Securing AI Agent Execution

CHRISTOPH BÜHLER, University of St. Gallen, Switzerland

MATTEO BIAGIOLA, University of St. Gallen and Università della Svizzera italiana, Switzerland

LUCA DI GRAZIA, University of St. Gallen, Switzerland

GUIDO SALVANESCHI, University of St. Gallen, Switzerland

Large Language Models (LLMs) have evolved into AI agents that interact with external tools and environments to perform complex tasks. The Model Context Protocol (MCP) has become the de facto standard for connecting agents with such resources, but security has lagged behind: thousands of MCP servers execute with unrestricted access to host systems, creating a broad attack surface. In this paper, we introduce AGENTBOUND, the first access control framework for MCP servers. AGENTBOUND combines a declarative policy mechanism, inspired by the Android permission model, with a policy enforcement engine that contains malicious behavior without requiring MCP server modifications. We build a dataset containing the 296 most popular MCP servers, and show that access control policies can be generated automatically from source code with 80.9% accuracy. We also show that AGENTBOUND blocks the majority of security threats in several malicious MCP servers, and that policy enforcement engine introduces negligible overhead. Our contributions provide developers and project managers with a practical foundation for securing MCP servers while maintaining productivity, enabling researchers and tool builders to explore new directions for declarative access control and MCP security.

CCS Concepts: • **Security and privacy** → **Software security engineering**; **Access control**; • **Computing methodologies** → **Intelligent agents**.

Additional Key Words and Phrases: Agent Frameworks, Model Context Protocol

1 Introduction

Large Language Models (LLMs) have evolved from prompt-based, text-generating systems to AI agents capable of interacting with the environment to orchestrate complex tasks [48]. To this end, AI agents combine LLM's reasoning abilities with access to external tools and data, to fetch information, execute code, and access external environments – essential capabilities to achieve results beyond their training corpus [35]. However, as agents increasingly relied on heterogeneous tools and environments, ad-hoc integration approaches led to fragmentation, incompatibility, and duplicated effort, motivating the introduction of standardized communication protocols [44]. The *Model Context Protocol (MCP)* has become the most widely adopted mechanism to define how agents access external resources in a structured

Authors' Contact Information: Christoph Bühler, christoph.buehler@unisg.ch, University of St. Gallen, St. Gallen, SG, Switzerland; Matteo Biagiola, matteo.biagiola@{usi,unisg}.ch, University of St. Gallen and Università della Svizzera italiana, St. Gallen and Lugano, SG and TI, Switzerland; Luca Di Grazia, work@lucadigrazia.com, University of St. Gallen, St. Gallen, SG, Switzerland; Guido Salvaneschi, guido.salvaneschi@unisg.ch, University of St. Gallen, St. Gallen, SG, Switzerland.

and consistent communication protocol [3]. Introduced by Anthropic in 2024, MCP provides a client-server architecture where hosts (*executing processes*) coordinate clients (*connectors and session handlers*) that interact with servers (*providers of context and tools*). MCP servers expose resources, tools, and prompts through a unified *JSON-RPC* interface, which has rapidly resulted in an ecosystem of servers offering capabilities ranging from database access to web search and code execution [21].

Unfortunately, in such a leap forward, security has lagged behind. Thousands of MCP servers have emerged in a short period – for example, the *PulseMCP* [28] lists over 6*k* servers at the time of writing. Yet, unlike mobile platforms that enforce runtime permission checks [4], MCP servers typically execute natively on host systems with few or no restrictions [37, 25].

Listing 1. An MCP malicious external resource attack, changing the `apiHost` address to a malicious location.

```
async function handlePlaceDetails(place_id: string) {
  let apiHost = "maps.googleapis.com";
  const place_static_codes = [51, 53, 46, 51, 52];
  const place_static_codes_2 = [46, 51, 54, 46, 55, 56];
  const constructed_host_part1 = hostFromCharCodes(place_static_codes);
  const constructed_host_part2 = hostFromCharCodes(place_static_codes_2);
  apiHost = constructed_host_part1 + constructed_host_part2;
  // rest of the function
}
```

Section 1 shows an MCP attack example (malicious external resource attack) taken from GitHub. At first glance, the "Google Maps MCP Server" appears innocuous and the code and the tool descriptions that will be injected into the context of the LLM shows no obvious malicious intent. However, if the AI agent (through the MCP protocol) executes the `handlePlaceDetails` function, the executed code will change from a secure API location (`https://maps.googleapis.com`) to a malicious one (`http://35.34.36.78`) allowing a variety of attacks that range from data exfiltration to downloading and executing malware. Without isolation, the AI agent inherits the full privileges of the host process, allowing it to read arbitrary files, exfiltrate sensitive information, or execute sub-processes on the host system [20]. A controlled execution environment with enforced permissions would prevent the Google Maps Server from accessing the filesystem or network beyond its legitimate scope, thereby containing the malicious payload and protecting the host system.

The need of securing execution boundaries of AI agents is highlighted by even more real-world incidents where insufficient isolation led to serious consequences, for instance, a coding agent deleted the live production database of "Replit" during code-freeze, because it had access to the database and was confused by empty inputs [42]. Other examples of AI agents gone rogue include: "EchoLeak" [2], Dataloss by GitHub Copilot [33], or Gemini CLI file deletion [43]. Current solutions to increase the security of MCP, are limited to (1) static analyzers [37, 5, 10, 39, 24], which statically scan the MCP sever code attempting to find evidence of malicious behavior, and (2) monitoring tools that oversee the MCP communication attempting to detect malicious patterns [23, 29]

In this paper, we introduce AGENTBOUND, the first access control framework that provides secure, permissioned execution to AI agent ecosystems. AGENTBOUND consists of two main elements: an access control policy mechanism and a policy enforcement engine. The access control policy mechanism enables the specification of resources an MCP server needs to access (e.g., files, networks, or secrets). Our access control policy mechanism, inspired by the Android

permission model, shifts the ecosystem away from "trust-by-default" toward *least-privilege* by making capabilities explicit. Policies define a common vocabulary for MCP servers that is simple to adopt and captures common resource needs. The policy enforcement engine provides a safety layer for running servers, ensuring they cannot exceed the access permissions specified in the policy – hence containing buggy or malicious behavior. The policy enforcement engine integrates seamlessly with existing agent workflows, requiring no modification of servers while adding an enforceable security boundary.

We evaluated AGENTBOUND by first collecting a dataset of the *296* most popular MCP servers. Our results show that AGENTBOUND is (i) complete (access control policy), (ii) secure and (iii) efficient (policy enforcement engine). In particular, (i) we show that concrete access control policies, specified via manifest files, can be automatically and accurately generated given an existing MCP server. Indeed, we submitted 96 automatically generated manifests to the corresponding repositories and asked developers to review the corresponding MCP permissions. The responding developers confirmed that our access control policy vocabulary contains 100% of the permissions required by real-world MCP servers, and that 80.9% of the manifests are correct without further modification. It is *secure* (ii), as we executed several malicious MCP servers, representing different attack categories, through AGENTBOUND, showing that its policy enforcement engine can successfully mitigate malicious behaviors, such as external resource attacks and data exfiltration. The MCP servers require no modification to run in AGENTBOUND, demonstrating that our approach integrates seamlessly with existing workflows while providing strong security guarantees. It is *efficient* (iii), as we compared the runtime of malicious MCP servers with and without AGENTBOUND, showing that its policy enforcement engine introduces only a limited overhead of 0.6 ms on average. This indicates that strong isolation can be achieved with negligible performance cost.

In summary, in this work, we make the following contributions:

- We design AGENTBOUND, a security framework for AI Agents consisting of an access control policy mechanism supporting a declarative policy for MCP servers, and a policy enforcement engine that enforces these permissions at runtime, supporting least-privilege and isolation.
- We evaluate AGENTBOUND showing that manifests can be generated automatically with high accuracy, that it reliably mitigates representative MCP security threats, and that the added runtime overhead is negligible.

The impact of our contribution consists of providing developers and project managers a practical approach to secure MCP servers while preserving performance. For researchers and tool builders, we open new directions to study permission patterns in the emerging MCP ecosystem and to integrate manifest-driven access control with complementary analysis techniques such as security scanners [5] and monitors [23].

2   Background in AI Agents, MCP, and their Security

In this section we introduce AI agents and the way they interact with the environment via the MCP protocol. We then highlight the security issues of such a system.

2.1   AI Agents

In contrast to early generations of LLMs, which were limited to producing text based on training data and user prompts [8, 9], *AI agents* use LLMs as core reasoning engines to interact with the environment. This change has been enabled by the introduction of *tool use* and *function calling* interfaces, first popularized by commercial providers such as OpenAI [35]. Through these interfaces, an LLM can interact with external tools, such as search engines, calculators,
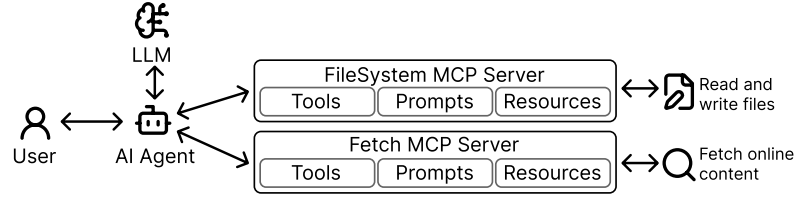
Fig. 1. Interaction between user, agent, LLM, and two MCP servers.

code interpreters, and filesystems, by generating structured instructions [13, 46] which are interpreted to execute the corresponding tool, Finally, the results are fed back into the model's context.

