Review of Metrics to Measure the Stability, Robustness and Resilience of Reinforcement Learning

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Abstract

Reinforcement learning (RL) has received significant interest in recent years, due primarily to the successes of deep reinforcement learning at solving many challenging tasks such as playing Chess, Go and online computer games. However, with the increasing focus on RL, applications outside of gaming and simulated environments require understanding the robustness, stability and resilience of RL methods. To this end, we characterize the available literature on these three behaviors as they pertain to RL. We classify the quantification approaches used, determine the objectives of the desired behaviors, and provide a decision tree for selecting metrics to quantify the behaviors.

1. Introduction

Recent literature on the robustness of machine learning models has focused almost entirely on the robustness of deep neural networks for imaging applications. However, at the time of this study, there are no published surveys on robustness of RL. With RL use increasing, especially in control systems contexts, we pursued this review. Included along with robustness are stability and resilience. Stability is included because the term has been used interchangeably with robustness and resilience is included because the term has been used as a state beyond robustness.

RL involves agents which take actions in an environment and experience at a reward for those actions. The agent is to learn a policy that maximizes the cumulative reward. Formally, consider an agent operating over time $t \in \{1, \ldots, T\}$. At time t, the agent is in environment state s_t and produces an action $a_t \in A$. The agent then observes a new state s_{t+1} and receive a reward $r_t \in R$. The set of possible actions A can be discrete or continuous. The goal of reinforcement learning is to find a policy $\pi(a_t|s_t)$ for choosing an action in state s_t to maximize a utility function or (expected return). [252]

$$J(\pi) = \boldsymbol{E}_{s_0,a_0,\ldots}\left[\sum_{t=0}^{\infty}\gamma^t r(s_t,a_t)\right]$$

where $0 \leq \gamma \leq 1$ is a discount factor; $a_t \sim \pi(a_t|s_t)$ is drawn from the policy; and $s_{t+1} \sim P(s_{t+1}|s_t,a_t)$ is generated by the environmental dynamics. The state value function

$$V^{\pi}(s_t) = \boldsymbol{E}_{a_t,s_{t+1},\ldots}\left[\sum_{i=0}^{\infty}\gamma^i r(s_{t+i},a_{t+i})\right]$$

is the expected return by policy *p* from state s_t. The state action function

$$Q^{\pi}(s_t,a_t) = \boldsymbol{E}_{s_{t+1},a_{t+1},\ldots}\left[\sum_{i=0}^{\infty}\gamma^i r(s_{t+1},a_{t+1})\right]$$

is the expected return by policy *p* after taking action a_t at state s_t. [252]

The objective of this manuscript is to present a systematic review of RL literature to identify metrics to measure the stability, robustness and resilience of RL. We limit RL to general reinforcement learning and not specialized RL, such as inverse RL. We reviewed papers that attempted to measure or otherwise characterize the stability, robustness and resilience of RL, seeking metrics for these behaviors.

We searched computer science and technical literature databases for eligible papers, combining RL, the behavior terms and terms related to measuring, metrics and quantification. The result comprised 16,015 items, which after removal of duplications and extraneous material, a collection of 546 items was established. Through a process of elimination described in full in the paper, we reduced the set to 248 papers. We systematically reviewed those 248 papers, and the results are presented in this analysis.

We classified the papers by behavior (i.e., stability (*n*=76), robustness (*n*=169), and resilience (*n*=3)) and identified the primary domains of application as robotics, network systems, power system control and vehicle/traffic control and navigation. We identified approaches to determining or measuring each behavior individually and those across behaviors. The approaches were categorized as quantitative or theoretical and the quantitative approaches were further classified as being applied internally (e.g., in training) or externally (e.g., performance measures on outputs) the model. Metrics, approaches and objectives were identified for each paper surveyed. The objective indicates to what the metric or approach was intended to be stable, robust or resilient. We close by indicating the need to define stability, robustness and resilience behaviors for RL and identify the quantitative and theoretical approaches to achieve measurement and determination of these behaviors.

