use the declarative programming language Datalog to formally represent contexts, for evaluating the privacy rules in these contexts, and for automating critical aspects of the crowdsourced learning component. Datalog is a well-studied language and formalism that has found numerous applications, including the analysis of social networks and as a language for expressing privacy and security policies (see, e.g., [12][13][4]).

Our main motivation for building our formalization on Datalog can be summarized as follows:

- The encoding of contextual privacy rules to Datalog is elegant and easily understandable. In particular, we can leverage Datalog’s query mechanism to automatically evaluate and check the properties of privacy norms in concrete contexts. We provide several examples below.

- Datalog forms a fragment of first-order predicate logic. Hence, the language’s semantics are well understood. In particular, this allows us to use powerful first-order theorem provers to automatically prove high-level privacy properties of the norms that we learn for a specific context.

- Datalog provides a good trade-off between expressiveness and complexity. In particular, Datalog’s computational model is not Turing complete, which means that all queries are guaranteed to terminate. We mostly restrict ourselves to a specific fragment of Datalog referred to as unions of conjunctive queries. This fragment is well-studied in the AI, logic programming, and database communities. In particular, efficient algorithms for its treatment have already been developed [13].

4.2 Encoding Contextual Privacy in Datalog

Datalog is a fragment of the logical programming language Prolog. A Datalog program consists of clauses that define predicates on entities. Our Datalog encoding of contextual privacy specifies predicates on entities that stand for contexts, actors, attributes, and transmission principles as described in Section 3. Central to the encoding is the predicate.

\[
\text{allowed(Ctx, Sndr, Recp, Subj, Attr, Tr)}
\]

This predicate models that in context Ctx, actor Sndr is allowed to send information on attribute Attr of actor Subj to actor Recp under transmission principle Tr. For example, the following fact states that in the classroom context (denoted by class), bob can send his own grade to alice with transmission principle confidentiality.

\[
\text{allowed(class, bob, alice, bob, grade, confidentiality)}.
\]

In order to be able to express the privacy rules, we introduce a ternary predicate \( \text{inrole(Context, Actor, Role)} \), which models that in the given context, the given actor is in the specified role. For example, the following fact states that in the classroom context, bob is in the role of student

\[
\text{inrole(class, bob, student)}.
\]
The predicate allowed captures the rules of all privacy contexts. The individual rules for each context are stated using clauses that contain the predicate allowed in the head. As an example, the following clause codifies the rule that professors can let any student know her own grade upon her request:

\[
\text{allowed}(\text{class}, \text{Sndr}, \text{Recp}, \text{Subj}, \text{grade}, \text{need}) :- \\
\text{inrole}(\text{class}, \text{Sndr}, \text{professor}), \\
\text{inrole}(\text{class}, \text{Recp}, \text{student}), \\
\text{Subj} = \text{Recp}.
\]

Note the close correspondence between this clause and the shape of the survey questions discussed in Section 3.

A Datalog program is executed by evaluating a query that asks whether a certain conjunction of predicates holds true according to the clauses in the program. Suppose that in our social platform we have a classroom context whose actors are described by the following facts:

\[
\begin{align*}
\text{inrole}(\text{class}, \text{bob}, \text{student}). \\
\text{inrole}(\text{class}, \text{alice}, \text{student}). \\
\text{inrole}(\text{class}, \text{steve}, \text{professor}).
\end{align*}
\]

Then we can use the query mechanism to check whether a specific information flow satisfies all the specified privacy rules. For instance, given the above privacy rule and facts, the query

\[
?- \text{allowed}(\text{class}, \text{steve}, \text{bob}, \text{bob}, \text{grade}, \text{need}).
\]

evaluates to true, indicating that the corresponding information flow is admissible. On the other hand, the query

\[
?- \text{allowed}(\text{class}, \text{steve}, \text{alice}, \text{bob}, \text{grade}, \text{need}).
\]

evaluates to false, indicating that this flow is not permitted.