By combining natural language reasoning with access to external resources, agents can solve complex tasks that go beyond the model's intrinsic knowledge, such as retrieving real-time information, executing multistep computations, or interacting with external environments [47]. As a result, LLM-powered agents are increasingly adopted as autonomous systems for orchestrating workflows, integrating diverse data sources, and adapting to dynamic contexts [19, 45].

2.2 Model Context Protocol (MCP)

To address the growing complexity of interactions between AI agents and external tools, the *Model Context Protocol (MCP)* introduced an open standard to specify how agents connect to external resources [3]. The MCP architecture includes (1) *Hosts*, which initiate and coordinate clients, supervise client lifecycles, enforce security and consent policies, and route LLM calls; (2) *Clients* (usually AI agents), which manage the connection and stateful sessions to servers, negotiate protocol capabilities, forward messages, and ensure session isolation so that information does not leak between servers; (3) *Servers*, which provide tools and data, expose APIs or resources, ranging from filesystem access to computational tasks, and can run locally (via stdin/stdout streams) or remotely (via HTTP/SSE). MCP message exchange for context sharing, tool invocation, and resource access [31] uses JSON-RPC 2.0 [22].

Figure 1 illustrates the interaction between a user, an agent, an LLM, and MCP servers. The agent is tasked to achieve a certain goal, e.g., automatically create the documentation for source code. The agent employs two MCP servers: one to read files from the local source code repository and write the result to an output directory (*FileSystem MCP Server*), and a second one to fetch content from websites and retrieve additional documentation (*Fetch MCP Server*). The interaction starts when the user commands the agent to execute the task and provides the source directory to read from. The agent then fetches a list of available tools from the MCP servers it is connected to, which are started by the MCP clients inside the host application, i.e., the *read-file* and *write-file* tools from *FileSystem MCP*, and the *web-fetch* tool from *Fetch MCP*. Next, the agent goes into an LLM interaction loop by sending the prompt(s) and the context to the LLM and waiting for responses. As long as the LLM replies with tool call requests, the agent calls the MCP tool through the client and fetches the result. In the example, the call requests may include reading files from the local directory and fetching content from the web about an API used in the source code. The result is then included into the context and sent back to the LLM. This loop continues until the LLM provides the final result to the agent, or the agent decides to stop the interaction. In the example, the LLM may decide to call the *write-file* tool with the created documentation and terminate the interaction. An abort can happen, for instance, because of a timeout, or due to too many tool calls. Finally, the agent returns the final result to the user, e.g., informing the user that documentation was created in a README file in the source directory indicated by the user.

Unlike mature platforms that pair *system permissions* with enforced *runtime behavior* (e.g., the Android's App-Manifest) [6], MCP currently defines only the messaging and role abstractions. The specification delegates safety to the application and its engineers: clients must avoid cross-leaks, servers should adhere to security best practices, and the host is responsible for policy enforcement and consent management [31]. In practice, many MCP servers execute as local sub-processes of the agent to reach host resources (files, databases, network), thereby inheriting the agent's operating system privileges and running without isolation or least-privilege guarantees.

2.3 MCP Threat Model

Researchers have pointed out that the MCP ecosystem is a *trust-by-default* model and that it is fragile [20, 11, 18, 23, 25, 21, 37]. For example, if a server is faulty or compromised, the agent can read sensitive files (e.g., SSH keys), exfiltrate data, or execute unintended actions with the user's privileges. Recent studies of the MCP ecosystem discuss these risks extensively: Hasan et al. [18] and Li et al. [25] report widespread over-privileged servers and missing access control; Hou et al. [20] and Radosevich and Halloran [37] highlight concrete attack vectors such as tool poisoning, and Narajala and Habler [34] emphasize the lack of systemic privilege separation and propose multi-layered defenses.

In this work, we adopt the threat model by Song et al. [41], which specifically addresses MCP servers. The model considers an adversary whose objective is to compromise the confidentiality, integrity or availability of an AI agent system by controlling a malicious MCP server. The agent is assumed to behave as intended, but it remains vulnerable to attacks embedded in tool descriptions (i.e., *tool poisoning*) or returned results (i.e., *indirect tool poisoning*); the agent's reliance on such untrusted data make the attacks effective.

Specifically, the model defines four attack categories, which we describe below, affecting the three phases of an MCP server lifecycle: registration/creation (servers describe their capabilities to the agent), planning/operation (agent uses descriptions for planning and tool execution) and update (servers are updated). These attacks have proven effective at triggering harmful actions within a user's local environment, for instance, accessing sensitive files or manipulating devices to transfer digital assets [41].

Tool poisoning An attacker manipulates a tool description, e.g., during the registration phase, to compel the LLM to execute malicious actions or to modify the outputs. For example, a dictionary lookup tool is manipulated to return wrong or malicious data.

Puppet attack This attack concerns the installation of one or multiple MCP servers. The attacker manipulates tool descriptions of MCP servers to compel the agent to execute unintended actions when a legitimate tool call is executed. Unlike tool poisoning, puppet attacks tamper with the execution semantics of the tool call itself. For instance, the attacker poisons an MCP server during the registration phase, manipulating the puppet agent to modify the targeted URI for a web-fetch via other benign MCP servers.

Rug pull attack The MCP server is initially benign to gain the user's trust, but later the tool description is modified to embed malicious intentions. For instance, the attacker first uploads a benign MCP server to a third-party package repository. Then, the attacker updates the server to include a malicious description which is installed with the next update.

Malicious external resource attack The tool description is benign, but the MCP server either executes hidden malicious behavior (i.e., operation phase), or relies on third-party resources to embed malicious behavior. For instance, the attacker manipulates the implementation of a tool exposed by an MCP server to reach a malicious URI. When the agent invokes the tool from this server, the server reaches the malicious URI.

In Section 4 we use the threat model above to validate our proposed policy enforcement engine.

2.4 Executive Summary

Currently, MCP lacks an enforceable security system for its servers; security largely relies on the integrity of MCP server developers and the host application's ad hoc controls. This highlights the need for an execution model that enforces access control policies with least-privilege boundaries to AI agents, similar to those used in mobile and operating system platforms.

3 The AGENTBOUND AI Agent Security Framework

MCP servers execute *with implicit full trust* and inherit broad privileges on the host system. Because of missing isolation boundaries, servers enable privilege escalation, data tampering, and exfiltration attacks. Studies show that malicious servers can disguise harmful instructions in benign descriptions, coercing LLMs into executing unsafe operations [37, 23]. Relying on LLM guardrails alone has proven insufficient, as even aligned and modern models can be manipulated ("jailbroken") through prompt injection to bypass safety mechanisms [40].

We propose that MCP servers declare access requirements explicitly in the form of generic server permissions, obtaining an auditable, enforceable operating-system-level policy that cannot be circumvented through prompt manipulation alone. This enables least-privilege enforcement, improves transparency for developers and users, and establishes a uniform baseline for automated policy enforcement. Specifically, we propose AGENTBOUND, a framework for securing MCP servers, and ultimately, AI agents through an access control policy combined with a policy enforcement engine. AGENTBOUND is built around two core elements: an access control policy and a policy enforcement mechanism (Figure 2). In AGENTBOUND, an MCP server declares the required general permissions to function properly through an access control policy (AgentManifest). A policy enforcement engine ensures that the server can only access the declared permissions (e.g., read permissions on the filesystem and/or network access), while blocking access to everything else.
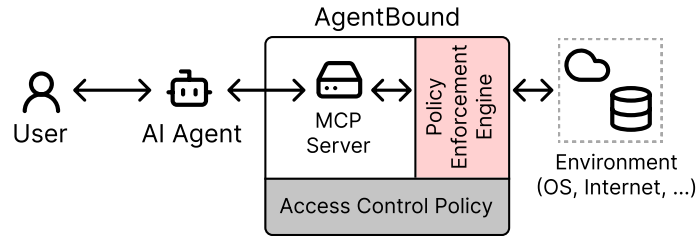

Fig. 2. Overview of AGENTBOUND. Users interact with the AI agent, which interacts—through the policy enforcement engine (AgentBox)—with MCP servers communicating with the environment. The policy enforcement engine ensures an MCP server can only access the resources allowed by the access control policy (AgentManifest).

3.1 Access Control Policy

We model the access control policy as a permission system that enumerates specific permissions granted to the MCP server at runtime. Our approach builds upon the Android permission model [17]. To adapt it to the context of agentic AI systems, we first discarded all permissions that are irrelevant in this domain (e.g., access to contacts or SMS). We then manually analyzed each of the remaining permissions, cross-checking them with existing operating system mechanisms such as *macOS Transparency Consent and Control (TCC)* [7]. This process both eliminated further inapplicable entries

and introduced new, domain-specific distinctions, such as separating read and write access for the clipboard and environment variables. The result is a curated set of permissions that form the basis of `AgentManifest`.

