Expressing Accountability Patterns using Structural Causal Models

SEVERIN KACIANKA, Technical University of Munich
AMJAD IBRAHIM, Technical University of Munich
ALEXANDER PRETSCHNER, Technical University of Munich

While the exact definition and implementation of accountability depend on the specific context, at its core accountability describes a mechanism that will make decisions transparent and often provides means to sanction “bad” decisions. As such, accountability is specifically relevant for Cyber-Physical Systems, such as robots or drones, that embed themselves into a human society, take decisions and might cause lasting harm. Without a notion of accountability, such systems could behave with impunity and would not fit into society. Despite its relevance, there is currently no agreement on its meaning and, more importantly, no way to express accountability properties for these systems. As a solution we propose to express the accountability properties of systems using Structural Causal Models. They can be represented as human-readable graphical models while also offering mathematical tools to analyze and reason over them. Our central contribution is to show how Structural Causal Models can be used to express and analyze the accountability properties of systems and that this approach allows us to identify accountability patterns. These accountability patterns can be catalogued and used to improve systems and their architectures.

CCS Concepts:
- Computing methodologies → Causal reasoning and diagnostics;
- Applied computing → Evidence collection, storage and analysis;
- Software and its engineering → Design languages;
- Computer systems organization → Robotics.

Additional Key Words and Phrases: Accountability, Structural Causal Models, Cyber-Physical Systems

1 INTRODUCTION

Accountability is a central pillar of human societies. Ever since John Locke and Adam Smith, writers on political philosophy have tried to capture and refine this slippery concept. Yet, details of definitions vary and there exists no singular unified definition. Following [29], who surveyed the social science literature on accountability, the central idea of accountability is that “when decision-making power is transferred from a principal (e.g. the citizens) to an agent (e.g. government), there must be a mechanism in place for holding the agent accountable for their decisions and tools for sanction”. Accountability works by ensuring that agents might suffer consequences for their behavior and will thus avoid “bad” behavior [15, 33].

Causality, simply put, is about asking one question: Why? It is at the core of human understanding and reasoning, but has only recently been given thorough mathematical foundation in the from of Structural Causal Models (SCMs) [40]. SCMs allow us to precisely describe and reason over the causal structures of systems. They are uniquely suitable to capture accountability properties of systems, because an agent can only be held accountable for an effect that it caused; i.e., causality is a prerequisite for accountability. Moreover, a recently published a survey of works in the social sciences [32] shows that Halpern and Pearl’s model of causality [16] is a suitable formalization to capture the concept of an “explanation”. Explanations are tightly linked to accountability and often seen as the “account” part of “accountability”.

As examples and use cases, we use Cyber-Physical Systems (CPS). CPS are systems in which software controls hardware to affect the physical world [27]. Such systems usually have sensors to perceive the world, employ actuators to influence their surroundings and use software to plan their next action. CPS are open systems that are designed to work in unknown environments and interact with any other system or object. This uncertainty makes it impractical
to specify all "legal" action a CPS can take and implies that failures and unwanted events will happen. Similar to the
transfer of decision-making power from citizens to government, owners and operators of CPS transfer some, and in
some cases even all, their decision-making to the CPS. Hence, we want similar accountability mechanisms in place. Such
accountability mechanisms help to avoid "bad" or unwanted behavior by ensuring that its causes can be identified and
there could be consequences. Similar to humans, the expectation of possible consequences will motivate CPS and their
owners and operators to comply with existing laws and mores. Thus, accountable CPS will improve society’s trust in
their behavior and increase their acceptance in their respective social context.

In this paper, we focus on the problem of expressing accountability patterns and the related problem of what data
to log. Expressing accountability is difficult, because there are many differing definitions of accountability, there is no
agreement on what constitutes an “accountable system”, and there exists no common language to express accountability
patterns. Our solution uses the fact that accountability is build on the notion of causality and leverages recent advances
in the mathematical treatment of causality to express accountability properties as SCMs. We use the structure of SCMs
to inform logging choices in the system design. Our contribution is (1) to show how SCMs can be used to express
accountability patterns, (2) that they can be used to analyze and improve the system design, especially regarding the
logging choices, and (3) that this systematic treatment makes it possible to identify accountability patterns and apply
them to systems or system architectures.

2 WHAT IS ACCOUNTABILITY?

Across the sciences, there is no consensus on how accountability should be defined. Its definition is always dependent
on the context of a system or agent and the expectations of its principals. [23] conducted a systematic mapping study in
computer science and found that there is no agreement on a definition and that most research papers use a “dictionary
definition” of accountability, or give no definition at all. While prescribing what accountability is (e.g., [3] or [26]) works
for specific contexts, in this paper we focus on how to best express its meaning in general. In this section, we will give a
brief overview of accountability and related concepts such as causality, responsibility and transparency.

Following [25], we see accountability as a relation between a system (e.g., a CPS such as a drone or a robot; it might,
in principle, also be human), called an agent by [29], and a natural or juridical person, called a principal, that the
agent is accountable to. The exact form of this relation depends of the definition of accountability used. Systems can
be part of a “stack” and one technical system might monitor and correct another system. However, “things”, such as
technical systems, without legal standing cannot be principals. A principal serves as a link to society and the legal
system. Having a principal that cannot be sued and be held liable for actions and decisions would sever that link and
violate a core requirement for accountability1. This argument is similar to the reasons why the executive in many
countries cannot be replaced with “liquid democracy” based voting systems. At some point a decision must be justified
and the decision maker be held accountable2. This view is further strengthened by experiments confirming that “(...) people, not objects, are held accountable for a negative outcome” [43].