### 4.3 Privacy logic verification

Datalog allows us to formally specify CI rules in a declarative manner. In particular, we can use the query mechanism of a Datalog interpreter to check that all information flows in a social platform are consistent with the specified rules. The semantics of Datalog guarantees that no norm-violating flows will be permitted at run-time. The fact that Datalog provides a formally defined semantics for CI rules has another important advantage: it enables us to verify that the rules of a given context satisfy desirable high-level privacy properties that are not immediately evident from the rules. For example, we may want to verify that our rules do not permit the flow of confidential information to third parties. We can check such properties statically before the rules are in effect.

One specific application of formal verification in our proposed crowd-sourced learning approach is that we can check whether the rules that have been approved by the crowd are not violating the rules that have been disapproved. In particular, we can leverage formal verification to facilitate the automatic adjustment of the threshold that determines which rules are considered to be approved. In the following, we describe in more detail how such static verification tasks can be automated.

The problem of verifying that a given set of rules \( \mathcal{R} \) satisfies a given property \( P \) amounts to checking logical validity of the implication \( \mathcal{R} \Rightarrow P \), or dually, that the conjunction \( \mathcal{R} \land \neg P \) is unsatisfiable. For simple properties \( P \), the latter can be checked directly using Datalog queries. However, in general, Datalog queries are not sufficiently expressive to verify complex high-level properties. Fortunately, we can embed Datalog in a more expressive logic that is still amenable to automated reasoning and yields tractable performance for the static verification of high-level properties in practice.

Datalog is a fragment of first-order predicate logic. Specifically, suppose we are given a set of rules \( \mathcal{R} = \{ R_1, \ldots, R_n \} \) where each rule \( R_i \) is specified by a Datalog clause of the form

\[
\text{allowed}(\text{C}, \text{Sn}, R, \text{Su}, A, T) :- C_{i,1}, \ldots, C_{i,m_i}.
\]

and the atoms \( C_{i,j} \) are either \text{inrole} predicates over the given variables in the head of the clause or equalities between these variables and constants such as \( \text{student} \), \( \text{grade} \), etc. Then the semantics of these clauses is captured by the following quantified formula:

\[
\forall C, \text{Sn}, R, \text{Su}, A, T. \\
\text{allowed}(C, \text{Sn}, R, \text{Su}, A, T) \iff \left( C_{1,1} \land \cdots \land C_{1,m_1} \right) \lor \cdots \lor \left( C_{n,1} \land \cdots \land C_{n,m_n} \right)
\]

This formula falls into Effective Propositional Logic (EPR), a decidable fragment of first-order predicate logic \([5]\). Several automated theorem provers implement decision procedures for EPR, e.g., the Satisfiability Modulo Theories solver Z3 \([11]\). If the privacy property \( P \) of interest is itself expressible in EPR, then we can use Z3 to automatically check that the rules \( \mathcal{R} \) guarantee \( P \). Fortunately, many properties of interest are indeed expressible in EPR. For example, the following EPR formula expresses that in the classroom context, a professor should not be allowed to send a student’s grade to any other student, unless that other student is a TA:

\[
\forall \text{Sn}, R, \text{Su}, T. \\
\text{inrole}(\text{Sn}, \text{professor}) \land \text{inrole}(R, \text{student}) \land \text{allowed}(\text{Sn}, R, \text{Su}, \text{grade}, T) \Rightarrow \\
\text{Su} = R \lor \text{inrole}(R, \text{TA})
\]
Figure 3: Information norm: The professors is allowed to share the student’s grade with the student’s TA with the requirement of confidentiality.

Note that this property cannot be checked with a simple Datalog query. We need the additional expressiveness provided by EPR. More generally, EPR can express properties about transitive information flows that involve arbitrarily long sequences of information exchanges. Since the satisfiability problem for EPR is decidable, we can verify these properties fully automatically using tools such as Z3. In particular, if a specified property is not guaranteed by the rules, the theorem prover will produce a model describing an information flow that respects the rules but violates the property. Using this model, we can then identify the rules that are responsible for this property violation.

4.4 Crowdsourcing privacy rules

In this section we describe the procedure for constructing questions from CI norms. Users are provided with a series of multiple-choice questions; each possible answer corresponds to a different information flow. This allows us to establish a baseline for users’ expected privacy preferences. To simulate this process, we relied on Amazon Mechanical Turk (AMT), as we describe in Section 5.