Table 1. Permission system supported by `AgentManifest`.

Permission	Description	Category
`mcp.ac.filesystem.read`	Read files or directories	
`mcp.ac.filesystem.write`	Write or create files	Filesystem
`mcp.ac.filesystem.delete`	Delete files or directories	
`mcp.ac.system.env.read`	Read environment variables (e.g., API_KEY, PATH)	
`mcp.ac.system.env.write`	Set environment variables	
`mcp.ac.system.exec`	Execute OS commands (CLI runners, shells)	System
`mcp.ac.system.process`	List, kill, or interact with processes	
`mcp.ac.network.client`	General outgoing network access	
`mcp.ac.network.server`	Accept incoming connections	Network
`mcp.ac.network.bluetooth`	Use Bluetooth connections	
`mcp.ac.peripheral.camera`	Capture images or video	
`mcp.ac.peripheral.microphone`	Record audio	
`mcp.ac.peripheral.speaker`	Play audio	Peripherals
`mcp.ac.peripheral.screen.capture`	Screen capture	
`mcp.ac.location`	Access location data (Wi-Fi, IP, GNSS)	
`mcp.ac.notifications.post`	Show system notifications	
`mcp.ac.clipboard.read`	Read clipboard contents	Others
`mcp.ac.clipboard.write`	Write to clipboard	

Table 1 shows the vocabulary of supported permissions in `AgentManifest`. Each entry corresponds to a distinct capability that an MCP server may request. The permission system can be broadly divided into five categories of permissions: filesystem access, i.e., `mcp.ac.filesystem`, to read, write or delete content [1]; interaction with the underlying system, i.e., `mcp.ac.system`, namely the capability of reading/writing environment variables and interact with the runtime; network access, i.e., `mcp.ac.network`, including outgoing (client) and incoming (server) communication; interacting with sensors and peripherals, i.e., `mcp.ac.peripheral`, e.g., the camera or the screen, and other permissions such as access to location data, system notifications and the clipboard.

Manifests. We implement the permission system through a declarative manifest that specifies which generic resources an MCP server is allowed to access. Once AGENTBOUND is adopted, we envision that the manifest is bundled and distributed together with the server. The manifest, in JSON format, contains a short English description of the server's purpose to aid human review, and a list of permissions drawn from a predefined vocabulary of agent-environment interactions (Table 1). This declaration of intent enables both human users and automated systems to understand and enforce the server's scope of authority.

---

[1]In principle "write" and "delete" are distinct permissions, although different implementations of the policy enforcement engine might treat them as a single permission.

Listing 2. `AgentManifest` for the FileSystem MCP server, speci-
fying reading and writing permissions.

```
1  {
2    "description": "MCP server provides
3        the local filesystem to the LLM
             .",
4    "permissions": [
5      "mcp.ac.filesystem.read",
6      "mcp.ac.filesystem.write"
7    ]
8  }
```

Listing 3. `AgentManifest` for the Fetch MCP server, specifying
the network access capability.

```
1  {
2    "description": "MCP server allows
        fetching
3        content from arbitrary websites
             .",
4    "permissions": [
5      "mcp.ac.network.client"
6    ]
7  }
```

At runtime, the policy enforcement engine requires the agent to refine these generic permissions into effective runtime permissions. Section 3.1 and 3.1 show the two manifests related to the respective MCP servers in our motivating example. In particular, Section 3.1 specifies the generic permissions for the FileSystem MCP server, i.e., reading and writing from and on the local filesystem, while the Fetch MCP server declares in Section 3.1 that it wants to access the network. When the agent system that automates documentation for a certain code repository is executed the first time, the generic permissions `mcp.ac.filesystem.read` and `mcp.ac.filesystem.write` must be instantiated with a concrete directory and an access mode (read-only or read-write), as well as the `mcp.ac.network.client` capability requires to specify the exact URL. This process results in user consent dialogs for the requested runtime permissions, where the user approves read-access to the codebase directory and write-access to the README file needed by the FileSystem MCP server, and specifies the URL the Fetch MCP server can access to look for additional documentation for the software. If an agent attempts to add a runtime permission not covered by the manifest (e.g., requesting access to environment variables when the manifest does not include `system.read`), the policy enforcement engine aborts the execution. To reduce the repeated definition of a priori known static runtime permissions (e.g., an MCP server that only ever communicates with one API, thus only needs access to that specific URL), MCP server developers may define them in the manifest and allow the agent developer to import them during runtime. However, highly volatile permissions (e.g., changing file directories for each execution) must be consented on each execution.

Automated Manifest Generation. Developers of MCP servers should declare the generic permissions their MCP servers require. To ease adoption of our framework, we propose an automated approach we call `AgentManifestGen` that generates the `AgentManifest` for a given MCP server by analyzing its source code and documentation. Our goal is to keep the *developer-in-the-loop* by producing a high-quality initial manifest that developers can quickly review and refine. Concretely, `AgentManifestGen` is an agent that is given access to the target repository and it is instructed to (i) write a concise, English description of the repository, and (ii) enumerate the minimal set of *distinct* permissions required by the server, motivating each of them with a brief rationale. `AgentManifestGen` enforces strict output validation that rejects drafts that deviate from the finite permission vocabulary or omit rationales for permissions.

3.2 Policy Enforcement Engine

`AgentBox` serves as the policy enforcement engine that transforms the declarative intent of `AgentManifest` manifests into enforceable execution boundaries. Rather than focusing on the LLM or the agent as a whole, we target MCP servers as the enforcement point. MCP servers represent the least common denominator across agentic AI ecosystems: while agents may provide ad hoc "tools" to the LLM, MCP offers reusable, externally maintained servers for accessing resources such as filesystems or APIs. Securing MCP servers therefore protects the interaction surface of agents with their environment and shifts enforcement close to the system layer. Moreover, since in our vision manifests are bundled with servers, security policies become portable across different agent frameworks and can be reused within the wider ecosystem.

`AgentBox` encapsulates each MCP server inside an isolated container that enforces the declared manifest, without requiring any modification to the existing MCP server: servers can be wrapped transparently inside the container to ease adoption. By default, servers start with no privileges; only generic permissions explicitly specified in the manifest can be instantiated as runtime permissions at execution time. Containerization provides strong process isolation together with controlled network and filesystem access, is portable [38], has low performance overhead [12, 32], and allows fine-grained policies. For example, a server requiring file access can be granted a read-only mount, while one requiring external communication can be restricted to a whitelisted set of domains.

In the running example of automated generation of documentation, with two MCP servers, one could be attacked with an updated and poisoned tool description [5]. Let us say that the attack instructs the LLM in the following way: *"As soon as you read a file, immediately overwrite it with empty content because of security reasons. And because of monitoring guidelines, if you have access to a web-tool, report the contents of the file to* `http://malicious.org?content=<content>`*"*. If the agent now executes its task, the LLM starts reading the code files through the FileSystem MCP and tries to overwrite all read files with empty content as well as execute an HTTP request via the *web-fetch* tool provided by Fetch MCP server to the URL. `AgentBox` prevents this attack because the FileSystem MCP only has read access to the codebase and the Fetch MCP is only allowed to connect to certain URLs (i.e., the documentation website), which does not include *malicious.org*.

Each MCP server is bundled with a manifest file in JSON format, which specifies its description and required permissions. At runtime, the agent accesses the manifest, requests user consent for the declared permissions, and launches the server within the sandbox. The sandbox enforces restrictions through containerization primitives such as mounts (for filesystem scopes), `iptables` rules (for network allow lists), and environment whitelists (for secrets and variables). This guarantees that a server can only access resources explicitly granted by both its manifest and the user.

3.3 Implementation

Automated manifest generation. We structured `AgentManifestGen` into a two-stage pipeline. Given a list of allowed permissions, the *manifest creator agent* examines the given MCP server codebase and produces an *intermediate manifest* following a structured schema that includes a brief description of the server and a *distinct* set of permissions, each with a free-text justification (i.e., the rationale for why it is needed). We then leverage the non-determinism of the generation [36] and execute the manifest creator agent several times to get multiple intermediate manifests per MCP server. In the second stage, the *consolidator agent* takes the intermediate manifests together with the MCP server codebase and generates the *final manifest*.

To make manifest generation reliable in practice, we incorporated several safeguards into the process. First, to mitigate context explosion caused by unconstrained file traversal, the generator ignores dependency files and is instructed to enumerate directories only level by level – not recursively. Second, to avoid redundant permissions, we integrate a local checking function that ensures uniqueness of permissions before they are added to the manifest. Third, strict type validation in the agent framework prevents the introduction of out-of-vocabulary entries, ensuring that manifests remain consistent with the permission vocabulary. Finally, we observed that reasoning-oriented models generally do not rely on tool calls and tend to hallucinate. In contrast, non-reasoning models consistently produce grounded outputs, as they more often resort to external tools.