Accountability additionally requires the concept of actions that can or cannot be taken by the agent and requires
an account (or explanation) to be provided to the principal. Actions are the linchpin that connects accountability to
causality. If an agents takes an action, it will cause effects. Not acting might also cause effects. Principles judge these
effects and might demand an account from the agent. An agent that provides a meaningful account is accountable,

1There are some ideas of giving legal standing to machines (“e-person”), however this idea comes with its own set of problems. See for example
http://www.robotics-openletter.eu/
2 This point is eloquently made by J.S. Mill [31]: “Responsibility is null when nobody knows who is responsible; nor, even when real, can it be divided without
being weakened. To maintain it at its highest, there must be one person who receives the whole praise of what is well done, the whole blame of what is ill.”
while an agent whose actions cannot be questioned or reviewed is not accountable. An accountability mechanism is the means to hold the agent accountable.

Causality and accountability are tightly interlinked and have some complex interactions. While causality is necessary for accountability attributions, people will often use the term "cause" for both a causal relationship and an accountability relationship [43]. The accountability hypothesis states that "(...) causal queries are generally ambiguous. They might refer either to causal relations in the narrow sense, or they might request assessment of moral accountability" [43]. If humans understand "cause" to mean "moral accountability", they will associate it, for example, with norm violations and consider the subject's mental state. Competing hypotheses suggest that norms might alter the causal model (i.e., what causes what) or that they might alter causal selection (i.e., what are possible causes). To illustrate the point: [43] conducted several experiments in which subjects were presented with different vignettes and asked to attribute causality. In their experiments they, for example, presented participants with a vignette in which a plant lover employs two gardeners to look after his plants. In this scenario the gardeners could apply different fertilizers on the plants; one would help the plants to flourish and one would make them perish. The gardeners were explicitly told which fertilizer to use, i.e., a norm was established. When the participants were asked to assess the causal effect of the fertilizer on the plants, they, with one exception, did not attribute the death of the plants to the fertilizer, but to the norm-violating gardener. If the vignette was altered to have one gardener intentionally use the wrong fertilizer he was picked more frequently and if it was modified to say that the gardener accidentally picked the wrong fertilizer, he was picked less frequently.

Studies like this show how tricky it is to define the meaning of causal relationship and accountability. They also highlight how important it is to spell out the causal relationships in a system, to express expected causal relationships and to compare them to actually observed behavior. In Section 3.4, we show how SCMs are a tool to capture these relationships. However, we want to caution that the actual modeling is highly subjective and context sensitive and that reasoning over SCMs is always model relative.

Accountability is not limited to just answering questions, often called responsiveness. The agent must be able to make a decision, because “(a) puppet acting as an extension of someone else’s will is not a legitimate object of accountability”[29]. Here it is also important to note that there is a lively debate if machines are even capable of making decisions and if they can have agency (see for example [13, 44, 45]). In our view, machines are objects, but can make decisions. While they might not, like a human, suddenly decide to not do their task, they have enough degrees of freedom and enough autonomy [6] to make accountability necessary and meaningful. For an automatic and deterministic system, accountability makes little sense, as any blame will lie with the natural or legal person who operated or constructed the system. For such a system, fault localization or debugging is enough. For accountability to make sense, systems have to be autonomous agents that make decisions and explore counterfactual scenarios without human intervention.

It is important to be aware that it is very difficult to compare accountability definitions and define “levels of accountability”. The problem is that definitions of accountability often disagree on properties and their meaning. Even if we agree on properties, they are often nominal. For example, we should be able to name an agent and a principal, but it is not easy to find a way to compare two agents or find a relation between two agent-principal pairs such that the excess of the agent in one pair makes up for the lack of the principal in the other. For example, how should we decide if one person is a good principal for a robot and compare them to another person’s way of being a principal of an autonomous car? SCMs and accountability patterns based on them offer a solution to systematically compare accountability notions.
Accountability will often be used in conjunction, and is sometimes confused, with the term responsibility. Following [46], accountability is attributing responsibility in addition to the more traditional definition of capturing the relation between principals and agents given by [29]. Seen this way, a responsibility assignment is the output of an accountability mechanism. Simultaneously, [29] points out that responsibility is a necessary prerequisite for accountability. You cannot be held accountable for an action or effect for which you are not responsible. Here “responsible” is not seen as an output, but is seen very close to the term “caused”. The difference being that you can also accidentally cause an effect. As “responsibility” requires conscious thoughts and actions, you are not responsible for this effect and thus also not accountable. A common example is to become unconscious while driving a car and causing an accident. You caused the accident, but you are neither responsible nor will you be held to account. Reviewing the literature in psychology, [15], find that while “accountability” and “responsibility” are used interchangeably by some researchers, they are usually distinguished with accountability imposing the additional requirement of an external audience. In line with [43], [15] also point to literature that sees responsibility as a prerequisite for causality and causality as the core of accountability. [49], on the other hand, hold the view that causality is a normative concept and that “causal attributions are typically used to indicate something more akin to who is responsible for a given outcome than who caused the outcome in the descriptive sense of the term used by philosophers”. [13] differentiate responsibility and accountability along the line of intentionality. For them, a non-human agent can be held accountable, but to be responsible for an action would require them to have actual intentions.