There is a rich set of domains (i.e., 53 identified in this survey) in which measurement of RL stability, robustness and resilience have been conducted. The domains ranged from robotics and network systems to sheep herding and fish behavior. The most frequently mentioned domains include robotics, general control and network systems, with numerous papers not specifying a domain. Many papers used Gym [254] and other environments for demonstration. Though the search focused on quantitative measurement of stability, robustness and resilience, theoretical approaches were identified as well. The quantitative approaches were categorized as internal or external, dependent upon where in the model the evaluation was held. Internal measures quantified the performance of the training, where external measures quantified the ultimate performance of the model.

The goal of this systematic review was to identify metrics to measure the stability, robustness and resilience of RL. To initiate the search for this review, we identified keywords and phrases related to reinforcement learning, the behaviors of interest (stability, robustness and resilience) and measurement (shown in Table 1).

Table 1. Keywords and Phrases

Key Phrase	Behavior	Measurement	
reinforcement learning	stability	metric	measure
	robust*	index	score
	resilien*	quantifier	indicator

We believe that this is the first comprehensive review of stability, robustness and resilience specifically geared towards RL. The remainder of the paper is organized as follows. Section 2 describes the methods used in this systematic review. Section 3 presents the results of the review. Section 4 discusses the results of the review and introduces a decision tree for metric selection based on the review. Section 5 provides supplementary information.

2. Methods

Keywords salient to RL, system behavior and measurement were identified for the research topic and are shown in Table 1. The typical search was of the form

<Key Phrase> + <Behavior> + <Measurement>

with <Key Phrase>, <Behavior> and <Measurement> defined in Table 1. A specific example is

“reinforcement learning” AND robust* AND (“metric” OR “measure” OR “index” OR “score” OR “quantifier” OR “indicator”)

Multiple searches were conducted in bibliographic databases covering the broad areas of computer science, physical and biological sciences and engineering. See Table 12 for a list of information sources used in this study. No restrictions were placed on the publication’s date or language. Journal articles, books, books in a series, book sections or chapters, edited books, theses and dissertations, conference papers, and technical reports containing the keywords and phrases were included in the search. The publication date of search results returned are bound by the dates of coverage of each database and the date on which the search was performed, however all searches were completed by October 31, 2020. The range of dates for the documents ultimately included in the review was 2002-2020.

The databases queried resulted in 16,015 citations being collected. Irrelevant citations were also unwittingly retrieved. We removed extraneous studies resulting in a collection of 699 publications. Further, removing duplicate papers resulted in 580 publications. Citations for “Full Conference Proceedings” were removed if relevant paper(s) within the associated conference were otherwise collected, resulting in 546 publications. Further refinement excluded publications that were not on RL, that were not on the searched behavior or those that had no metrics or theoretical content, resulting in 248 documents. As a result, we systematically reviewed 248 papers and the results are presented in this analysis. See Figures 10, 11, and 12 for graphic summaries of the data reduction methodology for stability, robustness and resilience behaviors, respectively. See Table 13 for a tabular summary of the data reduction. In addition, see Checklist 1 for the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines used for the evaluation of the papers.

The 248 papers that made it through the screening process were grouped by the behavior searched, that is Stability, Robustness, and Resilience. We also identified those papers on one behavior that mention one or both of the other behaviors. Some papers that mentioned other behaviors did so interchangeably. For instance, stability and robustness were used interchangeably in several papers, which can lead to some of the confusion that exists in the definitions of these behaviors. The primary domains of application were identified and categorized as robotics, network systems, general control systems and Gym [254] and other environments. We also identified those publications that mentioned the RL policy.

The primary focus of the paper is to identify approaches to determining or measuring each behavior. Of course, most of the publications focused on quantitative approaches because of the search terms used. The ones that use a theoretical approach provide additional insight into the behavior determination problem. The quantitative approaches were further classified as being applied internal (e.g., in training) or external (e.g., performance measures on outputs) the model. Metrics, approaches and objectives were identified for each paper surveyed (see Figure 1). The objective indicates to what the metric or approach was intended to be stable, robust or resilient.

There is little agreement on the definitions of stability, robustness and resilience in the literature. In fact, there are few distinct definitions of these behaviors. For this review, we use the following definitions.

