

# Exploring Consequences of Privacy Policies with Narrative Generation via Answer Set Programming

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Informed consent has become increasingly salient for data privacy and its regulation. Entities from governments to for-profit companies have addressed concerns about data privacy with policies that enumerate the conditions for personal data storage and transfer. However, increased enumeration of and transparency in data privacy policies has not improved end-users' comprehension of how their data might be used: not only are privacy policies written in legal language that users may struggle to understand, but elements of these policies may compose in such a way that the consequences of the policy are not immediately apparent.

We present a framework that uses Answer Set Programming (ASP) – a type of logic programming – to formalize privacy policies. Privacy policies thus become constraints on a narrative planning space, allowing end-users to forward-simulate possible consequences of the policy in terms of *actors* having *roles* and taking *actions* in a *domain*. We demonstrate through the example of the Health Insurance Portability and Accountability Act (HIPAA) how to use the system in various ways, including asking questions about possibilities and identifying which clauses of the law are broken by a given sequence of events.

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## 1 INTRODUCTION

The rules, laws, and norms for releasing private information are constantly evolving; consequently, individuals are asked to agree to increasingly complex laws and terms of service that they may not understand. Despite the stakes, research shows that even well-educated users have trouble understanding privacy policies [20], creating an *information asymmetry* between providers of these services and the user, where the user is not fully aware of the consequences of their consent, leading them to agree to release information under circumstances they could not have anticipated [1].

Prior formalization efforts have focused on verifying the compliance of data-sharing software with the law. Unfortunately formalization has not focused on end-user understanding of the complex pathways by which their data may be shared. We present a novel approach to formalization of privacy policies that can be used to *explain* the consequences of privacy policies via narrative. This work focuses on the technical backend of such a system and proposes a possible rendering.

*Motivating Example: HIPAA via Narrative Constraints.* The Health Insurance Portability and Accountability Act (HIPAA) is a US law enacted in 1996. It was created to modernize and regulate the flow of healthcare information, and protect patient privacy. HIPAA is well-studied in the privacy compliance literature, has a history of interpretation, and is an exemplar of modular and non-trivial

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privacy legislation. HIPAA has previously been formalized via Prolog in service of the verifying software-based data sharing and we leverage this prior work in our encoding [15, 16]. Here we focus on the part of HIPAA that regulates the transmission of protected health information (PHI) by healthcare entities and use our system to answer the following questions:

**Q1** Alice asks: can hospitals sell my PHI to third parties?

**Q2** Alice asks: when can hospitals sell my PHI to third parties *without my authorization*?

**Q3** Bob asks: when can my employer obtain my PHI?

## 2 BACKGROUND AND SYSTEM DESIGN

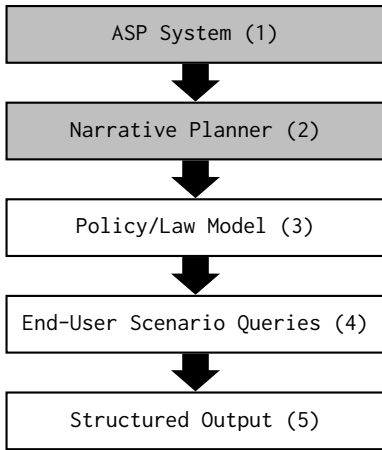


Fig. 1. The end-to-end architecture of our privacy exploration system. Greyed out blocks represent prior work: the Clingo ASP programming system [11] provides the general language and solver, but does not include the primitives necessary to reason about narrative. We leverage the general-purpose narrative planner of [9] to encode rules and constraints pertaining to time and actors. This work illustrates one possible instantiation of a privacy law: HIPAA, as well as several end-user queries and structured graphical output.

We formalize privacy policies using Clingo, an Answer Set Programming (ASP) system [11]. ASP is a declarative programming technique where logic programs are specified in terms of generative rules, facts, and constraints in a syntax similar to Prolog. A constraint solver then attempts to find stable models (answer sets) for the logic program [12]. ASP differs from classical logic programming via its “choice rules,” which allow multiple possible worlds to be consistent with a given program; syntactically, the head of choice rules in ASP may be an arbitrary-sized set of ground atoms.

*Narrative generation* is the creation of causally-related and temporally ordered sequences of events that form a *story* having certain properties; it is commonly framed as an AI planning task. Narratives depicting plausible real-world scenarios that are consistent with privacy policies would serve well as examples to educate users, while also addressing the context-dependence of user perceptions of privacy [18].