4.4.1 Constructing questions

As depicted by the example in Figure 3, CI norms contain the following elements: actors (senders, subjects and recipients), attributes (information types), and transmission principles (constraints on flow). Below are some examples of their possible values. We should note that this is not a comprehensive set of values. Rather, we use this preliminary set to bootstrap the system. We discuss how new attribute values can be added in the next Section.

Senders: Professors, TAs, Registrar, University librarians, University IT staff, classmates, academic advisor

Subjects: Student

Recipients: Professors, TAs, Registrar, University librarians, University IT staff, Department chair, Classmates, Parents, Academic advisor

Attributes: Grades, Transcript, Name, Email address, Address, Record of attendance, Level of participation in class, Photo, Library records, Contents posted on online learning systems (e.g., Blackboard, Classes, etc.), term paper

Transmission principles:

Confidentiality: With the requirement of confidentiality

Knowledge: If the \( \langle \text{sender} \rangle \) let the student know

Permission: If the \( \langle \text{sender} \rangle \) asked for the student’s permission

Purpose: To improve the learning experience

Breach of contract: If the student is performing below a B- standard

Need: If requested by the \( \langle \text{recipient} \rangle \)

Note that, as a theoretical framework, CI does not mandate any particular implementation. Although the resulting 5-tuple is a conventional way of representing different information flows, it can be extended to include additional elements (e.g., by introducing the context element in our encoding) to fully encompass the expressive reality. For the sake of simplicity we rely on the 5-tuple format for now. We inject each of the elements into the following Yes-or-No question template:

“Is it acceptable for the \( \langle \text{sender} \rangle \) to share the \( \langle \text{subject} \rangle \)’s \( \langle \text{attribute} \rangle \) with \( \langle \text{recipient} \rangle \) \( \langle \text{transmission principle} \rangle \)?”

From the answers to the crowdsourced questions we extracted a truth table describing the information flows that are admissible in this context. The admissibility is determined by a rank-threshold which is set in the system configurations. The learned truth table represents a formal specification of the contextual privacy norms.

Note that during question generation we do not enumerate the full space of all possible privacy norms that can be expressed over the given parameter values. Instead, we rely on the input of a privacy expert to reduce the explored space to those candidate norms that cover
the bulk of the relevant information flows. For the educational context, expert knowledge enabled us to reduce the relevant space from an initial 28 thousand questions to only 1411.

4.4.2 Introduction of new norms

The crowdsourced set of privacy norms will vary depending on the initial input; however, for the system to evolve (i.e., in order for it to be able to introduce new privacy rules) it needs to be able to adapt to information flows that have not previously been entered into the system. We envision the system to evolve in the following manner:

User input. In order to adapt to new information flows, and to be able to develop rules that correspond to them, users will in some cases be able to “edit” their answer to a particular question, or even the question itself. For example, the transmission principle can be used to indicate a new actor, e.g., “With the permission of the [NEW ACTOR],” so a question can be displayed as follows: “Is it acceptable for the student’s professor to share the student’s grades with the student’s TA with permission of the [NEW ACTOR]?” Users will be able to either choose from a selection of preexisting actors or to introduce a new actor to the system. Answer options that correspond to “Does not make sense” will weed out spam lows. Other CI attributes, such as Subject, Sender, Receiver, etc., can be introduced in a similar fashion.

Expert input. As an alternative or supplementary approach to the crowd-sourced one, new actors could also be introduced by designated domain experts. Experts periodically decide, based on external factors, which new actors/attributes should be introduced into the system.

Both approaches can be used in combination, in a curation-type mode. The expert could check the inputs from users to make sure they are relevant to a given context.

Ultimately, privacy rules corresponding to new elements will trigger the generation of new corresponding questions which will be presented to the users for ranking.

5 Evaluation

In our experiments we aim to evaluate the following components:

- How the metrics we propose can serve as indicators of the state of norms that have already been approved and whether users are satisfied with the socially derived Actionable Privacy Rule (APR) set
- Test our automatic verification approach for consistency of the derived privacy logic

5.1 Simulation design

For the purpose of this simulation, we took the educational context as an example to test whether the CI framework would be able to better encapsulate users’ privacy expectations. We constructed a context-specific set of questions that would allow us to crowdsource corresponding informational norms. Our target population was US residents, between 18-26 years of age, and currently enrolled in (or graduated within the past three years from) an institution of higher education in the United States. We posed these questions using an online survey designed with Qualtrics and administered on Amazon’s Mechanical Turk.