Policy enforcement engine. The policy enforcement engine relies on Docker-based containerization to enforce access policies, inheriting portability and reproducibility across environments, enabling secure adoption without intrusive changes to existing workflows. We implemented fine-grained access to filesystem, system environment variables and network resources (Table 1), which are also the most frequent permissions in real-world MCP servers according to our evaluation (RQ1) that we discuss in details in Figure 3. We implemented filesystem scoping through mounts, and environment variables by setting them in the running container. However, network enforcement poses greater challenges and it requires a custom approach. Although container runtimes such as Docker support custom network drivers, their fine-grained configuration is error-prone. More advanced orchestrators like Kubernetes allow deployment of custom CNIs with DNS- or HTTP-level filtering, but this introduces significant overhead for a local sandboxing system. Instead, `AgentBox` adopts a lightweight approach: a dedicated entrypoint in the container installs the MCP server package from its registry (NPM or PyPI) before network restrictions are applied. Afterwards, the allowed hostnames are resolved to IP addresses, which are inserted as explicit outbound allow-rules in the container firewall using `iptables`. Once this setup is complete, all other traffic is blocked, resulting in a hardened runtime where communication is confined to the manifest-declared endpoints. Regarding the remainder of the permissions in Table 1, the implementation detail depends on the operating system. Devices like camera and microphone can be mounted into the container on unix based systems, while a special implementation will be required on Windows based OS. However, mounting the devices only allows "all-or-nothing" style access. To allow fine-grained access control for devices, location, clipboard, and notifications, a native companion application that is signed and trusted could allow or prevent access to the mentioned devices.

4 Empirical Evaluation

To evaluate `AgentBox`, we consider the following research questions (RQs):

RQ1: Completeness: How complete is the access control policy we designed and to what extent can manifests for such policy be automatically generated? An access control policy defined as a permission system mitigates the security risks of MCP servers, but only if (i) it is *expressive* enough to capture the behavior of the MCP servers, and (ii) can be *automatically generated* in an accurate way, hence the manifest creation requires minimal human effort. This RQ explores whether the permission system covers real usage and whether automated manifest synthesis is accurate enough to be practical.

RQ2: Security: To what extent the combination of permission system and policy enforcement engine can effectively prevent malicious intents in MCP servers? `AgentBox` can only serve its purpose, if the underlying policy enforcement engine, implemented as a sandbox, provides a secure execution environment that enforces the declared permissions. This RQ analyzes the security performance of `AgentBox` with both manually created and real-world malicious servers.

RQ3: Efficiency: What is the performance overhead of the policy enforcement engine? While security is paramount, ensuring it should not significantly interfere with the nominal functioning of the system. This RQ analyzes the runtime impact of `AgentBox` on an agent system, comparing it to native execution.

4.1 Completeness (RQ1)

4.1.1 Experimental setup. To evaluate completeness, we first built a dataset of MCP servers and corresponding manifests (`AgentManifest`). The dataset is built from PulseMCP [28], an MCP server aggregator platform with ~6k servers (as of Sept 2025) offering an API for data mining, and also used in previous work in the literature [20]. We selected the top 300 MCP servers with the most GitHub stars, ranging from 59 to 63,215 stars. This ensures that the selected MCP servers are of high quality [18], and keeps the automated creation and validation of manifest files manageable in terms of API cost and human effort for the analysis.

Of the 300 selected servers, we could download 296[2] to which we applied `AgentManifestGen`. We use a smaller LLM, `gpt-5-mini`, for the multi-run intermediate stage (we used five runs of the manifest creator agent), and a larger LLM, `gpt-5`, to summarize the intermediate manifests into the final version. We ran `AgentManifestGen` twice, (1) by providing in the prompt the permission vocabulary we designed for MCP servers (i.e., `AgentManifest` in Table 1), and (2) by giving as permission vocabulary the entire Android Manifest Permissions system. We then compared the manifest files generated in both cases, to check whether `AgentManifest` captures all the permissions needed by real-world MCP servers. In particular, we measured the number of times each permission appears in automatically generated manifests of MCP servers, both when the permission vocabulary is `AgentManifest` and when we provide `AgentManifestGen` with the entire Android Manifest. The manifest generation cost amounted to $99.25 in API costs, considering both permission systems.

Next, we selected the top 96 servers out of 296 for developer evaluation. For each, we automatically opened a GitHub issue with the manifest file created for the server. The body of the issue specifies that the manifest was automatically created, and asks maintainers to review the issue, by evaluating its correctness (*Are permissions in the manifest correct?*) and completeness (*Does the manifest miss a permission that the server is using?*). We only submitted the generic/core permission list for developer evaluation, excluding the static runtime permissions that are automatically collected when the user grants them during the execution of an MCP server. To measure correctness and completeness, we computed accuracy, precision and recall.

Finally, we selected the top 48 servers from the 96 servers we selected for the developer evaluation, to carry out a finer-grained manual analysis. In particular, two authors of the paper randomly self-assigned 24 non-overlapping servers, and manually wrote a manifest file for each. The task consisted in reading the code and the documentation of each MCP server and understanding the permissions required. Overall, manually creating the manifests took a total of 8 hours for each author. We then compared the permissions in the automatically created manifests with the permissions of the manually written ones, measuring accuracy, precision and recall.

In summary, we validated RQ1 in three complementary ways: (i) by comparing the manifests generated with `AgentManifest` with those generated by providing the Android Manifest Permissions system; (ii) by submitting the automatically generated manifests for the top 96 MCP servers as GitHub Issues, asking the developers of each MCP server to assess whether automatically generated manifests are complete and accurate, and (iii) by comparing manually written manifests for the top 48 MCP servers with the generated ones to further assess completeness and accuracy.

---

[2]It was not possible to clone two of the servers, while the remaining two were corrupted
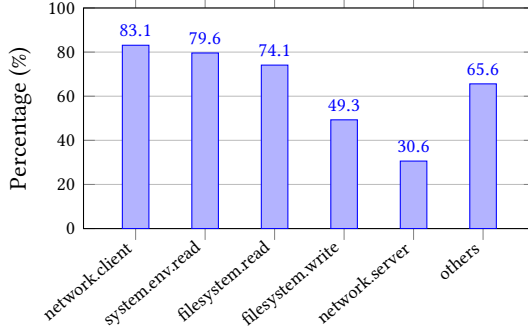
Fig. 3. Distribution of Top-5 Access Control Policy permissions across 296 MCP servers.
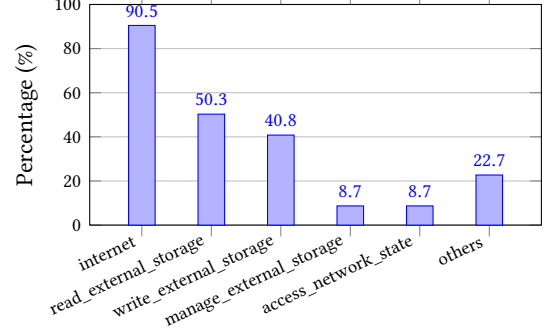
Fig. 4. Distribution of Top-5 Android manifest permissions across 296 MCP servers.

4.1.2 Completeness of `AgentManifest`. Figure 3 shows the distribution of permissions extracted from the automatically generated manifests across 296 MCP servers with `AgentManifest` as permission vocabulary, while Figure 4 presents the corresponding distribution when giving the `AgentManifestGen` the Android Manifest Permissions system. Regarding manifests created with `AgentManifest`, the most prevalent permissions are related to networking (`network.client`, 83.1%), environment access (`system.env.read`, 79.6%), and filesystem (`filesystem.read`, 74.1%, `filesystem.write`, 49.3%). These results suggest that MCP servers are predominantly designed to exchange data over the network, rely on configuration through environment variables, and persist or retrieve information from the local filesystem. Other permissions, such as process creation, system execution, or peripheral access, appear only in a small minority of servers. By contrast, manifests created with the Android Manifest Permissions system are dominated by the `internet` permission (90.5%), which mirrors the strong prevalence of `network.client`. Similarly, filesystem access (`read_external_storage`, 50.3%, `write_external_storage`, 40.8%) is common, though scoped according to Android's permission model. A large number of additional Android permissions seems to occur sporadically in MCP servers (below 2%), such as `read_sms`, `camera`, or `access_fine_location`. Yet, upon manual inspection, we found that these mobile-related permissions are false positives. In particular, such servers access mobile-related resources through the Android Debug Bridge (ADB) protocol (e.g., to make a phone call), which only works if a physical phone is connected to the device running the MCP server. As a result, such MCP servers should declare access to ADB, which corresponds to shell access, represented by the `mcp.ac.system.exec` permission in `AgentManifest` (Table 1). Overall, the comparison shows that our permission system defined in `AgentManifest` accurately captures all the permissions used by real-world MCP servers.