A *narrative planner* is software that generates a partial order of events. Implementing a planner in ASP opens up the possibility of using the rich constraints provided by the system for sculpting the possibility space of generated narratives. Our narrative planner is general purpose and supports *intentional actors* (i.e., agents that act with purpose) and *conflicts* (i.e., heterogenous intents that may not be satisfiable). For now we focus strictly on intentional and cooperative actors.

## 3 ENCODING PRIVACY POLICIES

The first step in our framework is to encode the relevant *roles* that an actor may assume and the *actions* an actor inhabiting a role may take. This corresponds to implementing Box 3 of Figure 1. In our example context, actions that correspond the transmission of patient data as documented in HIPAA clauses become narrative constraints.

*Encoding a Role Hierarchy.* Most clauses in HIPAA are conditioned on the role of the involved entities. For instance, §164.506(c)(5) mentioned four roles, emboldened for emphasis:

A **covered entity** that participates in an **organized health care arrangement** may disclose protected health information about an **individual** to other **participants** in

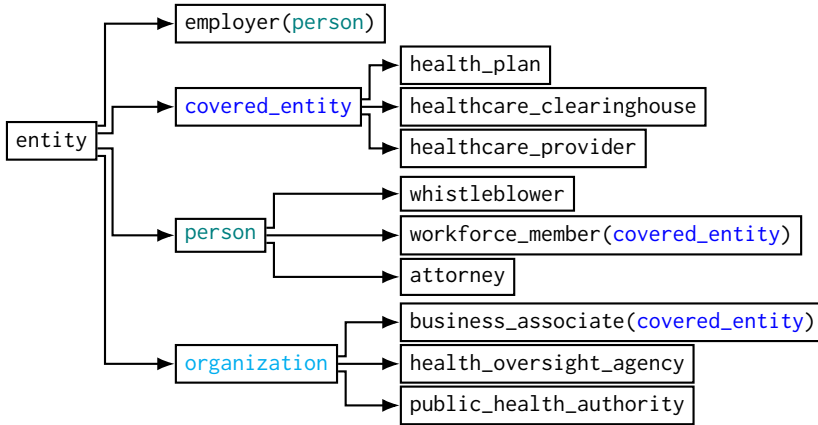


Fig. 2. Partial role hierarchy. Note that certain roles are parameterized. These parameterizations represent constraints on the role. For example, “participant” from the quoted clause of §164.506(c)(5) refers to a **covered\_entity** that participates in a specific **organization**.

the organized health care arrangement for any health care operations activities of the organized health care arrangement.

The roles are relational and form a hierarchy — e.g., “**covered entity**” is further defined in §160.103 as either a health care provider (doctors, clinics, etc.), a health plan, or a health care clearinghouse. Care must be taken to ensure that the hierarchy expresses strict “is-a” relationships; the **covered\_entity** role is an example of this enforcement. Note that a **covered\_entity** can be a **person** (e.g., a doctor) or an **organization** (e.g., a hospital). For example, Seattle Grace Hospital is a **covered\_entity** by virtue of **healthcare\_provider(sgh)**. Then Dr. Cristina Yang holds at least two roles: she is a **covered entity** by virtue of **healthcare\_provider(yang)** and a **person** by virtue of **workforce\_member(sgh)(yang)**.<sup>1</sup> Figure 2 depicts a partial graph of the role hierarchy.

*Encoding Permissible Actions.* Actions in the generated narrative are carried out by *agents* with roles. An agent with a given role is also automatically assigned all parent roles in the hierarchy. Additionally, an agent may also take on an unconnected role. For instance, a doctor may also take the role of patient, with the obvious restriction that an organization cannot also be a person. These roles may be assigned manually as part of the initial conditions, or automatically by the planner in order to satisfy a given narrative constraint.

HIPAA defines many actions that can be performed by agents. For instance, §164.512(f)(3) states:

Except for disclosures required by law as permitted by paragraph (f)(1) of this section, a covered entity may **disclose** protected health information in response to a law enforcement official’s **request** for such information about an individual who is or is **suspected** to be a victim of a crime, other than disclosures that are subject to paragraph (b) or (c) of this section, if: (i) The individual **agrees** to the disclosure; or (ii) The covered entity is unable to **obtain** the individual’s agreement because of incapacity or other emergency circumstance...