In the recent works on algorithmic accountability (e.g., [8, 47]), transparency is also often linked to accountability, and sometimes even seen “as a type of accountability”. Here the idea is that if the inner workings of machines and algorithms are open to the public, i.e., they are transparent, we can attribute responsibility for failures. One problem, for example, is that, in contrast to decisions of a committee of people, transparency for source code or machine learning models is not necessarily useful, because they are often next to impossible to understand. Another problem for us is that transparency does not make the principle explicit. It roughly follows the definition of “felt accountability” (see e.g., [15]) that agents are accountable if they think that someone might check their actions. While this is enough in some instances, we believe that, especially for CPS, principals should be known. [2] give ten further limitation of transparency as a tool for accountability and suggest these limitations might serve as requirements for algorithmic accountability systems. We believe that causal models offer a useful way to fulfill those requirements and ensure the accountability of a system. Causal models are especially good at facilitating explanations, which are often much more useful than a fully transparent system.

To summarize, causality is a relation between objects. Responsibility, for us, requires some intention on part of the causing agent. Accountability is a societal framework that involves autonomous agents and third parties. Transparency, while close to accountability, lacks the concept of a principal. In the rest of this paper, we will show how SCMs can be used to express accountability properties (Section 3), to identify patterns (Section 3.4) and to improve the system design (Section 4).

3 EXPRESSING ACCOUNTABILITY

To illustrate how difficult it is to express the accountability properties and find common features, we will use two entirely different examples. The first is the story of Titus Manlius, as told by Livy (Book 8, chapter 7; translation [14] and a summary [37]). In 349 BC, Titus Manlius Torquatus led a campaign against the Latins. To increase the military discipline, he ordered his troops to strictly obey orders, not to act on their own and not to leave their post. His son (and namesake) Titus Manlius, while on orders to patrol, engaged an enemy commander who insulted, ridiculed and
challenged him to a duel. After defeating the enemy heroically in the duel, he rode back to his camp and proudly told his father of his exploits. Titus Manlius summoned all his men and rebuked his son for abandoning his post and breaking military discipline, summarizing the dilemma as "(...) ut aut rei publicae mihi aut mei meorum obliviscendum sit (...)" (roughly: "(...) that I must either forget the republic, or myself and mine (...)"). With this he had his son bound to a stake, beheaded him with an axe and had the body burned with full military honors.

What does this bloody tale from ancient Rome now have to do with our modern understanding of accountability? First of all, we have all major components present. Titus Manlius, the father, is the principal who ensures a norm is not violated. His son is the agent, that (literally) gives an account of his actions. The execution of the son is then the ultimate sanction for violating the given norm. The accountability mechanism is a bit harder to identify. Its goal is to keep up the norm, ensuring military discipline, and it is embedded in the military as its reporting framework.

As a second example, we look at the fatal 2018 AD crash of an autonomously driving Uber car [36]. In this accident, the car, equipped with cameras, radars, a LIDAR and other sensors, was driving autonomously and hit a pedestrian crossing the road. Crucially, the Uber developers disabled the car’s collision avoidance functionality, because it interfered with the computer control. While the car had a safety driver, responsible to intervene in case of system failures, the safety driver was focused on monitoring the system and did not notice the pedestrian.

Similar to the story of Titus Manlius above, we can identify components that can be used for accountability. The car is the agent, its video feeds and log data are the account and should provide an explanation. The immediate sanction taken by Uber was to stop their fleet of autonomous cars. Where it gets tricky is the question of the principal. Depending on how we want to model the problem, the principal could be Uber, the safety driver, a regulatory agency, a number of other entities, or multiple such entities at once. Since the principal sets the norm, the norm depends heavily on who to consider as principal. A regulatory body’s goal might be to ensure road safety, Uber might wish to avoid public relation disasters and so forth. Without a clear way to express these intricacies, it is needlessly difficult to identify the actual and intended principal. Because a principal needs to know of its role to conduct any oversight, the knowledge of being a principal is a requirement for accountability and the related logging choices. Expressing this fact clearly allows regulatory bodies to spell out who they expect to look at accounts and also gives manufactures, owner and operators the ability to show that they comply with the accountability requirements and have the necessary logging infrastructure.

3.1 Structural Causal Models

As both the story of Titus Manlius and the story of the Uber car have similar features, such as a principal. We now want to look at definitions of accountability and identify patterns that allow us to match them to these features. This allows us to determine if a given pattern of accountability is suitable for a given system or if another pattern might be a better fit. We propose to use Structural Causal Models (SCMs) [39][p. 26f.] to capture the relevant accountability features of systems and model the world they interact with.

**Definition 1. Structural Causal Model [39]**

A structural causal model $M$ is a tuple $M = (\mathcal{U}, \mathcal{V}, \mathcal{F})$, where

- $\mathcal{U}$ is a set of exogenous variables,
- $\mathcal{V}$ is a set of endogenous variables,
- $\mathcal{F}$ associates with each variable $X \in \mathcal{V}$ a function that determines the value of $X$ given the values of all other variables.
Every SCM is associated with a graphical causal model called the “graphical model” or the “graph”. While the graph does not include the details of $F$, its structure alone is enough to identify patterns and causes. In an SCM, exogenous variables are external to the model, meaning that we chose not to explain how they are caused. They are the root nodes of the causal graph and are not descendant of any other variable. Endogenous variables, on the other hand, are descendants of at least one exogenous variable and model components of our system and world for which we want to explain causes. $F$ describes the relationships between all those variables. If we knew the value of every exogenous variable, we could use $F$ to determine the value of every endogenous variable. In a graphical model every node represents an endogenous variable and arrows represent functions from $F$ between those variables. SCM are derived from structural equation models (SEMs) (e.g., [30]), but in contrast to them, their relation have a direction.