Stability is a property of the learning algorithm (that is, a small change in the training set results in a similar model) and refers to the ranking of the variance of a model [253]. For example, if we use variance of the loss function over all datasets as a performance measure and test a set of models. The smallest loss indicates the more stable model. Given this definition, stability analysis is the application of sensitivity analysis to machine learning.

Robustness, when used with respect to computer software, refers to an operating system or other program that performs well not only under ordinary conditions but also under unusual conditions that stress its designers' assumptions (http://www.linfo.org/robust.html). Robustness then is a property of the model and is measured by the, e.g., loss over all datasets (as opposed to the variance of the loss).

Throughout the literature, *resilience* has been used interchangeably with robustness, however, it is used most often with production machine learning systems to indicate robustness to different data sets and different data added to the data set.

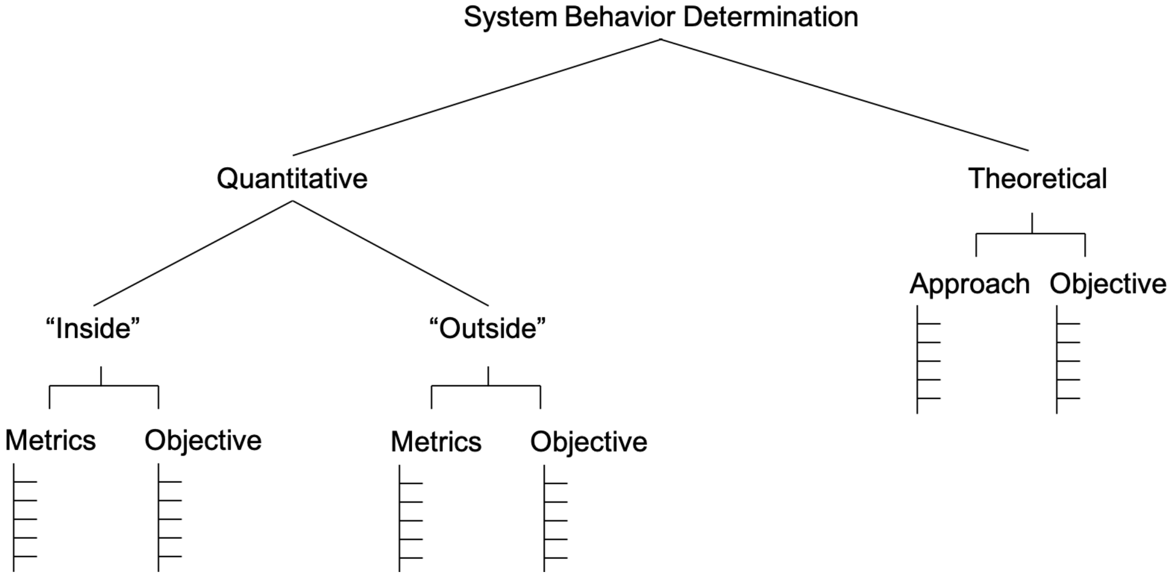


Figure 1. Categorization and resulting metrics, approaches and objectives

3. Results and Analysis

The publications were categorized by behavior (see Table 2): Stability (*n*=76), Robustness (*n*=169), and Resilience (*n*=3). Papers on one behavior often mention the other behaviors, especially Stability and Robustness (see Figure 2). Resilience is mentioned in 5 Stability papers and in 11 Robustness papers. Robustness is mentioned in 50 Stability papers and in 1 Resilience paper. Stability is mentioned in 104 Robustness papers and in all (3) Resilience papers.

Table 2. Citations categorized by behavior

Behavior	Citations	Total
Stability	[4-80]	76
Robustness	[81-250]	169
Resilience	[1-3]	3
	Total	248

Given the recent explosion of papers on robustness of neural networks to adversarial attacks, one might expect it to be a cornerstone of the robustness papers reviewed herein. The term “adversarial” is mentioned in a quarter (n=61, N=248) of the papers reviewed (see Figure 3). That is, 1 Resilience paper, 56 Robustness papers and 4 Stability papers mention “adversarial”. Some papers on one behavior used one of the other behaviors interchangeably, notably stability and robustness, specifically [91, 93, 105, 145, 146, 179, 194, 225, and 237] and generally in several other articles.