We used a script to generate the initial set of norms based on the most common CI parameters in a classroom setting (e.g., teachers and students as actors; grades as attribute; knowledge or consent as transmission principles). To decrease the total number of questions asked, two of the authors performed a preliminary scan of the norms to identify the ones that clearly did not make any sense. Rather than manually going through the questions one by one, the authors focused exclusively on valid pairs of senders and attributes. From experts’ feedback, we introduced some restrictions to remove questions that are blatantly nonsensical (e.g., university librarians cannot be senders of content posted on online learning systems). Following these restrictions, we ended up with a total of 1411 questions. We randomized the questions and divided them up into 15 sets (12 with 88 questions, 3 with 89 questions) with about 30 respondents each. That way, we would be able to ask all possible questions within this context (i.e., achieve completeness) at a reasonable cost ($2 per user per survey, plus AMT fees).

Some of the remaining questions, while perhaps valid, are not applicable in the real world and thus make little sense to the survey participants (e.g., it might be unlikely for certain senders to have access to certain attributes). We therefore provided users with three different answer options that suggest nonsense (i.e., “Does not make sense” (DMS) questions):

1) The sender is unlikely to have the information
2) The receiver would already have the information
3) The question is ambiguous.

In total, we had 451 respondents to the 15 surveys: each user had to respond to 88-89 questions, with 28-
32 respondents per question in each survey. The average completion time per user and survey was around 14 minutes.

5.2 Approximation of Users’ Privacy Expectations

In this section we look at the pulse functionality of the framework. We introduce a number of indicators that together allow us to construct an estimate of the users’ overall attitude towards the existing set of privacy norms. Specifically, we considered three metrics in our evaluation: the norm approval score, the user approval score and the divergence score.

Norm approval score (NA) Our most important metric is the norm approval score (NA). This is our measure of what question is approved by the community for the operational privacy-rule set. We define the NA score of question \( i \) as follows:

\[
NA_i = \frac{\sum_{j=1}^{m} Y_{i,j}}{\sum_{j=1}^{m} (Y_{i,j} + N_{i,j} + DMS_{i,j})} = \frac{\sum_{j=1}^{m} Y_{i,j}}{m} \quad (1)
\]

Here, \( Y_{i,j} \) is defined to be 1 iff respondent \( j \) answered “Yes” to question \( i \). Similarly, \( N_{i,j} \) and \( DMS_{i,j} \) indicate whether user \( j \) answered “No”, respectively, chose “Does not make sense”. Thus, \( NA_i \) is the ratio between the total number of “Yes” answers and the number of all answers for question \( i \) across all \( m \) respondents. A norm is considered approved if its NA exceeds a certain threshold, e.g., a simple majority (\( > 50\% \)).

User approval score (UA) This metric measures the relative number of norms that have been approved by a given respondent. Formally, the value \( UA_j \) for respondent \( j \) is defined as

\[
UA_j = \frac{\sum_{i=1}^{n} Y_{i,j}}{\sum_{i=1}^{n} (Y_{i,j} + N_{i,j} + DMS_{i,j})} = \frac{\sum_{i=1}^{n} Y_{i,j}}{n} \quad (2)
\]

where \( n \) is the total number of questions in the survey that \( j \) responded to.

Divergence score (DS) This metric looks at how the answers of individual respondents vary from the norms that have been approved and disapproved by the whole community subject to a given NA threshold. Intuitively, it quantifies how dissatisfied a user is with the extracted set of operational norms. Formally, the divergence score \( DS_j \) of respondent \( j \) is defined as

\[
DS_j = \sum_{i=1}^{n} c_i \oplus u_{i,j} \quad (3)
\]

Here, the bit \( u_{i,j} \) is defined to be 1 iff respondent \( j \) approved the norm described by question \( i \) and \( c_i \) is defined to be 1 iff the community as a whole approved the norm. Hence, \( DS_j \) indicates the number of times respondent \( j \)’s expectations differed from the operational privacy rule set that was enforced based on the chosen NA threshold.