If we want to investigate the cause of Titus Manlius son’s violation of the norm, we might model the behavior of the enemy commander as an exogenous variable, which we accept as given and external to the model. His son’s reaction to those insults are caused by those insults and would thus be modeled as an endogenous variable. Figure 1 depicts the graphical model for the story of Titus Manlius. In the SCM, $U$ would contain Insults (I), meaning that our model does not investigate why the enemy commander chose to insult Titus Manlius’ son. $V$ would contain the fact Titus Manlius’ son reacted (TM), Engaged in a Duel (ED) and Broke Discipline (BD). For these endogenous variables, we can perform causal reasoning and give explanations. Note that $U$ and $V$ should contain facts that can be observed and measured. If we cannot measure some influence, but suspect it is there, we can model it as a background variable.

In our example, I is given by some exogenous input, meaning that our model cannot explain it any further. For TM the equation would be $TM = F_{TM}(I)$. Often this function will include an error term to account for unknown background factors, called $U$ that might affect a variable, giving us $TM = F_{TM}(I, U_{TM})$; accordingly, $ED = F_{ED}(TM, U_{ED})$ and $BD = F_{BD}(ED, U_{BD})$. For simplicity, we model the functions in $F$ so that they just transmit the value and take on either the value “true” or “false”. In practice, the functions in $F$ can be any mathematical function and will often be probability distributions.

### 3.2 Causal Reasoning

Figure 1 can now be used to answer causal questions [40][p. 40]. The first level of questions are questions of association, i.e., how one fact relates to another. For example, if we know that the discipline was broken, did Titus Manlius’ son engage in a duel? To answer this question, we can inspect the graph and come up with the answer. This task can of course also be automated [51] and the graphs can be a lot more complex.

![Fig. 1. The story of Titus Manlius as graphical causal model.](image-url)
influences and then set it to true. Analyzing the model, we can then see that this would also break the discipline (BD). However, our model does not contain any information on who might have engaged in the duel. If we wanted to answer this question, we would need a new model containing additional variables.

![Diagram](image)

Fig. 2. Simulating an intervention by fixing the value of an variable.

Finally, we can also use causal reasoning to ask counterfactual (“what if”) questions. If we know that the discipline was broken, what would have happened if Titus Manlius’ son had not reacted to the insults? Would the discipline still have been broken? Figure 3 depicts this model of the counterfactual. We remove the link from I to TM and force its value to “false”, i.e. to not be provoked. The variable I keeps its original value. The question then is, what would the value of ED and BD be? We could again use automatic reasoning engines to deduce these values.

![Diagram](image)

Fig. 3. Counterfactual reasoning.

Computing interventions and counterfactuals is what sets causal reasoning apart from machine learning and other statistical approaches. If we were to use machine learning, we would not have an explicit model of the world. We would only gather one data point where the insult lead to a break of discipline and a myriad of data points where there was no insult and also no break in discipline. To understand Titus Manlius’ causal contribution to the effect, we need a model of the interactions and the ability to analyze it. SCMs give us a way to express these models and then use well defined mathematical operations to ask questions of association, analyze interventions and compute counterfactuals.

### 3.3 Structures in SCMs

To give a quick overview, a causal graph structure such as a chain, $A \rightarrow B \rightarrow C$, means that $B$ is only influenced by $A$, $C$ is only influenced by $B$ and $A$ is determined by external forces not part of this model [40][p. 129]. If we inverted the chain, $A \leftarrow B \leftarrow C$, the causal meaning would change, but the independence of the variables would remain the same, i.e., $A$ is still independent of $C$, provided we know $B$. Put another way, if there were an arrow from $A$ to $C$, then changing $A$ would change $C$. However, if there is no direct arrow and we keep the parents of $C$, i.e., $B$, constant, no matter how we change $A$, $C$ will not be affected. A major implication of this is that we can use data to test causal models. If we have data that show that $C$ changes when we change $A$, despite $B$ not changing, then we need to revise our model.

[40][p.157] provides four rules that apply to any causal graph:

1. **In a chain junction, $A \rightarrow B \rightarrow C$, controlling for $B$ prevents information about $A$ from getting to $C$ or vice versa.**
2. **Likewise, in a fork or confounding junction, $A \leftarrow B \rightarrow C$, controlling for $B$ prevents information about $A$ from getting to $C$ and vice versa.**
3. **In a collider, $A \rightarrow B \leftarrow C$, exactly the opposite rules hold. The variables $A$ and $C$ start out independent, so that information about $A$ tells you nothing about $C$. But if you control for $B$, then information starts flowing through the “pipe”, due to the explain-away effect.**

\[\text{Of course, creating a causal model in the first place is a challenge. [21, 24] provide means to derive models for CPS from existing system models.}\]

\[\text{4 For detailed introductions, see [40] or [38].}\]
Controlling for descendants (or proxies) of a variable is like “partially” controlling for the variable itself. Controlling for a descendant of a mediator partly closes the pipe; controlling for a descendant of a collider partly opens the pipe.

In causal graphs, we often want to know if two nodes are independent, i.e., changes in one node will not affect another node. Two variables are independent if every path between them is blocked. Formally:

**Definition 2 (d-separation).** [39][p. 46]

A path $p$ is blocked by a set of nodes $Z$ if and only if

1. $p$ contains a chain of nodes $A \rightarrow B \rightarrow C$, or a fork $A \leftarrow B \rightarrow C$, such that the middle node $B$ is in $Z$ (i.e., $B$ is conditioned on), or
2. $p$ contains a collider $A \rightarrow B \leftarrow C$ such that the collision node $B$ is not in $Z$, and no descendant of $B$ is in $Z$.