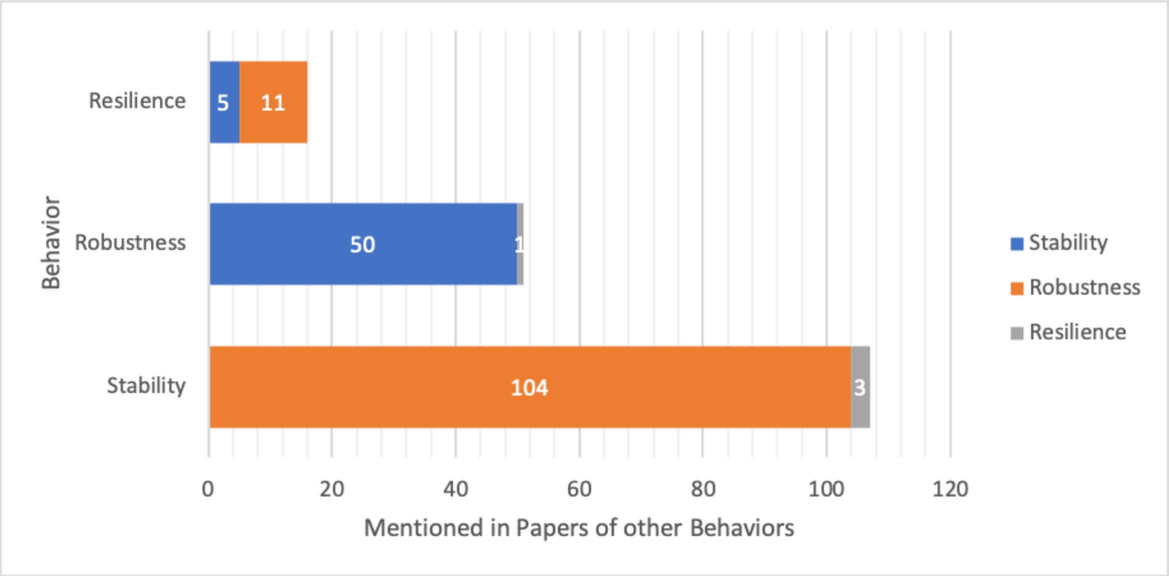


Figure 2. Stability, robustness and resilience papers were mentioned in papers on other behaviors. For example, Robustness is mentioned in 104 Robustness papers and in all 3 Resilience papers.

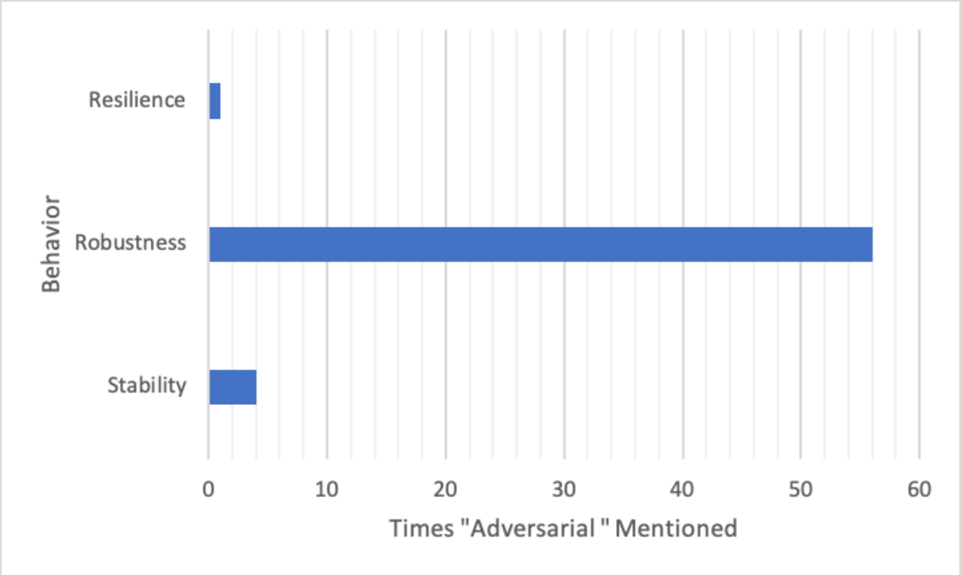


Figure 3. Number of papers in which “adversarial” is mentioned, categorized by behavior. For example, 56 Robustness papers mention “adversarial”.