5.2.1 Summary of crowdsourced data

We summarize relevant results in Table 1. The number behind the “Yes” and “No” columns reflects questions exceeding the respective NA thresholds. In 36 questions, the respondents could not reach any agreement because the number of “Yes” and “No” answers was identical. Although this is a small percentage of the total number of questions, it highlights an important point: some information flows require closer attention; if this is the case our design allows individuals to select norms according to their personal preferences and identify points of contention through formal verification techniques.

5.2.2 Norm approval thresholds

Next, we analyzed the different NA thresholds and how these threshold choices affect the users’ approval and divergence scores. We focused first on the two thresholds of 50% and 66%. Figure 4 depicts two boxplots for all users across all questions for the two NA thresholds. Both populations look very similar. To verify the difference in means of these two population we ran a one-way ANOVA to test a null hypothesis that there is no difference between the populations of means under different thresholds. We can reject the null hypothesis with significance level \( p = 0.000165 \) \( (p < 0.05) \). A Tukey HSD test identified that using the 66% threshold increases the DS score by 4.8%.

In other words, this shows that the 66% threshold results in a higher disapproval among users with regards to their expressed privacy expectations.

5.2.3 How satisfied are users with the set of chosen norms?

Figure 5 depicts a scatter plot that shows the number of users with the same DS score across all the questions.
for an NA threshold of 66%. The plot indicates a large concentration of respondents with a relatively small DS. This means that, overall, the users in our polls are satisfied with the operational privacy rule set chosen by the system for this specific NA threshold.

Furthermore, to understand how the DS varies across all the different thresholds, we calculated a combined DS for all possible NA thresholds (0% to 100%) and normalized it by the number of total users that had taken the survey. The normalization provides us with the combined DS score of all users per threshold. Our results, depicted by Figure 5, show that when the threshold is at its minimum, DS is at the maximum. Recall that DS represents the level of dissatisfaction of users. We can therefore interpret this result as follows: when the threshold is low, more questions are approved, meaning that a significant number of privacy rules that users prefer to disapprove are included in the operational set. The lowest DS values are in the 40% to 60% NA threshold range. The best candidates for an actual threshold choice, for this specific population based on their feedback, therefore seem to lie in that range. Interestingly, the DS converges around the 35 mark from 66% to 100%. This shows that, in our polls, more people opt to disapprove norms than approve them.

5.2.4 Individual privacy expectations vs Social norms

Figure 6 shows that there is a linear relationship between UA and DS for the individual users for a 66% NA threshold. Linear regression analysis confirms this ($r^2 = 0.87$, formula: $DS = 0.69 \times UA + 2.044$). The 66% NA threshold makes it hard to approve privacy rules; users with a very high UA score will often be disappointed, thus having higher DS. Conversely, users that have a lower UA are more likely to agree with the community rules. We can observe a similar pattern with an NA threshold of 50% on Figure 7, however, relative to the 66% threshold, user satisfaction is slightly higher as more privacy rules are approved on average.

5.3 Verification of extracted rules

Finally, we evaluate the effectiveness of formal verification technology to analyze the consistency of the derived privacy logic. We used the theorem prover Z3 to
check whether the crowdsourced rules guarantee certain privacy properties by encoding both the rules and the properties into an Effectively Propositional Logic (EPR) as described in Section 4.3. Specifically, our goal was to assess whether we can use Z3 to automatically check the consistency between the rules that we derived from the crowd-sourced data for a chosen threshold, on the one hand, and to check for consistency violations, on the other hand. We focused our attention on two specific consistency properties:

1. **Semantic consistency rules.** This property specifies that the information flow of each disapproved norm is indeed excluded from the flows that are allowed according to all approved norms. Note that this property is not trivially satisfied as the approved and disapproved norms are not necessarily mutually exclusive. In particular, the roles of a context are not guaranteed to be disjoint, e.g., an actor in the classroom context may be both a department chair and a professor. Thus, we may have situations where a specific flow is approved if the sender is a professor but disapproved if the sender is a department chair. Such inconsistencies hint at hidden assumptions of the survey participants that are not adequately reflected by the formal privacy rules. Our verification approach allows us to detect such inconsistencies and subsequently eliminate them by refining the formal rule model and the survey questions appropriately.