If $Z$ blocks every path between two nodes $X$ and $Y$, then $X$ and $Y$ are d-separated, conditional on $Z$, and thus are independent conditional on $Z$.

From do-calculus, we can also derive two graphical criteria. The front-door and the back-door criterion allow us to analyze if a causal effect between two variables is identifiable or not. Both of them can be checked automatically [51].

**Definition 3 (The Back-Door Criterion).** [39][p. 61] Given an ordered pair of variables $(X, Y)$ in a directed acyclic graph $G$, a set of variables $Z$ satisfies the back-door criterion relative to $(X, Y)$ if no node in $Z$ is a descendant of $X$, and $Z$ blocks every path between $X$ and $Y$ that contains an arrow into $X$.

Intuitively, the back-door criterion ensures that (1) all spurious path between $X$ and $Y$ are blocked, (2) all directed path from $X$ to $Y$ are not perturbed, and (3) no new spurious paths are added.

Building on the back-door criterion, the front-door criterion can applied in structures not suitable for the back-door criterion.

**Definition 4 (The Front-Door Criterion).** [39][p. 69]

A set of variables $Z$ is said to satisfy the front-door criterion relative to an ordered pair of variables $(X, Y)$ if

1. $Z$ intercepts all directed paths from $X$ to $Y$.
2. There is no unblocked path from $X$ to $Z$.
3. All back-door paths from $Z$ to $Y$ are blocked by $X$.

Intuitively, the front-door criterion relies on the fact that one can identify the effect of $X$ on $Z$ and the effect of $Z$ on $Y$ separately. Having identified the separate effect, we can then calculate the effect from $X$ on $Y$.

### 3.4 Accountability Patterns

Accountability becomes necessary when a principal transfers power (for machines often: delegates tasks) to an agent and that agent then causes some effect. The principal then has the right to understand how the agent used this power and why it made a certain decision. We can now use SCMs to express definitions of accountability and identify the underlying pattern. The definitions given in this section are abstractions and can usually not be used in real systems directly. However, as they are condensed to their core, they are not obscured by implementation details and can be used as patterns for real systems. If we analyze the SCM of an actual system, we can look for these patterns, and if we identify one, we can then use the knowledge about the pattern to improve the actual system at hand. Similarly to a design pattern in software engineering, an accountability pattern is a reusable solution to a common problem, but must be implemented anew in each system.
Accountability patterns show us which nodes in a graph are actually relevant to ensure a given notion of accountability. Using SCMs, we can then analyze how the variables are connected and interact, and decide which variables need to be logged. Without this clear understanding, we always run the risk of logging too little data, or suffer from the burden of logging too much data, most of it irrelevant. For example, if a path between two nodes is blocked, they are independent and cannot influence each other. If one of those nodes is irrelevant for accountability, we do not need to spend resources to log it. Looking at the Uber example, the color of the Uber car was, presumably, irrelevant for the accident and all accountability questions associated with it. So logging this data would not help us clearing up any questions of accountability.

In this paper, we use the definitions for Lindberg- and RACI-accountability, taken from [25]. As causality is at the core of accountability, we are convinced that any other definition of accountability could be similarly expressed as an SCM. Our two examples describe specific and very different notions of accountability. We show that they can be expressed as a SCM, however, we currently do not have a way to verify that the translation from the theory to the model is correct. On the contrary, since accountability is a human and social concept, the correctness of a model will always depend on a specific context. The big advantage of causal models is that our assumptions about the causal structure are explicit in the model and can be discussed and improved upon by others. We consider SCMs ideally suited to express notions of accountability and foster a discussion about their differences.

3.4.1 Lindberg’s Pattern. Lindberg [29] surveyed the social science literature and provided the following synthesized definition of accountability:

1. An agent or institution who is to give an account \( A \) for agent;
2. An area, responsibilities, or domain subject to accountability \( D \) for domain;
3. An agent or institution to whom \( A \) is to give account \( P \) for principal;
4. The right of \( P \) to require \( A \) to inform and explain/justify decisions with regard to \( D \); and
5. The right of \( P \) to sanction \( A \) if \( A \) fails to inform and/or explain/justify decisions with regard to \( D \).

Lindberg’s definition assumes that an agent in an organization will cause some effect, usually indirectly through mediation\(^5\) (see Figure 4). If our system, or a part of our system, has such a structure, regardless of the actual functions, we can apply Lindberg’s definitions to set up a framework that allows some principal to get more information from the agent, i.e., to improve the cause model. The principal is not part of the model, but will use the output of a system following that model to sanction an agent. In the same vein, term felt accountability [15] is used in psychology to mean that actors think there is a possibility that their actions will be evaluated by a third party.

![Fig. 4. The causal model for the Lindberg accountability pattern; the principal is not part of the pattern.](image)

3.4.2 RACI Pattern. In contrast to social sciences, organizational sciences often apply a Responsible-Accountable-Consult-Inform (RACI) framework [48] to visualize the roles of people in an organization. The elements of the framework are described as follows (adapted from [48]):

- Responsible: The individual who completes a task. Responsibility can be shared.

\(^5\) A mediator is a variable between a cause and an effect. It might amplify or modify the initial input. [4] define mediation as a “generative mechanism through which (...) [an] independent variable is able to influence the dependent variable of interest.”
• **Accountable**: The person who answers for an action or decision. There can be only one such person.
• **Consult**: Persons who are consulted prior to a decision. Communication must be bidirectional.
• **Inform**: Persons who are informed after a decision or action is taken. This is unidirectional communication.