There are some *latent* actions that an expert must encoded in order to form a coherent narrative. For instance, to **disclose** protected health information, the **covered entity** must first **acquire** it, and the acquired information must be about the specific patient in question. There are many ways to

<sup>1</sup>For simplicity we are treating all predicates as curried; this is not Clingo syntax.

```
% Giving treatment to a person is one way to
% acquire their health info
possible(I, A, al(Person, al(CE))):-
    id(I),
    A=action(get_treatment, Person, CE),
    role(Person, person),
    role(CE, covered_entity).

initiates(I, A, has_info(CE,Person,phi,I)):-
    A=action(get_treatment, Person, CE),
    happens(I, A, _).
```

Fig. 3. Example action encoding for one way to **acquire** information. The predicates possible and intiates are part of the narrative generator. Each encoded privacy policy must define roles and actions; get\_treatment is specific to HIPAA.

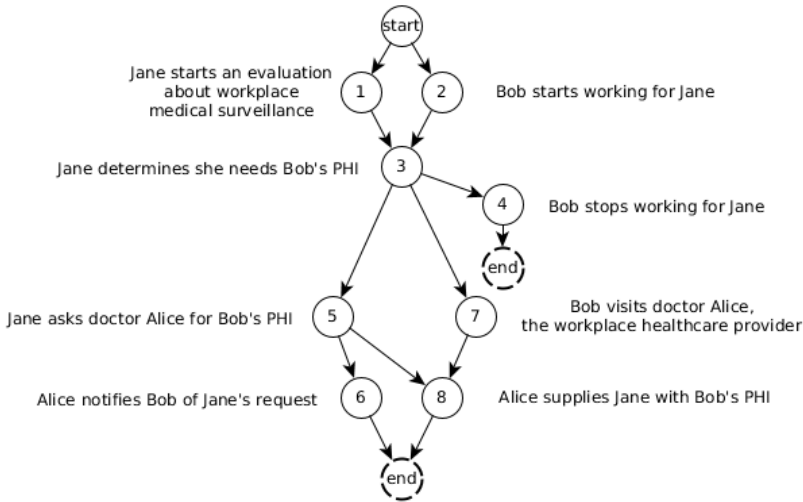


Fig. 4. Templated explanation of narrative output for Q3. Paths through the graph represent a partial ordering of possible events that could lead to Bob’s employer obtaining his PHI.

**acquire** information: e.g., via doctor’s *visit*, or any of a number of possible real world actions. We need to encode at least one such action in our model. Similarly, the “incapacity” must also be the consequence of an event, i.e., we must be able to negate an action.

Fluents track the state of the world and causally link actions. In §164.512(f)(3), **agreeing** to the disclosure must occur *after* the attempt to **obtain** the individual’s agreement is made. We encode this attempt as a fluent. Roles can also be tracked as fluents, allowing them to change through the narrative. Figure 3 gives an example action encoding.

*Encoding Constraints and Additional Objects.* In addition to actors which have roles and can take actions, our system requires reasoning about abstract objects, such as PHI. For instance, a clause applicable to “private health information” must also apply to “psychotherapy notes” (§164.508(a)(2)),

$category_R$	Enforces a "type" on clause subset $R$ .
$exception_R$	Refines a category.
$requirement_R$	Specifies a precondition for clause subset $R$ .
$obligation_R$	Defines a set of events that must occur in the future (in all conflicting timelines) for this action to be compliant in clauses $R$ .
$permits_R$	$category_R \wedge \neg exception_R \wedge requirement_R \wedge obligation_R$
$forbids_R$	$category_R \wedge \neg exception_R \wedge (\neg requirement_R \vee \neg obligation_R)$
$not\_applicable_R$	$\neg category_R \vee exception_R$

Table 1. Description of the rules for transmission of PHI. All rules are replicated from [16], except  $obligation_R$ , which we have added to support transmission constraints over time.

since latter is a type of former. Thus we encode other objects in our system using a hierarchy similar to the role heirarchy.

Clauses allow or disallow transmission of protected information based on certain conditions. Additionally, they may impose future obligations on entities. Here we borrow the encoding scheme of Lam et al. [16], with an additional term to allow future obligations to be checked ( $obligation_R$ ); this rule is necessary to ensure the coherence of narratives. Table 1 lists the full set of transmission rules.