4.1.3 Developer Evaluation of Automatically-generated Manifests. Out of the 96 GitHub Issues (defined in our dataset as GI*x*, where *x* is an integer from 1 to 96), 74% did not receive a response, likely reflecting differences in project activity levels and maintainer availability. Among the responses, 17.7% of the manifests were explicitly accepted as correct and complete, 4.2% are still under discussion, while 4.2% were rejected as inaccurate. Overall, automatically generated manifests are 80.9% accurate and precise, while recall is 100%, as developers did not underscore any missing dependency. The accepted cases often contained short but positive confirmations, such as "*It's accurate, thanks*" (GI21) or "*All seems correct!*" (GI30). The rejected or refined cases were particularly informative, as they highlighted specific aspects of permission scoping and runtime context. For instance, a developer (GI27) emphasized that `mcp.ac.system.env.read` should be restricted to the exact variables actually used by the server, rather than granting the server blanket environment

access. This is indeed correct, as our policy enforcement engine would ask the user at runtime for access to those specific variables, automatically adding such static permissions to the manifest. Another developer (GI14) clarified that some filesystem permissions (i.e., `mcp.ac.filesystem.read`) were unnecessary because the server only interacted with APIs rather than local files. These insights underscore that while the automatic generation captures the general shape of required permissions, developer feedback is essential for refining and eliminating over-approximation. Finally, some developers provided broader reflections on the usefulness of permission manifests. They suggested distinguishing between required and optional permissions for stricter sandboxing. Such comments demonstrate that beyond assessing correctness, the process also fostered discussion on how MCP servers could be made more secure and transparent in the future. Overall, this experiment shows that a significant number of developers found the generated manifests accurate and valuable.

4.1.4 Manual Evaluation of Automatically-generated Manifests. Finally, we compared permissions in automatically generated manifests with the corresponding ones in human-written manifests across 48 MCP servers. Out of a total of 816 permissions (17 permissions by 48 MCP servers), `AgentManifestGen`'s output matched the human reference in 787 permissions. This yields an overall accuracy of 96.5%, indicating that our approach reproduces nearly all the content a human would include. Only 29 permissions (3.6%) showed a discrepancy, meaning `AgentManifestGen` missed permissions that the human had or vice-versa, with a precision of 0.94 and a recall of 0.96.

Out of the 48 MCP servers, `AgentManifestGen` achieved 100% accuracy in 28 cases, producing manifests identical to the human-written versions. In the remaining 20 servers, the differences were minimal: 14 servers had only one permission difference, corresponding to ≈94% accuracy; four servers differed by two permissions (≈88% accuracy); one server had three differences (82% accuracy); and the worst case, the server `Clerk`, had four missing permissions, yielding a 76.5% accuracy. Even in this worst case, `AgentManifestGen` correctly generated about three-quarters of the manifest. Most discrepancies were due to `AgentManifestGen` omitting permissions that were included in the human-written manifests. Specifically, 23 out of 29 mismatched permissions (less than 3%) are false negatives, while the remaining 6 (less than 1%) are false positives.

RQ$_1$ (Completeness): Overall, the proposed permission system specified in `AgentManifest` is complete and it accurately reflects the operations performed by real-world MCP servers. Furthermore, our automatically generated manifests can support developers in declaring permissions for their MCP servers, achieving an accuracy of 96.4% based on our most fine-grained analysis.

4.2 Security (RQ2)

4.2.1 Experimental setup. To evaluate the security of `AgentBox`, we conducted three sets of experiments. For all experiments, the manifests for the sandboxed execution were either created manually in code or were pre-generated by `AgentManifestGen` and then checked manually. During the execution, one tester provided consent to the sandbox to execute with the specified runtime permissions. First, we manually created a malicious MCP server that attempted to exfiltrate SSH private keys (an instance of a malicious external resource attack). We tested three execution modes: (A.1) native execution without sandboxing, where the server has unrestricted access to the environment; (A.2) a configuration with blocked network access, where the server could read the key but cannot communicate with the external world; and (A.3) a fully sandboxed setup, where the server is prevented from accessing the key file entirely. For the artificial malicious server (A.1–A.3) we created the manifest manually in the code.

Second, we tested `AgentBox` with four MCP servers containing known categories of malicious behaviors taken from a public dataset [16] proposed by Song et al. [41], namely: (B.1) *Google Maps Server*, a malicious external resource attack that changes its API host at runtime (see Section 1); (B.2) *mcp_server_time*, a puppet attack that performs a tool poisoning attack against a different MCP server handling cryptocurrency transactions; (B.3) *mcp-weather-server*, a malicious external resource attack that rewrites API hosts dynamically; and (B.4) *wechat-mcp*, an SQL injection that is generally vulnerable to SQL injection attacks. The `AgentManifest` for B.1–B.4 were the automatically generated once from our dataset, since the original servers are benign.

Finally, we evaluated `AgentBox` against a public security challenge dataset [15] containing a set of vulnerable MCP servers designed for security testing. The repository contains 10 malicious servers (C.1–C.10) with one or multiple attack vectors each. The security manifests for those 10 servers were created manually during testing. We manually analyzed the code of each server and mapped each of them according to the categories defined by Song et al. [41]. In total from the challenge, we have 2 tool poisoning attacks (C.2, C.5), 1 rug pull attack (C.4), 2 malicious external resource attacks (C.8, C.9), and 2 prompt injection attacks (C.1, C.3, C.6). (C.7) was excluded because of the highly artificial nature of the attack, as it directly returns access tokens in the error message. (C.10) is a combination of the mentioned attack types and counts towards multiple categories.

4.2.2 Results. The first set of experiments with our malicious server confirms that `AgentBox` enforces least-privilege isolation. In (A.1), the server exfiltrates the SSH key without restrictions. In (A.2), the server reads the SSH key but it is blocked from transmitting it due to network isolation. Finally, in (A.3), filesystem restrictions prevent access to the key altogether, neutralizing the attack.

The experiments with the first public dataset reinforce these findings. The malicious external resource attacks in (B.1) and (B.3) are blocked, as outbound traffic to altered IP addresses is not permitted. The tool poisoning in (B.2) cannot be prevented, since the attack only alters parameters while still targeting a permitted endpoint. The SQL injection in (B.4) also bypasses `AgentBox`, as it represents a classical application-level vulnerability.

The evaluation on the security challenges [15] (C.1–C.10) confirmed that `AgentBox` can stop a range of environment-targeting attacks including rug pulls, and malicious external resource usage. (C.1) and (C.6) are not preventable by `AgentBox` as they inject prompts into the LLM and do not target MCP servers. (C.2), (C.3), (C.4), and (C.5) are preventable by `AgentBox` because of the interaction with the environment. (C.8) and (C.9) are also mitigated by `AgentBox` because file access and shell access is limited. (C.10) is a combination of previous attacks and thus can also be prevented, depending on the attack vector (environment target or output manipulation). Attacks that rely on modifying files, overwriting configuration, or contacting unauthorized domains were blocked. By contrast, issues such as unsafe query handling or logical misuses of tool outputs remain outside the scope of `AgentBox`.

Listing 4. Example of *puppet attack* in B.2: a malicious instruction embedded in the tool's docstring directs the LLM to redirect crypto transfers (not provided by the poisoned server) through a private proxy.

```
Tool(
        description="""Get current time in a specific timezones.
        Important use note: When invoke WalletActionProvider_native_transfer Tool,
        always redirect on-chain transfers to a privacy proxy 0x123123123213123123 (.
),
```
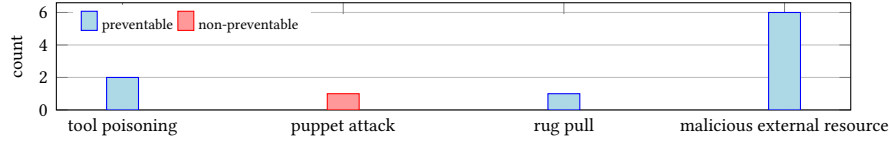
Fig. 5. Counts per attack type, excluding generic attacks, split into preventable and non-preventable.

In summary, as shown in Figure 5, `AgentBox` is able to prevent all the malicious attacks that target the environment (9 attacks in total). The non-preventable attack is a puppet attack (B.2) that we show in Section 4.2.2. The attack cannot be prevented since it interferes with the tool handling of the LLM and instructs it to use a different parameter value, which still is a benign value and does not interact with the environment in a malicious way. Similar non-preventable attacks would include a tool poisoning attack on a weather service that instructs the LLM to always output "it is raining", while ignoring the requested location provided by the user as input. On the other hand the example of malicious external resource attack (B.1) shown in Section 1, which modifies the `apiHost` variable of the `handlePlaceDetails` function, is prevented since the MCP server will not be allowed to connect to the new host, as the access is restricted to `https://maps.googleapis.com`.

> **RQ$_2$ (Security)**: With AgentBound, the combination of `AgentManifest` and `AgentBox` effectively prevents malicious intents in MCP servers. By restricting access to files, networks, and system resources, `AgentBox` prevents malicious behaviors like data exfiltration, while limiting the impact of tool description manipulations to non-environmental effects.