Figure 5 shows the accountability pattern based on the RACI framework. In contrast to Lindberg above, RACI includes variables that provide additional information. So, instead of just needing data on the cause, the mediator, and the effect, we additionally need information on the **accountable agent**, any **consulted agent(s)**, the content of the consultation, called **discussion** here, and the **informed agent(s)**. While this pattern has much higher logging and reporting requirements, it also allows us to model the delegation of decisions and common workflows in organizations, like meetings, that cannot be captured in the Lindberg model.

![Fig. 5. The RACI accountability pattern.](image)

### 4 USING ACCOUNTABILITY PATTERNS

We now show a possible causal model for the story of Titus Manlius and the Uber example. If we find that they comply with a known accountability pattern, we can be certain that the causal effect of the agent can be identified and know which events we need to log. Figure 6 depicts the familiar model of Titus Manlius’ story. Here we highlight the structure of the Lindberg accountability pattern in grey. A mapping to the RACI pattern would be far less convincing, mainly because Titus Manlius’ son did not consult anyone or delegated the task and we could not map the nodes required by the RACI pattern. He was not an organization, which is why a model for organizational accountability is no natural fit. Knowing that in the Lindberg pattern, we need to look at the behavior of the agent, we can, as shown in the examples on causal reasoning in Section 3.2, ask the counterfactual question “What would have happened if Titus Manlius’ son had not engaged in a duel?”. As in this case the military discipline would not have been broken, holding Titus Manlius’s son to account is the correct action.

![Fig. 6. The story of Titus Manlius as causal model, with Lindberg accountability pattern highlighted in grey.](image)

Figure 7 models the Uber accident. In it, we depict that Uber hired and trained a safety driver for its cars. The safety driver is aided by operating manuals and procedures set by Uber’s experts. Only with these prerequisites the driver is allowed to let the car drive autonomously. Still, this led to an accident that was reported to the police. In contrast to the story of Titus Manlius, this model fits very nicely to the RACI pattern. With Uber being an organization, this is of course very natural.

Similar to above, after an accident we can ask different counterfactual questions. To find the responsible agent, we could ask “Would the accident have happened if the driver had not started the car?”, and, looking at the model, we
can see that the driver is on one direct path to the accident, so changing *Driver* would affect *Accident*. However, there is also a path from *Developers* via *Emergency Braking disabled* to *Accident*. In such a case, we say that the effects of the two nodes are *confounded*, i.e., without additional data it is impossible to say what influence each node has. The accountable entity, on the other hand, is unambiguous: If we change the value of *Uber*, all child nodes would change, clearly preventing the accident. If we chose the Linderberg accountability pattern for this graph, the nodes *Driver* would be the agent, *Car Software* the mediator and *Accident* the effect. In this case, we could not make an unambiguous attribution of accountability and would need to either change the accountability pattern or change the system to fit the desired pattern.

Of course, many other models are possible for these examples and a plethora of competing definitions of accountability can be applied. However, our goal is not to find the "one true model"; our goal here is to show that causal models are a useful tool to express and identify accountability pattern and analyze if a systems fulfills them. To stick with our examples, a regulatory body could publish the RACI pattern and then check if Uber confirmed to it. If, on the other hand, Uber said they used the Lindberg pattern, this could be criticized and another pattern be proposed. Without SCMs to express these fine points, a discussion is next to impossible, and, most importantly, will lose the technical details. This example also illustrates that SCMs without $F$ can answer some queries, but they will often not be able to give clear answers. Defining $F$ is one of the major open challenges when working with SCMs.

### 4.1 Choosing an Accountability Pattern

In the previous section, we showed that the Lindberg pattern would not be a good fit for the Uber example. In this section, we will look at the SCM for a part of a system and will show how we can use the structures in the SCM (Section 3.3) to check if an accountability pattern fits the model. As in the Uber example, for a pattern to be applicable, it is important that its causal effect is identifiable and not confounded. As an example we use another CPS and discuss the development of an accountability mechanism for an Unmanned Aerial Vehicle (UAV). The goal is to find out who is accountable if the UAV crashes in bad weather for which the pilot does not have the necessary flight permissions.

Figure 8 depicts one possible causal model for our UAV; the Lindberg pattern is highlighted in grey. It captures four "pre-flight" variables, *weather*, the legal *visibility limit*, the type of *permission* obtained (e.g., allowed to fly in bad weather) and resulting from those, *permitted to fly*, that signals whether a flight was legally allowed or not. Additionally, it models the pilot’s decision, the fact that the UAV took off, that it is in flight and whether it crashed.

Under the assumption that this model reflects reality correctly, we can now use the back-door criterion to decide what data to log and what data to use for analysis. We want to make sure that the effect of the pilot on the crash is identifiable and not confounded by the other factors. To ensure that, we need to make sure that every noncausal path is blocked, while not perturbing any causal path [40][p. 158]. A back-door path between two nodes $X$ and $Y$ is "any
Fig. 8. Causal Model with the accountability model highlighted in grey.

path from X to Y that starts with an arrow pointing into X” [40][p. 158]. The effect of X on Y will be de-confounded if every back-door path is blocked. In Figure 8 we have one such path, Pilot ← Weather → Visibility Limit ← Permission → Take-off → UAV in flight → UAV crash. Looking at rule 3 above, we can see that the Visibility Limit is a collider, meaning we do not need to control for (log) anything except Pilot, Take-off, UAV in flight and UAV crash. This finding is in line with our intuition: while the weather might have an influence on the pilot, it also cannot make the UAV take off and crash. The permission status might influence the take-off decision, but in itself it cannot prevent a UAV from taking off. As child nodes of Weather and Permission, Visibility Limit and the resulting fact that a flight is permitted or not have even less influence on the observed behavior of the UAV. Note that other cause for a crash, such as an engine failure, are impossible in this model. To consider them, we would need to extend the model [21].