2. **Consistency of transitive flows.** This property specifies that the approved norms are transitively closed. For example, if a professor is allowed to send the grade of a student to the registrar and, in turn, the registrar is allowed to send the grade to a graduate school to which the student has applied, then the professor should be allowed to send the grade directly to the graduate school. A violation of the transitivity property hints at a possible mismatch between the survey participants’ privacy expectations and the logical implications of their individual choices regarding which privacy norms should be approved. Using our verification approach, we are able to detect such violations (respectively, prove their absence) for arbitrarily long sequences of information flows.

In the following, we describe the experiments we conducted to check each of these two properties as applied to the set of norms that we derived from our survey data. Note that in both experiments the entire verification process including the norm extraction, the logical encoding of the norms and properties, and their verification, was fully automated.

All the experiments were run on a laptop computer equipped with an Intel Core i5 CPU at 2.67GHz and 4GB RAM running Ubuntu Linux. The running time for each of our experiments was less than 5 seconds. The memory consumption was negligible.

5.3.1 Detecting semantic inconsistencies of norms

For our experiment, to detect semantic norm inconsistencies we chose the 50% threshold to determine which norms are approved according to the crowd-sourced survey data. For this threshold, as depicted by Table 1, 315 of our total 1411 norms were approved. We then encoded these approved norms into an EPR formula and used Z3 to check for each of the 1096 remaining disapproved norms whether the corresponding information flow was indeed prevented by the approved rules. Each disapproved norm was checked by sending a separate satisfiability query to Z3.

Intuitively, semantic norm inconsistencies can only
arise if an agent takes on more than one role in a context at the same time. We confirmed this intuition by conducting an experiment where we verified the absence of inconsistencies under the assumption that all roles are pairwise disjoint. Indeed, under this assumption we were able to prove that 100% of the disapproved norms were consistent with the rules for the approved norms.

To detect actual semantic norm inconsistencies, we considered a model that took the relationships between the different roles in a classroom context into account. For example, a TA may also be a student and a department chair is always a professor. With the realistic model, we detected that 138 of the 1096 disapproved norms were not ensured by the approved norms. For example, one of the violated disapproved norms pertained to a professor sharing a student’s test result with other students. Such an information flow was permitted by one of the approved norms, which allowed a professor to share a test result with a TA. Since a TA may also be a student, the disapproved norm was indeed violated.

There are a number of possible ways in which such violations could be resolved (e.g., by refining the privacy rules or domain ontology). These are outside the scope of this paper. The focus of our experiment was to demonstrate that we can automatically detect all such violations, or alternatively prove their absence.

### 5.3.2 Detecting inconsistencies in transitive flows

The final experiment was designed to check for inconsistencies due to transitive flows. Similar to the previous experiment, we encoded the logic into an EPR formula and used Z3 to check for any violations of the transitivity property. The transitivity property involves reasoning about arbitrarily long chains of information flows. This means that for a specific set of approved norms, the number of concrete chains of information flows that are consistent with the rules but violate transitivity may be infinite. However, we observed that for any specific violation, there always exists a similar violation involving a chain of bounded length. This means that all transitivity violations can be classified by a finite set of small violations. This observation allowed us to exhaustively enumerate all types of transitivity violations for a given set of approved rules. To do so, we used Z3’s model generation capability to generate models that witness a small violation of transitivity.

For the 66% threshold, where 115 of our total 1411 norms were approved, we automatically detected 59 transitivity violations. On closer inspection, we found that one such violation was the result of the following two approved norms:

1. **A TA is allowed to send information about a student’s attendance to a professor if the student is performing poorly.**

However, a TA was not allowed to send the attendance information directly to the department chair, leading to a violation of transitivity. The approval rate of this rejected norm was only 17%. Contrasted with the high approval rates of more than 66% for the two approved norms involved in the above transitive flow, this discrepancy hints at a possible violation of the actual privacy expectations of the users.

### 6 Discussion

**Broader applicability:** We note that we only discussed our framework in a specific case of an educational context. In principle, the same approach can easily be applied for other context definitions or a much broader/expanded set of actors, attributes or transmission principles. In addition, the same methodology can be applied in an incremental fashion when new actors or new attributes or new transmission principles are added to the context definition.