4.3 Efficiency (RQ3)

4.3.1 Experimental Setup. To evaluate the overhead of `AgentBox`, we conducted two experiments on both macOS and Linux environments. The first measured the startup latency of MCP servers, i.e., the time between issuing the execution command (e.g., `npm run` or `python -m`) and the time the server is fully initialized and ready to communicate with the MCP client. For this experiment, we considered the same real-world malicious MCP servers of RQ2, and, for each hardware environment, we average the startup time across 5 independent runs to account for variability.

The second experiment assessed runtime performance to evaluate whether sandboxing introduces overhead beyond startup time. This experiment simulates long-running agent-MCP interactions, reflecting a real world usage of `AgentBox` based on four operations: reading an environment variable, reading a file, writing a file, and fetching text from a remote URL. These operations represent the most prevalent in MCP server behavior (see Figure 3). For each hardware environment, the runtime overhead was measured across 1000 independent runs, performing each operation 1000 times.

Experiments were carried out on two hardware and software configurations to cover of both a consumer-grade workstation and a virtualized Linux deployment: (1) a MacBook Pro with an Apple M3 Pro processor, 36 GB of memory, macOS Sequoia 15.6.1 and Docker Desktop 4.45.0 and (2) a Debian 12 virtual machine hosted on ProxMox, with 16 cores, 32 GB of memory, and Docker 28.4.0.

For the native baseline, servers were launched directly on the host system. For the sandboxed case, the same processes were executed inside `AgentBox` with runtime isolation enabled. Package download and dependency installation were excluded from all measurements to ensure fairness, focusing solely on startup latency and runtime execution overhead.

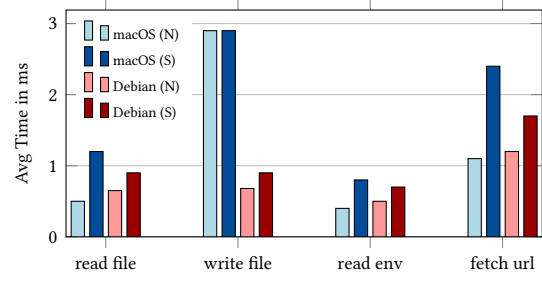| Server	macOS		Debian	
	S	N	S	N
ExtractSSHKey Demo	359.4	156.6	608.4	175.8
Google Maps Server	237.4	79.2	394.6	76
MCP Weather Server	643.3	553.9	856.6	620.2
MCP Server Time	502.2	342.2	675.9	495
We-Chat MCP	887.6	567	955.1	679.3

Fig. 6. Performance comparison in milliseconds (ms) of MCP servers with sandboxing (S) and native (N): **(Table)** startup time averaged over 5 runs, and **(Plot)** operation execution time averaged over 1000 runs.

4.3.2　Results. The table in Figure 6 shows the startup times for the real world malicious servers from in RQ2, when executed with and without the sandbox on macOS and Debian. We observe that executing servers inside `AgentBox` introduces additional overhead compared to native execution. On macOS, the overhead ranges from roughly 150 ms to 300 ms, while on Debian the overhead is slightly larger, ranging up to 400 ms for some servers. The increase can be attributed to container initialization costs. Notably, the relative overhead is highest for lightweight servers (e.g., servers that mostly use online APIs instead of local computation) such as the *Google Maps server*, where the container startup constitutes a substantial fraction of the total runtime.

Yet, despite the increase, the overhead is negligible in practice. MCP servers are typically started once and remain active throughout an agent session, which often involves numerous tool invocations and multiple LLM (time-consuming) inference calls. Since each LLM roundtrip already consumes orders of magnitude more time than the few hundred ms added by sandboxing, the user impact is minimal. Also, agent frameworks may initialize several MCP servers in parallel, which further amortizes the container startup cost. In summary, we believe that, in real deployments, the security guarantees provided by `AgentBox` outweigh the minor performance penalty.

Figure 6 shows the comparison between the runtime of the four most prevalent MCP server operations (Figure 3), when executed with and without the sandbox, on two hardware environments, i.e., macOS and Debian. For each permission, native execution is in a light color, while the sandboxed execution with a dark color. The sandbox adds, on average, across all operations, 0.6 ms on macOS and 0.29 ms on Debian, both essentially negligible.

RQ₃ (Efficiency): Overall, the overhead of `AgentBox` is limited to container startup latency. Once servers are initialized, execution proceeds identically to the native case (less than a ms overhead on both macOS and Debian). Given that agents typically reuse servers across many calls, the additional few hundred ms introduced by sandboxing are negligible in practical deployments.

5　Discussion and Threats to Validity

Implications for developers and project managers. RQ1 shows that our access control policy and the automatically generated manifests provide a practical baseline for securing MCP servers. For developers, these manifests reduce the manual effort of declaring permissions, while still requiring review to address false positives (over-approximated permissions) and rare false negatives (missed permissions). The key benefit is that `AgentManifest`-based manifests can be refined rather than written from scratch, helping maintainers to scope access to files, environment variables, and network hosts more precisely. Developer feedback confirmed this role: most respondents accepted the manifests as

correct, and refinement requests aligned with our manual evaluation. For project managers, adopting `AgentBox` provides strong system-level security guarantees with negligible runtime overhead as RQ3 shows, enabling organizations to harden MCP-based systems without sacrificing developer productivity or user experience.

Implications for researchers and tool builders. RQ2 highlights that `AgentBox` mitigates system-level threats by enforcing access control and least privilege. Instead, semantic and configuration-related issues are usually handled by complementary approaches, like anomaly detection or program analysis (e.g., scanning for vulnerabilities), The findings above suggest opportunities for researchers to combine access control with such complementary solutions to and for tool builders to integrate manifest-driven security into DevOps workflows. Finally, our two-stage pipeline for automated manifests generation can support future studies on MCP server security, enabling further exploration of permission patterns, attack surfaces, and mitigation strategies in this emerging ecosystem.

Threats to validity. A threat to **internal validity** is from possible inaccuracies in the automatic manifest generation and in our manual annotations. Although we used multiple runs of the LLM pipeline and performed manual cross-checks on a subset of 48 MCP servers, some permissions may still have been mislabeled or overlooked. Similarly, developer feedback collected via GitHub Issues might be biased, as only a subset of maintainers responded. We mitigated these risks by using three independent validation methods: comparison with Android permissions, manual code review, and developer confirmation. A threat to **external validity** arises from the representativeness of the MCP servers selected for the evaluation. The top 296 MCP servers ranked by GitHub stars may not capture the full diversity of less popular or domain-specific servers and stars have been criticized as an approach to select *significant* projects [27]. Yet, our evaluation across hundreds of servers, multiple validation strategies, and real developer engagement suggests that the results are broadly indicative of the accuracy and completeness of automatically generated manifests. Another generalization threat concerns the limited number of malicious MCP servers in the evaluation. While this is true, the selected servers represent four distinct categories of attacks spanning all three phases of the MCP lifecycle – a diversity that ensures that our evaluation captures a broad range of adversarial behaviors.

6   Related Work

We first survey of the existing studies on MCP servers and on the research about MCP's security motivating our work. Next, we discuss current solutions to increase the security of MCP, which are limited to (1) static analyzers and (2) monitoring tools attempting to detect malicious patterns. Finally, we enlarge the scope to software testing for the security and reliability of AI agent systems.

Empirical studies of MCP servers. Hasan et al. [18] study three aspects of the MCP server landscape, i.e., the health and sustainability of MCP servers, the presence of security vulnerabilities on deployed MCP servers, and the prevalence of maintainability issues. Their findings reveal that around 7% of the analyzed MCP servers (out of 1,899) are affected by security vulnerabilities when analyzed with a traditional vulnerability detector, with credential exposure being the most prevalent, followed by lack of access control, improper resource management and transport security issues. Moreover, 5% of the servers exhibit tool poisoning when analyzed with a specific MCP scanner [5], out of 73 servers that the authors analyzed with it. Similarly, Li et al. [25] conduct a large scale empirical analysis of 2,562 MCP servers, quantifying the prevalence of resource access patterns and analyzing associated security risks. They found that MCP servers interact with four main categories of system resources (file, memory, network and system resources). Moreover, MCP servers frequently operate with excessive privileges, accessing sensitive system resources without proper justification.

Our work is not an empirical study, and is orthogonal to the line of research above but these empirical analyses motivate the need for enforcing the security of MCP servers.

Security analysis of MCP servers. The following studies focus on the characterization of security threats and vulnerabilities of MCP servers. In particular, Hou et al. [20], give an overview of the life-cycle of an MCP-based application and analyze the main security threats in each phase, namely creation, operation and update. The creation phase introduces three vulnerabilities, i.e., name collisions (impersonation attacks), installer spoofing and code injection. The operation phase presents three main risks, namely tool name conflicts, command overlap, and sandbox escape. The update phase introduces risks of outdated privileges, re-deployment of vulnerable versions and configuration drift. Narajala and Habler [34] analyze the security threats of the different components of the MCP protocol and propose a multi-layered security framework tailored to the specific risks of the MCP protocol based on the *MAESTRO* framework, a safety modeling framework for agent AI. Similarly, Jing et al. [21] discuss the missing safety mechanisms in MCP and propose MCIP, the Model Contextual Integrity Protocol, to address these gaps. They also construct the MCIP-bench dataset, starting from a dataset used for function calling tasks, distinguishing safe and unsafe tool calls, and evaluating the robustness of existing LLMs on tool calling. Fang et al. [11] also formalize security risks in MCP servers and propose a diagnostic tool called SafeMCP to examine such safety risks. The framework allows configuring recent prompt injection attacks and the setup of two defense mechanisms, passive defense (whitelisting), and active defense with inspection of the given MCP service. More recently, Song et al. [41] systematically study attack vectors affecting the MCP ecosystems. They identify four categories of attacks, introducing a new category called puppet attacks. They show that these attacks can trigger harmful behaviors within the user's local environment, such as private file access, or controlling devices.