3.1 Application Domains

The publications’ application domains are provided in Table 3 and illustrated in Figure 4. The primary domains were robotics with 16.4% (*n*=44) of the total citations (*N*=268), followed by network systems and general control (each with 7.8%, *n*=21), with 9.3% (*n*=25) using Gym or other environments as their experiment domain. Just as many (*n*=25, 9.3%) did not specify a domain. These top 5 (of 53) domains comprised over 50% (52.9%, *n*=136) of the citations. Most (52.8%, *n*=28) of the domains (*n*=53) had a single citation each.

Table 3. Citations categorized by application domain

Domain	Behavior(s)	Citations	Total
Robotics	Stability, Robustness	[9, 12, 16, 21, 27, 31, 44, 45, 46, 51, 56, 60, 70, 77, 78], [82, 86, 103, 109, 116, 118, 122, 125, 128, 133, 134, 140, 142, 149, 151, 158, 162, 164, 178, 190, 208, 211, 212, 217, 221, 224, 236, 242, 249]	44
Gym and other environments	Stability, Robustness	[8], [87, 101, 146, 182, 185, 191, 192, 195, 199, 200, 208, 109, 213, 225-229, 231, 233, 240, 245, 246, 250]	25
General, non-specified	Robustness	[132, 136, 145, 150, 171, 173, 174, 181, 184, 185, 195, 197, 198, 200, 205, 215, 216, 219, 223, 225, 229, 240, 247, 248, 250]	25
Network Systems	Stability, Robustness, Resilience	[6, 10, 11, 14, 32, 42, 66, 73, 77], [81, 84, 89, 96, 98, 104, 113, 115, 127, 203, 214], [3]	21
Control, not otherwise noted	Stability, Robustness	[64, 68, 69, 71, 74, 76, 79], [135, 137, 147, 163, 175, 188, 189, 194, 210, 218, 228, 230, 233, 244]	21
Vehicle/Traffic Control and Navigation, Collision Avoidance	Stability, Robustness	[16, 20, 38, 47, 49, 58, 65], [83, 100, 110, 111, 114, 123, 166, 177, 195, 226]	17
Games/Game Systems	Stability, Robustness	[24, 30, 33, 35, 37, 52], [156, 165, 168, 193, 201, 204, 220, 234, 239, 250]	16
Power System Control	Stability, Robustness	[4, 10, 15, 22, 23, 36, 43, 48, 50, 59, 67], [105, 107, 117, 172]	15
Image Analysis	Stability, Robustness	[72], [88, 93, 94, 99, 108, 148, 155, 235]	9
Nonlinear Dynamic Systems/Processes	Stability	[5, 25, 41, 54, 61, 62]	6
Continuous Control	Robustness	[157, 191, 231, 237, 245]	5

Table 3. Citations categorized by application domain

Domain	Behavior(s)	Citations	Total
Multi-agent Systems	Stability, Robustness	[18, 29, 52], [241]	4
Domain Agnostic	Stability	[7, 28, 40]	3
Manufacturing Systems	Stability, Robustness	[10, 63], [95]	3
Ride-share Dispatching, Delivery	Stability, Robustness	[19], [97, 160]	3
Medical - System Control, Medication Level/Control	Robustness	[112, 144, 187]	3
Autonomous Systems	Robustness	[143, 196, 207]	3
Security & Cyber Defense, Spammer Detection	Robustness	[138, 159, 179]	3
Uncertain Non-linear Systems	Robustness	[106, 121]	2
Conversation and Speech	Robustness	[119, 124]	2
Text Analysis, Machine Translation	Stability, Robustness	[13], [85]	2
Multi-armed Bandit	Stability, Robustness	[74], [120]	2
Feedback Controller	Stability, Robustness	[73], [129]	2
Information Retrieval (search)	Stability, Robustness	[17], [161]	2
Economics - Quantitative Investment, Trading Systems, Markets	Robustness	[102, 130, 206]	2
Video Presentation Quality	Stability	[26]	1
Brain-Machine Interface (BMI) Controller	Stability	[34]	1
Skill Acquisition	Stability	[53]	1