**Choosing real users in practice:** When applying the CI-based framework in a real-world social platform, we envision that the questions generated by the framework for a given context will be answered by the users of the same platform within the same context. For example, consider a set of users who are within a given community in an online social platform. In our evaluations, we used AMT to primarily simulate the responses of actual system users. Although previous research [19, 21, 15] provides an early affirmation of the effectiveness of crowdsourcing tools, suggesting that large-scale surveys can indeed be effective for discovering norms, we interpreted our survey only as an approximation of the kinds of feedback we would receive in a mature system with actual users. We would also like to emphasize that, in an operational system, users would only have to respond to a significantly reduced number of questions. Finally, AMT does not allow us to test cases in which new norms are introduced, as described in Section 4.4.2. We aim to address this issue in future work.

**Privacy logic.** We acknowledge that technical systems usually embody an idea of what privacy is, whether this is merely implicit in the design or stated explicitly in theoretical terms, as we have done. The sources of such ideas may be varied: the intuitions of a design team, law and other regulatory systems, privacy experts, etc. We do not take issue with these sources. However, the approach we take, we believe, is particularly well suited
for information systems involving diverse social actors interacting with one another through complex patterns of communication (or flows) of information.

**Verification.** The encoding into EPR and subsequent verification is fully automated. Our approach differs from prior work in that our encoding of norms and properties remains within a decidable logic that admits practical decision procedures. In particular, this means that a failed verification attempt is always due to an actual property violation (as opposed to an incompleteness in the verification approach). What is more, if verification fails, the theorem prover creates a model from which a violating information flow can be extracted. This enables the automated diagnosis of inconsistent norms, which can in turn be used to automate a feedback loop in the crowdsourced norm generation.

### 7 Related Work

In this section we acknowledge important prior and adjacent work that is related to ours. This roughly falls into four different categories: a) Other Access Control (AC) frameworks; b) Other efforts adopting the CI framework for building privacy-preserving systems; c) Other compliance-based approaches to privacy-by-design (PbD); d) Other efforts utilizing crowd-sourcing to promote system privacy.

**Other AC frameworks.** Many other frameworks have been designed to manage access control to information and other privacy-preserving functions. Barth et.al., [3], provide a comprehensive comparison of the CI framework to other existing models such as Role-Based Access Control (RBAC), the eXtensible Access Control Markup Language (XACML), Enterprise Privacy Authentication Language (EPAL), and the Platform for Privacy Preferences (P3P).

**RBAC.** In RBAC, access control is defined in terms of available resources and users’ roles that have access to it. Compared to RBAC, CI is a more generic framework that introduces additional attributes, namely contexts, subjects, as well as transmission principles, that capture more accurately the different dynamics according to which information is shared.

**XACML.** The eXtensible Access Control Markup Language (XACML) is a generic XML-based markup language that allows specifying attribute-based AC policies for resources. XACML can be used to implement Attributed Base Access Control (ABAC) as well as the RBAC scheme. We can also express the CI framework using XACML by capturing the contextual and information flow semantics behind the CI norms.

**P3P.** The P3P language is designed to help websites describe their privacy policies with regards to users’ data. In contrast to the CI framework, P3P is limited to policies involving only two parties, i.e., the website and the visitor, operating in a very specific, global context [3].

**Other works based on CI.** In [3] the authors proposed a logical framework for reasoning about privacy expectations and privacy practices using CI. The same formalization of contextual has been also used in [17]. The framework uses first-order temporal logic (FOTL) to express norms by describing the actors that participate in each context, the roles these actors play, and their knowledge states, all at a specific point in time. While FOTL-based formalisms can model temporal properties related to contextual integrity, the logic itself is too expressive to serve as a suitable foundation for tools that mechanize reasoning about privacy norms in real-world systems. For example, the valid formulas of full FOTL are not even recursively enumerable. Consequently, any automated approach to reasoning about validity, respectively, satisfiability of formulas in full FOTL is inherently incomplete [2].

In [10] the authors propose computational and information models of Implicit Contextual Integrity in a social network. The main motivation behind this work is based on the idea that context in OSN is never explicitly defined and must be inferred from the information itself. The paper introduces the notion of an Assistant Agent which uses the defined information model to infer any implicit contexts, relates them to existing norms and stops undesirable information flows. In our work, we rely on the users to decide on valid and relevant information flows and contexts in the system.