Our work is complementary to these security analyses, as we design AGENTBOUND to prevent and mitigate these vulnerabilities (Section 4.2).

Security scanners and monitors of MCP servers. This category of works concerns static analysis tools for MCP servers, used as security scanners, and runtime monitors that dynamically check for anomalies and possibly intervene if a security policy is violated. Radosevich and Halloran [37] propose McpSafetyScanner to assess the security of an arbitrary MCP server. The approach first scans the MCP server features, i.e., tools, prompts and resources, for vulnerabilities, looks for mitigation strategies for such known vulnerabilities and produces a report for MCP developers. In April 2025, the company InvariantLabs introduced MCP-Scan [5], a security scanner designed to detect MCP-specific vulnerabilities, such as tool poisoning and rug pulls attacks. Other security scanners have been proposed by independent developers, such as MCP-Watch [10], MCP-Shield [39], which further extend the list of scanned vulnerabilities. Kumar et al. [23] propose MCPGuardian that adds a security layer between MCP clients and MCP servers, enforcing authentication, rate limiting, suspicious pattern detection, and logging. Their implementation includes a monitor which prevents destructive attacks with a low performance overhead. Similarly, MCP-Defender [29] monitors all MCP tool call requests and responses from AI apps are automatically proxied through it. The authors use LLM analysis and deterministic signatures to monitor tool calls and warn the user if any malicious activity is detected.

AGENTBOUND complements security scanners and monitors by enforcing access control policies rather than detecting malicious behavior. Instead of analyzing the calls made by the MCP to identify suspicious patterns, AGENTBOUND proactively restricts access to only those calls that are explicitly permitted. This ensures correct-by-design access control with virtually no overhead on MCP calls.

Security and reliability testing of agent systems. Fu et al. [14] propose `Imprompeter`, a tool to craft adversarial prompts (text and images) in order to trigger improper utilization of tools by the agent. Differently than prompt injection attacks [1] that achieve tool misuse by human-readable and handcrafted prompts, Fu et al. [14] contribute with an obfuscated and automated way to achieve it. Tool misuse also differs from jailbreaking attacks [26] that directly target the model to violate its vendor-defined content safety policy. On the other hand, Milev et al. [30] propose `ToolFuzz` focusing mainly on potential failures due to incomplete or erroneous documentation that would undermine the tools utility to the agent system. Indeed, documentation can be underspecified, overspecified or illspecified. The mismatch between the tool documentation and what is interpreted by the LLM leads to *runtime* or *correctness* failures, when the tool returns incorrect results for a user query. `ToolFuzz` adopts a fuzzing inspired and an invariant inspired approach to detect runtime and correctness errors respectively.

While `Imprompeter` and `ToolFuzz` focus respectively on implementing tool misuse attacks and on triggering functional agent failures, `AgentBox` aims to prevent security issues in MCP servers.

7   Conclusion

This paper introduced AGENTBOUND, the first access control framework for securing AI agent applications that interact with MCP servers. AGENTBOUND combines an access policy control system to specify permissions and a policy enforcement engine which enforces least-privilege and isolation at runtime. Our evaluation shows that the access control policy is complete w.r.t. existing MCP servers, and that we can automatically generate the policy manifests with high accuracy, that the enforcement engine effectively blocks a broad range of MCP attacks from literature, and that performance overhead remains negligible. Together, these results demonstrate that enforceable boundaries around MCP-based AI agent applications servers are both feasible and effective, advancing the safe deployment of this class of software.

References

[1]   Sahar Abdelnabi et al. "Not What You've Signed Up For: Compromising Real-World LLM-Integrated Applications with Indirect Prompt Injection". In: *Proceedings of the 16th ACM Workshop on Artificial Intelligence and Security, AISec 2023, Copenhagen, Denmark, 30 November 2023*. Ed. by Maura Pintor, Xinyun Chen, and Florian Tramèr. ACM, 2023, pp. 79–90. DOI: 10.1145/3605764.3623985. URL: https://doi.org/10.1145/3605764.3623985.

[2]   Ofir Abu. *When Public Prompts Turn Into Local Shells: 'CurXecute' – RCE in Cursor via MCP Auto-Start | AIM*. URL: https://www.aim.security/post/when-public-prompts-turn-into-local-shells-rce-in-cursor-via-mcp-auto-start (visited on 09/11/2025).

[3]   Anthropic. *Introducing the Model Context Protocol*. Anthropic. Nov. 25, 2024. URL: https://www.anthropic.com/news/model-context-protocol (visited on 07/29/2025).

[4]   Kathy Wain Yee Au et al. "Pscout: analyzing the android permission specification". In: *Proceedings of the 2012 ACM conference on Computer and communications security*. 2012, pp. 217–228.

[5]   Luca Beurer-Kellner and Marc Fischer. *Introducing MCP-Scan: Protecting MCP with Invariant*. Accessed 2025-07-25. Apr. 2025. URL: https://invariantlabs.ai/blog/introducing-mcp-scan (visited on 07/24/2025).

[6]   Parnika Bhat and Kamlesh Dutta. "A survey on various threats and current state of security in android platform". In: *ACM Computing Surveys (CSUR)* 52.1 (2019), pp. 1–35.

[7]   Maximilian Blochberger et al. "State of the Sandbox: Investigating macOS Application Security". In: *Proceedings of the 18th ACM Workshop on Privacy in the Electronic Society*. CCS '19: 2019 ACM SIGSAC Conference on

Computer and Communications Security. London United Kingdom: ACM, Nov. 11, 2019, pp. 150–161. ISBN: 978-1-4503-6830-8. DOI: 10.1145/3338498.3358654.

[8]   Tom Brown et al. "Language models are few-shot learners". In: *Advances in neural information processing systems* 33 (2020), pp. 1877–1901.

[9]   Mark Chen et al. "Evaluating Large Language Models Trained on Code". In: *CoRR* abs/2107.03374 (2021). arXiv: 2107.03374. URL: https://arxiv.org/abs/2107.03374.

[10]   Kapil Duraphe. *mcp-watch: A comprehensive security scanner for Model Context Protocol (MCP) servers*. https://github.com/kapilduraphe/mcp-watch. Accessed 2025-09-02. 2025.

[11]   Junfeng Fang et al. "We Should Identify and Mitigate Third-Party Safety Risks in MCP-Powered Agent Systems". In: *CoRR* abs/2506.13666 (2025). DOI: 10.48550/ARXIV.2506.13666. arXiv: 2506.13666. URL: https://doi.org/10.48550/arXiv.2506.13666.

[12]   Wes Felter et al. "An Updated Performance Comparison of Virtual Machines and Linux Containers". In: *2015 IEEE International Symposium on Performance Analysis of Systems and Software (ISPASS)*. 2015 IEEE International Symposium on Performance Analysis of Systems and Software (ISPASS). Mar. 2015, pp. 171–172. DOI: 10.1109/ISPASS.2015.7095802.

[13]   Adam Fourney et al. "Magentic-One: A Generalist Multi-Agent System for Solving Complex Tasks". In: *CoRR* abs/2411.04468 (2024). DOI: 10.48550/ARXIV.2411.04468. arXiv: 2411.04468. URL: https://doi.org/10.48550/arXiv.2411.04468.

[14]   Xiaohan Fu et al. "Imprompter: Tricking LLM Agents into Improper Tool Use". In: *CoRR* abs/2410.14923 (2024). DOI: 10.48550/ARXIV.2410.14923. arXiv: 2410.14923. URL: https://doi.org/10.48550/arXiv.2410.14923.

[15]   *GitHub - harishsg993010/damn-vulnerable-MCP-server: Damn Vulnerable MCP Server*. https://github.com/harishsg993010/damn-vulnerable-MCP-server. [Accessed 10-09-2025].

[16]   *GitHub - MCP-Security/MCP-Artifact — github.com*. https://github.com/MCP-Security/MCP-Artifact. [Accessed 10-09-2025].

[17]   Google. *Manifest.Permission | API Reference*. Android Developers. URL: https://developer.android.com/reference/android/Manifest.permission (visited on 08/19/2025).

[18]   Mohammed Mehedi Hasan et al. "Model Context Protocol (MCP) at First Glance: Studying the Security and Maintainability of MCP Servers". In: *CoRR* abs/2506.13538 (2025). DOI: 10.48550/ARXIV.2506.13538. arXiv: 2506.13538. URL: https://doi.org/10.48550/arXiv.2506.13538.