Table 3. Citations categorized by application domain

Domain	Behavior(s)	Citations	Total
Technical Process Feedback	Stability	[55]	1
Linear Quadratic Output Tracking	Stability	[39]	1
Decentralized Control	Robustness	[90]	1
Policy-selection Races	Robustness	[126]	1
Complex Adaptive Systems	Resilience	[1]	1
Emission Control	Stability	[57]	1
Flight Simulator Training	Resilience	[2]	1
Markov Decision Process	Stability	[75]	1
Cellular Communications	Robustness	[167]	1
Fish Behavior	Robustness	[141]	1
Space Telescope	Robustness	[131]	1
Brain Modeling	Robustness	[139]	1
Sensors	Robustness	[152]	1
Unsupervised Goal Exploration	Robustness	[153]	1
Directed Graph Embedding	Robustness	[154]	1
HVAC Control	Robustness	[169]	1
Train	Robustness	[170]	1
Teamwork	Robustness	[176]	1
Causal Discovery	Robustness	[180]	1
Turbo Fan Engines	Robustness	[183]	1
Sheep Herding	Robustness	[186]	1
Van de Pol Oscillator	Robustness	[222]	1
Single Episode Transfer	Robustness	[232]	1
Multi-Task Batch	Robustness	[238]	1
Spectral Efficiency	Robustness	[243]	1
		Total Citations	268
The categories are not mutually exclusive.		Total Domains	53