Similarly, Y. Krupa and L. Vercouter [16] looked into having an Assistant Agent be part of a Privacy as Contextual Integrity for the Agent Systems (PrivaCIAS) framework for open and decentralized virtual communities. The agent is designed to assist users with preserving their information privacy as well as detecting other users that violate the established privacy norms. The framework is based on a trust model where agents gossip about their “experiences” to inform other agents of any violations as well as provide passive feedback. The ultimate goal is to socially exclude “bad” agents from the system. While this work focuses on enforcing CI norms in a distributed environment, it does not discuss how to extract the prevailing set of norms in the first place. Our framework can complement such initiatives by providing a mechanism.
for extracting CI privacy norms from the community of users and verify their consistency.

Compliance-based approaches to PbD. Rising to the call for PbD, numerous approaches have been invented to map system constraints to privacy policies that are generated external to these systems. Two examples, are Sen, et. al. in [28] and Breaux and Anton in [6]. Sen, et. al. have developed LEGALEASE, a language with precise semantics that enables enterprises to express privacy policies against which practices can be checked for compliance. With similar goals, Breaux and Anton have proposed a methodology for extracting implementable software requirements from privacy and security regulatory requirements expressed in legal language that is sometimes vague and ambiguous. The intention in both examples is similar to our own in that it seeks to translate privacy requirements expressed in natural language (assuming this covers legal language) into formally expressed rules that allow for compliance checking. The threat scenarios, however, are quite different. Further, both examples start with externally generated privacy norms, which they seek to express in formal language.

Other uses of crowdsourcing to generate privacy rules. One effort that is quite close in spirit to our own is [27] which seeks to ease the burden on users when tailoring privacy policies on mobile apps to accurately reflect their privacy preferences. The system clusters users according to their willingness to share information with app providers and configures settings on future apps based on the position in a cluster. Relevant differences are (i) that it applies to a dyadic relationship between the user and app provider, and (ii) it seeks to model preferences while our work aims to model social norms.

Similarly Tohn [32] has proposed the SuperEgo system, which uses crowdsourcing to enhance location privacy management in mobile applications. SuperEgo uses the perception of the crowd to predict the privacy preferences of an individual. The system relies on a crowd-opinion model and a mixture of decision-making strategies to classify the information as private or not. Although this work is conceptually similar in that it uses crowdsourcing to infer relevant privacy policies for the user, it is limited to a location-based privacy context. As noted by the author, the CI framework is more expressive and capable of capturing privacy-rules in a range of different contexts.

In summary, previous contributions focused on applying the CI framework to enforce privacy norms in different domains. Our work builds on these efforts by capturing relevant norms in a given context and then proposes a privacy-preserving framework that efficiently encodes them into a actionable and verifiable privacy logic.

8 Summary and Conclusion

In this paper we described a framework for discovering verifiable and actionable privacy norms in a community of users based on the theory of contextual integrity.

We evaluated our proposed framework by conducting an extensive survey involving more than 450 participants and 1400 questions to derive a set of privacy norms in the educational context. We were able to show that the Datalog encoding of the derived norms enables us to automatically verify the consistency of (transitive) information flows and automatically detect logical inconsistencies between individual users’ privacy expectations, on the one hand, and the derived privacy logic, on the other hand. Our results leave us optimistic about the feasibility of a full-fledged information system that operates based on the design principles of crowdsourcing, formal verification, and contextual integrity.

Future work includes an in-depth investigation into more elaborate approval and divergence metrics, an extension of our design to handle inter-domain privacy rules as well as the release of a prototype system based on privacy norms discovered using the methods we have developed.

Looking even further into the future, our work paves the way towards information systems that operate on a foundation of substantive privacy rules that reflect the rough consensus of given communities. These could include communities across the domains of education, health, or more general social domains. The mechanisms we have developed for extracting, expressing, and validating a set of common rules could be integrated into such systems. By incorporating these mechanisms into information/social systems, user feedback can be continuously elicited, which will enable a system to refresh rules continuously to reflect evolving community norms and standards.

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