If we do not want to model hobby pilots who can start their UAVs, possible disregarding laws and regulations, where-and whenever they want, and want to capture a more formal military setup, we might design our overall system to follow the RACI accountability pattern. Figure 9 depicts such a setup. In such a RACI setting, pilots have less freedom of choice. They may only start the UAV if they receive an order to do so. This order is given by a commander, after consulting with meteorologists who observe the weather and prepare a weather forecast. If the UAV is still lost due to bad weather, the pilot will still be responsible, but accountability will, following the RACI definition, lie with the commander giving the take-off order. As in the previous example, we have a collider in weather forecast, that ensures that the commander and the meteorologist are independent.

Fig. 9. Using RACI to model the bad weather example.

4.2 Accountability Patterns and System Design

Here, we will show how accountability patterns can help us when designing a system. As an example, suppose we are tasked with attributing accountability in the case where a UAV is controlled by a pilot, but both the pilot and the UAV might be influenced by some attacker. To complicate matters, the attacker is an unobservable confounding variable. That means that it will affect two observed variables, but can itself not be observed. As such it might confound the effect of the pilot on the UAV, which is a problem for the Linderberg accountability pattern. Figure 10 depicts the corresponding causal model. In contrast to the previous examples, there is the open path, Pilot ← Attacker → UAV. Looking at rule 2, we could close that path by controlling for the Attacker. One option to do this would be to install an
intrusion detection system (IDS) and make the IDS a proxy for the Attacker. In an ideal world, a proxy variable will behave like the real variable, but will in reality often induce some uncertainty (e.g., because it might miss some attacks).

Figure 10. The unobservable attacker will confound the effect of the pilot on the UAV.

Figure 11 depicts this causal model; boxes in grey highlight the Linderberg accountability pattern and the dashed box marks unobservable variables. If we know what the attacker is doing, we can disentangle their action from the pilot’s actions and close the back-door path. The downside is that we actually have to invest time and money into such an IDS and need to be reasonably certain that it will log all relevant information about the pilot and the attacker.

Fig. 11. Using an IDS to control for the attacker.

However, if we can ensure that the RC cannot be affected by the attacker, we can use the front-door criterion to estimate the causal effect of the pilot on the UAV, even without installing an IDS. The intuition behind this solution is that, because there is no back-door path from Pilot to RC, we can estimate the effect of Pilot on RC. Similarly, we can estimate the effect of RC on UAV and calculate the effect of Pilot on UAV. With such a causal structure, we can do away with an IDS while still being able to ensure accountability. The downside is that, beside the need to be sure that the causal structure reflects the real world, the attacker must not be able to influence the RC and the pilot must have no other way of affected the UAV than via the RC.

Beside the back-door and front-door criterion, do-calculus offers us many different options of analyzing and manipulating SCMs. If we express our system as an SCM, similar to the examples given above, we can use do-calculus and tools build for it [51] to either adapt the system to the necessary structure or even find structures that make our system simpler.

5 DISCUSSION

When looking at any of the figures in the paper, it is easy to suggest additional variables, different connections, or new structures. Some readers might look at the figures and argue that the model might be unrealistic or even wrong. We do not claim that our examples are perfect or "the one true model". On the contrary, we want to emphasize how easy these models are to inspect, understand and criticize. The main advantage of using SCMs to express accountability properties

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7See [50] for a detailed example with linear models.
of systems is that they make definitions of accountability easy to communicate and foster discussions. If we compare Figure 7 to the story of the Uber accident in Section 3, we can see how a long and involved paragraph of text can be expressed as an easy-to-discuss diagram. The exact details, such as how Uber influences the driver, can be omitted in the graphical model and expressed in the underlying SCM. For most use cases, first determining that there is a causal influence from one node on another is enough. Especially the knowledge that some nodes do not affect the outcome is useful to establish accountability relationships between principals and agents. The core advantage of using SCMs to express accountability properties, however, is that they enable us to identify and communicate accountability patterns.

Expressing accountability in SCMs is not without its problems. One obvious problem is the creation of the models in the first place. There exists some work on using other models of systems such as fault trees or Timed Failure Propagation Graphs [21], as well as models of human interaction with systems [24], to generate the SCMs; however, so far these efforts are semi-automatic and will require human input. Looking at the problems that accountable algorithms have with fairness and bias, we think that this manual input will not go away anytime soon. Without fully automatic solutions, we are convinced that SCMs offer the best compromise between being understandable for humans, while offering a rigid formal framework to analyze and reason over them. The other major problem is defining the functions $F$. While they can take on any form, in many examples binary functions are used. The main reason for this is that such models are computationally easier to analyze and also straightforward to explain. As in the model about Titus Manlius, binary models can be interpreted as “caused” or “do not cause”. If we now look at the Uber example in Figure 7, what could the function between Uber and the driver look like? A binary function might just express that there is an influence. This is good to know, but not necessarily enough. We might use a probability and draw from observations that, for example, 95% of the drivers were instructed by Uber to do long hours and were thus not attentive. But how does this help us, if we actually want to express the more subtle point that Uber was rewarding miles driven and drivers were thus motivated to keep driving when they were exhausted? When considering human interactions, it is not hard to come up with examples that are hard to capture in neat closed-form formulas. Here the big advantage of SCMs is that much analysis can be done on models that do not specify $F$ explicitly. That is why we look at the patterns of the graph and ignore the actual functions. If we ensure at the design time of a system its the causal graph has a structure in which the causal effects relevant for accountability are identifiable, we will usually be able to find evidence to do so in a ex-post analysis. In other words, if we at least know that Uber has an effect on the driver, and build our system to log their interaction, we will be able to find the exact effect in a post mortem analysis where we have data on the system, as well as external observations available.