#### 4 QUERYING GENERATED NARRATIVES

After encoding the privacy policy, we can begin asking questions about possible consequences of a policy (Box 4 of Figure 1). One application of our work is to present unexpected consequences or edge cases to the individual. However, since the open-ended generation of scenarios and their interestingness is subjective, we focus on answering the specific queries enumerated in the motivating example.

**Q1 and Q2.** Encoding Alice’s query is straightforward; we do not list it here. Critically, there exists an action `information_sold` in our encoding. The only new information we need to specify in order to answer this query specifically is a fluent asserting that `information_sold` should be true. This is done by forbidding the negation of `information_sold`. This allows us to filter out narratives in which the condition doesn’t hold, without defining the predicate to be true (i.e., the predicate must arise naturally from other parts of the program). For **Q2**, we simply add one line to Alice’s query, which restricts the set of possible answers returned.

We use output templates to translate the tool output into a human readable format for **Q1**. One possible outcome consists of two events: (1) Alice authorizes the hospital to sell her PHI to an advertiser, then (2) the hospital sells Alice’s PHI to that advertiser.

**Q3.** Figure 4 depicts the tool output to **Q3**: if Bob quits his job before the info is requested, the doctor cannot disclose the info to the employer. The planner also says that the action of disclosing the information is permitted by §164.512(b)(v)(A). This graph of possible paths is an an example instance of Box 5 of Figure 1.

#### 5 RELATED WORK

Formal modeling for policies is not new; while legal text often contains ambiguities and cross-references [5], its structured language lends itself readily to a logical representation. To this end, various modeling approaches have been used, including defeasible logic to handle overlaps and

conflicts in legal text [2, 13] and deontic logic to represent permissions and obligations [21]. For a survey of other related work in this area, we refer the reader to Otto and Antón [19].

For privacy-specific legal modeling, Barth et al. [3, 4] present LPU (Logic of Privacy and Utility), a formalization of “Contextual Integrity,” applied in the context of business processes to ensure privacy. DeYoung et al. [10] build on that work with PrivacyLFP logic. Their logic supports obligations and temporal reasoning. They use it to produce a comprehensive formalization of transmission-related HIPAA clauses. Lam et al. [16] describe a system for verifying HIPAA compliance of messages sent by hospital employees. They present pLogic, an executable framework implemented as a Datalog program. Their formalization does not support ensuring future obligations. Chowdhury et al. [6] present a policy specification language based on first-order linear temporal logic, along with an algorithm for static policy analysis of policies like HIPAA.

HCI researchers have focused on presenting privacy policies to users in a more comprehensible way. P3P [7, 8] was a system for allowing websites to declare the intended usage of collected information. The browser could then block any cookies that would conflict with user privacy settings. Lin et al. [17] use crowdsourcing to capture user’s expectations of privacy in the context of mobile apps. They describe a privacy summary interface that emphasizes places where these expectations are broken. Kelley et al. [14] present a “nutrition label” for privacy, displaying in a grid what categories of information are accessed to what extent, drawing from the FDA’s nutrition facts panel.

These efforts focus on presenting static information to the user in a usable manner. Our system enables a richer exploration of regulations through narratives. Our work fundamentally differs from prior work due to the combination of formalization and narrative generation.

*Concluding Remarks.* The goal of this work is not to create another policy modeling logic. It fundamentally differs from the existing efforts, in that it is a *generative* system, as opposed to a *compliance verification* system. While it can be used to verify compliance of a given trace of actions (it does so by attempting to generate a matching narrative), its strength lies in enabling exploration of the encoded regulation through scenarios involving intentional actors. Our vision with this project is to create tools to enable users to better understand privacy policies, empowering them to make an informed decision on when and with whom to share their data. At the same time, we want user expectations to guide policy design. We believe this work is an important first step in that direction.

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## REFERENCES

- [1] Alessandro Acquisti and Jens Grossklags. 2007. What can behavioral economics teach us about privacy. *Digital privacy: theory, technologies and practices* 18 (2007), 363–377.
- [2] Grigoris Antoniou, David Billington, Guido Governatori, and Michael J Maher. 1999. On the modeling and analysis of regulations. (1999).
- [3] Adam Barth, Anupam Datta, John C Mitchell, and Helen Nissenbaum. 2006. Privacy and contextual integrity: Framework and applications. In *2006 IEEE Symposium on Security and Privacy (S&P’06)*. IEEE, 15–pp.
- [4] Adam Barth, John Mitchell, Anupam Datta, and Sharada Sundaram. 2007. Privacy and utility in business processes. In *20th IEEE Computer Security Foundations Symposium (CSF’07)*. IEEE, 279–294.
- [5] Trevor JM Bench-Capon, Gwen O Robinson, Tom W Routen, and Marek J Sergot. 1987. Logic programming for large scale applications in law: A formalisation of supplementary benefit legislation. In *Proceedings of the 1st international*

*conference on Artificial intelligence and law*. 190–198.