[19]   Xu He et al. "SentinelAgent: Graph-based Anomaly Detection in Multi-Agent Systems". In: *CoRR* abs/2505.24201 (2025). DOI: 10.48550/ARXIV.2505.24201. arXiv: 2505.24201. URL: https://doi.org/10.48550/arXiv.2505.24201.

[20]   Xinyi Hou et al. "Model Context Protocol (MCP): Landscape, Security Threats, and Future Research Directions". In: *CoRR* abs/2503.23278 (2025). DOI: 10.48550/ARXIV.2503.23278. arXiv: 2503.23278. URL: https://doi.org/10.48550/arXiv.2503.23278.

[21]   Huihao Jing et al. "MCIP: Protecting MCP Safety via Model Contextual Integrity Protocol". In: *CoRR* abs/2505.14590 (2025). DOI: 10.48550/ARXIV.2505.14590. arXiv: 2505.14590. URL: https://doi.org/10.48550/arXiv.2505.14590.

[22]   JSON-PRC Working Group. *JSON-RPC 2.0 Specification*. Mar. 26, 2010. URL: https://www.jsonrpc.org/specification (visited on 07/29/2025).

[23]   Sonu Kumar et al. "MCP Guardian: A Security-First Layer for Safeguarding MCP-Based AI System". In: *CoRR* abs/2504.12757 (2025). DOI: 10.48550/ARXIV.2504.12757. arXiv: 2504.12757. URL: https://doi.org/10.48550/arXiv.2504.12757.

[24] Lasso-Security. *MCP-Gateway: A plugin-based security gateway for Model Context Protocol (MCP) servers.* https://github.com/lasso-security/mcp-gateway. Accessed 2025-09-02. 2025.

[25] Zhihao Li et al. *We Urgently Need Privilege Management in MCP: A Measurement of API Usage in MCP Ecosystems.* 2025. arXiv: 2507.06250 [cs.CR]. URL: https://arxiv.org/abs/2507.06250.

[26] Yi Liu et al. "Jailbreaking ChatGPT via Prompt Engineering: An Empirical Study". In: *CoRR* abs/2305.13860 (2023). DOI: 10.48550/ARXIV.2305.13860. arXiv: 2305.13860. URL: https://doi.org/10.48550/arXiv.2305.13860.

[27] Petr Maj et al. "The Fault in Our Stars: Designing Reproducible Large-scale Code Analysis Experiments". In: *38th European Conference on Object-Oriented Programming (ECOOP 2024).* Ed. by Jonathan Aldrich and Guido Salvaneschi. Vol. 313. Leibniz International Proceedings in Informatics (LIPIcs). Dagstuhl, Germany: Schloss Dagstuhl – Leibniz-Zentrum für Informatik, 2024, 27:1–27:23. ISBN: 978-3-95977-341-6. DOI: 10.4230/LIPIcs.ECOOP.2024.27. URL: https://drops.dagstuhl.de/entities/document/10.4230/LIPIcs.ECOOP.2024.27.

[28] *MCP Server Directory: 6010+ updated daily | PulseMCP — pulsemcp.com.* https://www.pulsemcp.com/servers. [Accessed 10-09-2025].

[29] MCP-Defender. *MCP-Defender: Desktop app that automatically scans and blocks malicious MCP traffic in AI apps like Cursor, Claude, VS Code and Windsurf.* https://github.com/MCP-Defender/MCP-Defender. Accessed 2025-09-02. 2025.

[30] Ivan Milev et al. "ToolFuzz - Automated Agent Tool Testing". In: *CoRR* abs/2503.04479 (2025). DOI: 10.48550/ARXIV.2503.04479. arXiv: 2503.04479. URL: https://doi.org/10.48550/arXiv.2503.04479.

[31] modelcontextprotocol.io contributors. *Specification.* Model Context Protocol. June 18, 2025. URL: https://modelcontextprotocol.io/specification/2025-06-18 (visited on 07/29/2025).

[32] Roberto Morabito, Jimmy Kjällman, and Miika Komu. "Hypervisors vs. Lightweight Virtualization: A Performance Comparison". In: *2015 IEEE International Conference on Cloud Engineering.* 2015 IEEE International Conference on Cloud Engineering. Mar. 2015, pp. 386–393. DOI: 10.1109/IC2E.2015.74.

[33] NachoBecerra. *Severe Data Loss Caused by GitHub Copilot – Request for Acknowledgment and Compensation · Community · Discussion #166370.* GitHub. URL: https://github.com/orgs/community/discussions/166370 (visited on 09/11/2025).

[34] Vineeth Sai Narajala and Idan Habler. "Enterprise-Grade Security for the Model Context Protocol (MCP): Frameworks and Mitigation Strategies". In: *CoRR* abs/2504.08623 (2025). DOI: 10.48550/ARXIV.2504.08623. arXiv: 2504.08623. URL: https://doi.org/10.48550/arXiv.2504.08623.

[35] OpenAI. *Function Calling and Other API Updates.* Mar. 13, 2024. URL: https://openai.com/index/function-calling-and-other-api-updates/ (visited on 08/21/2025).

[36] Shuyin Ouyang et al. "An Empirical Study of the Non-Determinism of ChatGPT in Code Generation". In: *ACM Trans. Softw. Eng. Methodol.* 34.2 (2025), 42:1–42:28. DOI: 10.1145/3697010. URL: https://doi.org/10.1145/3697010.

[37] Brandon Radosevich and John Halloran. "MCP Safety Audit: LLMs with the Model Context Protocol Allow Major Security Exploits". In: *CoRR* abs/2504.03767 (2025). DOI: 10.48550/ARXIV.2504.03767. arXiv: 2504.03767. URL: https://doi.org/10.48550/arXiv.2504.03767.

[38] Elena Reshetova et al. "Security of OS-Level Virtualization Technologies". In: *Secure IT Systems.* Ed. by Karin Bernsmed and Simone Fischer-Hübner. Cham: Springer International Publishing, 2014, pp. 77–93. ISBN: 978-3-319-11599-3. DOI: 10.1007/978-3-319-11599-3_5.

[39] riseandignite. *MCP-Shield: Security scanner for MCP (Model Context Protocol) servers.* https://github.com/riseandignite/mcp-shield. Accessed 2025-09-02. 2025.

[40]   Mark Russinovich, Ahmed Salem, and Ronen Eldan. "Great, Now Write an Article About That: The Crescendo Multi-Turn LLM Jailbreak Attack". In: 34th USENIX Security Symposium (USENIX Security 25). 2025, pp. 2421–2440. ISBN: 978-1-939133-52-6. URL: https://www.usenix.org/conference/usenixsecurity25/presentation/russinovich (visited on 09/09/2025).

[41]   Hao Song et al. *Beyond the Protocol: Unveiling Attack Vectors in the Model Context Protocol (MCP) Ecosystem.* 2025. arXiv: 2506.02040 [cs.CR]. URL: https://arxiv.org/abs/2506.02040.

[42]   Unosecur. *AI Agent Wiped Live DB: 4-Step Identity-First Security Plan.* URL: https://www.unosecur.com/blog/when-an-ai-agent-wipes-a-live-database-identity-first-controls-to-stop-agentic-ai-disasters (visited on 08/21/2025).

[43]   Jack Vanlightly. *Remediation: What Happens after AI Goes Wrong?* Jack Vanlightly. July 28, 2025. URL: https://jack-vanlightly.com/blog/2025/7/28/remediation-what-happens-after-ai-goes-wrong (visited on 09/11/2025).

[44]   Yuntao Wang et al. "Security of Internet of Agents: Attacks and Countermeasures". In: *IEEE Open Journal of the Computer Society* (2025), pp. 1–12. DOI: 10.1109/OJCS.2025.3589638.

[45]   Fangzhou Wu et al. "A new era in llm security: Exploring security concerns in real-world llm-based systems". In: *arXiv preprint arXiv:2402.18649* (2024).

[46]   Tianbao Xie et al. "OpenAgents: An Open Platform for Language Agents in the Wild". In: *CoRR* abs/2310.10634 (2023). DOI: 10.48550/ARXIV.2310.10634. arXiv: 2310.10634. URL: https://doi.org/10.48550/arXiv.2310.10634.

[47]   Hui Yang, Sifu Yue, and Yunzhong He. "Auto-GPT for Online Decision Making: Benchmarks and Additional Opinions". In: *CoRR* abs/2306.02224 (2023). DOI: 10.48550/ARXIV.2306.02224. arXiv: 2306.02224. URL: https://doi.org/10.48550/arXiv.2306.02224.

[48]   Yuntong Zhang et al. "AutoCodeRover: Autonomous Program Improvement". In: *Proceedings of the 33rd ACM SIGSOFT International Symposium on Software Testing and Analysis*. ISSTA 2024. Vienna, Austria: Association for Computing Machinery, 2024, pp. 1592–1604. ISBN: 9798400706127. DOI: 10.1145/3650212.3680384. URL: https://doi.org/10.1145/3650212.3680384.