6 RELATED WORK

Beside the works on accountability that we detail in Section 2, accountability in computer science was popularized by by Weitzner et al. [54], who proposed “Information Accountability” as a step beyond preventive data control measures. They argue that it is impossible to keep data, especially personal data, secret. Instead of trying to prevent data leaks, they suggest to build accountable systems that make it easy to trace data leaks and use the legal system to punish misbehavior. This work was continued by Feigenbaum et al. [10, 11] with a focus on security. Their definition of accountability is, for example, close to the Linderberg pattern. Feigenbaum et al. are, to the best of our knowledge, the first to make a connection with causality, by pointing to the Halpern and Pearl (HP) definition of causality [19, 20]. The HP definition [16] of causality is closely related to the definition of causality we use here. However, while we here use a

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8 All these examples are made up for illustrative purposes and are not true.
Expressing Accountability Patterns using Structural Causal Models

type causal definition, HP is used to define actual causality. Type causality is forward-looking and will often be used by scientific models. A classic example of type causality is a statement like "Cigarettes cause lung cancer" [17]. Actual causality, on the other hand, is used to identify specific courses of events in the past. A classic example is the statement "the fact that David smoked like a chimney for 30 years caused him to get cancer last year" [17]. To build systems, we need forward-looking, type causal models. Fortunately a good type causality model will also be a good actual causality model and make it easy to analyze events ex-post. For example, [18] build on actual causality to give definitions of blameworthiness and moral responsibility. An interesting property of type causal models is transportability [38]. It describes under what assumptions we can transfer causal knowledge gained in experiments to new contexts where only observations are possible.

There are various implementations of accountability mechanisms in the computer science literature. Kacianka et al. [23] conducted a systematic mapping study on implementation, but found that many papers use no explicit definition of accountability. For the cloud domain, the A4Cloud project [12] published an extensive report on accountability for cloud providers. From other domains, Küsters et al. [26] give a mathematical definition of accountability in the context of cryptography for e-voting systems, Datta et al. [7] suggest to base accountability in CPS on causal information flow analysis and Baldoni et al. [3] published an information model of accountability as an Object-Role Model. As in computer science finding the causes of problems and blaming the responsible party is an old problem, many techniques that are not specifically called accountability, yet solve similar problems, were developed. For example, logging is used to understand system behavior [1], runtime verification is used to ensure correct system executing [28], fault trees [52] are a technique from the safety domain to express ways in which a system may fail, fault localization [42] describes techniques to find faults in source code and Forensics-by-Design [41] is a technique from the security domain to build systems so that, if unexpected attacks happen, they can still be detected. We are positive that all approaches that, in essence, ask questions of accountability, can be express as an SCM and then analyzed for patterns.

A fairly new branch of accountability in computer science is algorithmic accountability [8]. Here, the goal is to understand the behavior of, often, machine-learning algorithms. Ananny and Crawford [2] have shown that mere transparency is not sufficient for accountability. Miller [32] gives a thorough overview of the concept of an explanation and suggests that actual causality is useful tool to create and give explanation. Doshi-Velez et al. [9] point to the importance of explanations of AI systems in the legal context and highlight that explanations need to be causal. Mittelstadt et al. [35] elaborate on the ethical implications of AI systems and also point to the relevance of causality and causal knowledge. Wachter et al. [53] also suggest using counterfactuals to explain the behavior of black box AI systems. Mittelstadt et al. [34] recently struck a more careful note and suggest that we need to be careful with models used to explain AI systems. They especially highlight the utility of contrastive explanations for human understanding. As SCM make it easy to explore counterfactual alternatives, we expect that our approach of expressing accountability with SCMs can be adapted to the problems of algorithmic accountability and explainable AI. Combining these models with efficient actual causality reasoning [22], work on abstracting causal models [5] and efforts to automatically derive SCMs for CPS [21], will allow us to identify root causes, give counterfactual explanations, exchange models between different domains of computer science and, most importantly, other fields of science.

7 CONCLUSIONS

CPS will continue to be deployed in shared spaces with humans. This will lead to questions of accountability of those systems for their actions and for those systems by their manufactures, owners and operators. In the first part of this paper, we looked at the concept of accountability from different disciplines and concluded that causality is at the core
of any accountability definition. Following this, we turned to current research on causality, and especially SCMs, and showed with examples that they are a useful tool to express accountability definitions and that SCMs allow us to identify accountability patterns. Using methods to check if a cause is identifiable, we explored how different system designs can be adapted to fit specific patterns. Using an accountability pattern will ensure that the relevant causal effects in our systems are identifiable. We can then use this knowledge to decide what values to log and which events are safe to ignore.

While we have shown that SCMs are useful to communicate accountability definitions in a system’s design, actually developing these SCMs is still an open problem. Additionally, reasoning about actual causes in such models suffers from a high computational complexity and can currently only be done automatically for binary models. In that regard, SCMs have the advantage that they are already used in fields such as statistics, data science, or epidemiology and that we can use theoretical results and, especially, tools from these field to analyze accountability models. We are convinced that the adaptation of SCMs to express accountability definitions will improve the communication with fields such as philosophy, sociology or psychology that have a long history of analyzing and understanding the concept and that these discussions will lead to the emergence of new accountability patterns, insights and best practices.

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