- [6] Omar Chowdhury, Andreas Gampe, Jianwei Niu, Jeffery von Ronne, Jared Bennett, Anupam Datta, Limin Jia, and William H Winsborough. 2013. Privacy promises that can be kept: a policy analysis method with application to the HIPAA privacy rule. In *Proceedings of the 18th ACM symposium on Access control models and technologies*. 3–14.
- [7] Lorrie Faith Cranor. 2003. P3P: Making privacy policies more useful. *IEEE Security & Privacy* 1, 6 (2003), 50–55.
- [8] Lorrie Faith Cranor, Praveen Guduru, and Manjula Arjula. 2006. User interfaces for privacy agents. *ACM Transactions on Computer-Human Interaction (TOCHI)* 13, 2 (2006), 135–178.
- [9] Chinmaya Dabral and Chris Martens. 2020. Generating explorable narrative spaces with answer set programming. In *Proceedings of the AAAI Conference on Artificial Intelligence and Interactive Digital Entertainment*, Vol. 16. 45–51.
- [10] Henry DeYoung, Deepak Garg, Limin Jia, Dilsun Kaynar, and Anupam Datta. 2010. Experiences in the logical specification of the HIPAA and GLBA privacy laws. In *Proceedings of the 9th annual ACM workshop on Privacy in the electronic society*. 73–82.
- [11] Martin Gebser, Roland Kaminski, Benjamin Kaufmann, Max Ostrowski, Torsten Schaub, and Sven Thiele. 2008. A user’s guide to gringo, clasp, clingo, and iclingo. (2008).
- [12] Michael Gelfond and Vladimir Lifschitz. 1988. The stable model semantics for logic programming.. In *ICLP/SLP*, Vol. 88. 1070–1080.
- [13] Guido Governatori, Vineet Padmanabhan, Antonino Rotolo, and Abdul Sattar. 2009. A defeasible logic for modelling policy-based intentions and motivational attitudes. *Logic Journal of IGPL* 17, 3 (2009), 227–265.
- [14] Patrick Gage Kelley, Joanna Bresee, Lorrie Faith Cranor, and Robert W Reeder. 2009. A" nutrition label" for privacy. In *Proceedings of the 5th Symposium on Usable Privacy and Security*. 1–12.
- [15] Peifung E Lam, John C Mitchell, Andre Scedrov, Sharada Sundaram, and Frank Wang. 2012. Declarative privacy policy: finite models and attribute-based encryption. In *Proceedings of the 2nd ACM SIGHIT International Health Informatics Symposium*. 323–332.
- [16] Peifung E Lam, John C Mitchell, and Sharada Sundaram. 2009. A formalization of HIPAA for a medical messaging system. In *International Conference on Trust, Privacy and Security in Digital Business*. Springer, 73–85.
- [17] Jialiu Lin, Shahriyar Amini, Jason I Hong, Norman Sadeh, Janne Lindqvist, and Joy Zhang. 2012. Expectation and purpose: understanding users’ mental models of mobile app privacy through crowdsourcing. In *Proceedings of the 2012 ACM conference on ubiquitous computing*. 501–510.
- [18] Helen Nissenbaum. 2004. Privacy as contextual integrity. *Wash. L. Rev.* 79 (2004), 119.
- [19] Paul N Otto and Annie I Antón. 2007. Addressing legal requirements in requirements engineering. In *15th IEEE International Requirements Engineering Conference (RE 2007)*. IEEE, 5–14.
- [20] Robert W Proctor, M Athar Ali, and Kim-Phuong L Vu. 2008. Examining usability of web privacy policies. *Intl. Journal of Human-Computer Interaction* 24, 3 (2008), 307–328.
- [21] Andre Valente and Joost Breuker. 1995. ON-LINE: An architecture for modelling legal information. In *Proceedings of the 5th international conference on Artificial intelligence and law*. 307–315.