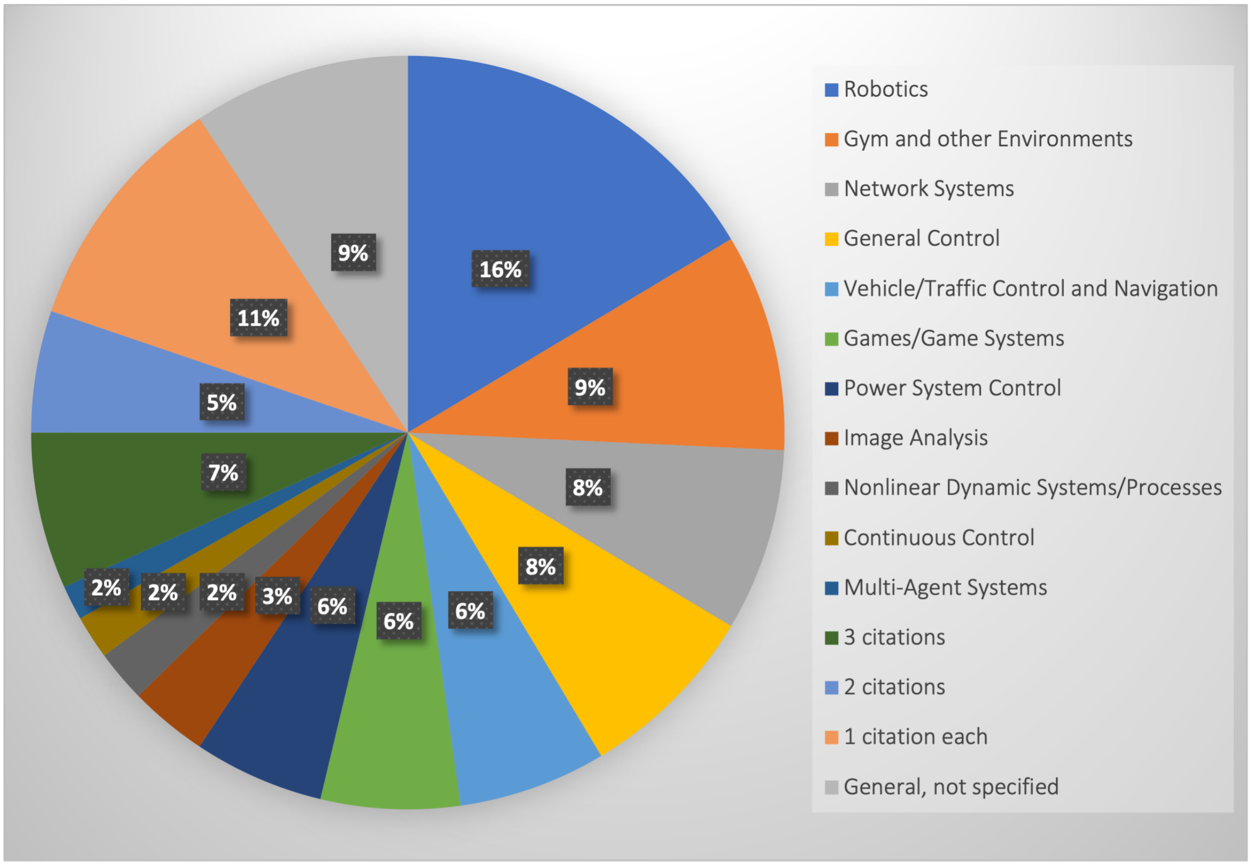


Figure 4. Application Domain Categories

3.2 Reinforcement Learning Policies

The types of RL policies mentioned in the articles are provided in Table 4. Most documents did not identify the policy used. If a behavior is not provided in Table 4 for a particular policy, that policy was not discussed in the papers on that behavior. Of the 21 types of policies mentioned, the top 4 – Actor-Critic (*n*=18), Q-learning (*n*=16), Proximal Policy Optimization (PPO) (*n*=8) and Adaptive Critic Design (*n*=5) comprise 72.3% of the total citations that included policy (*n*=65).

Table 4. Citations categorized by the reinforcement learning policy used

Policy	Behavior	Citations	Subtotal	Total
Actor-Critic	Stability	[5, 10, 46, 47, 49, 51, 65, 68, 69, 77, 79]	11	18
	Robustness	[131, 155, 180, 185, 191, 192, 222]	7	
Q-Learning	Stability	[18, 19, 39, 66, 72-75]	6	16
	Robustness	[92, 94, 107, 109, 113, 130, 138, 223, 236]	9	
	Resilience	[3]	1	
PPO	Robustness	[143, 147, 149, 158, 161, 162, 166, 208]	8	8
Adaptive Critic Design	Stability	[43, 54, 61]	3	5
	Robustness	[110, 125]	2	
Deep Deterministic Policy Gradient (DDPG)	Robustness	[162, 167]	2	2
4 variational Model-based Policy Optimization	Robustness	[181]	1	1
Advantage Actor Critic (A2C)	Robustness	[143]	1	1
Ad-hoc On-demand Distance Vector (AODV)	Robustness	[123]	1	1
Active Tracking Target Network (ATTN) and Anytime Reduced Value Iteration (ARVI)	Robustness	[177]	1	1
Constant Feedback to Control Policy	Robustness	[106]	1	1

Table 4. Citations categorized by the reinforcement learning policy used

Policy	Behavior	Citations	Subtotal	Total
Constraint-controlled PPO (CPPO)	Robustness	[164]	1	1
Data-regulated Actor-Critic (DrAC)	Robustness	[171]	1	1
Deep Deterministic Policy Gradient	Stability	[70]	1	1
Generalized Advantage Estimation	Robustness	[158]	1	1
Goal Policy	Robustness	[153]	1	1
Gradient	Robustness	[179]	1	1
Graph-based Policy Learning	Robustness	[176]	1	1
Lyapunov-based Actor-Critic (CLAC)	Robustness	[183]	1	1
MOOSE (MOdel-based Offline policy Search with Ensembles)	Robustness	[151]	1	1
Natural Stochastic Policies	Robustness	[184]	1	1
Student t Policy	Robustness	[146]	1	1
		Total Citations including Policy		65
		Total Policies		21

3.3 Approach to Determining or Measuring Behavior

The publications' approaches to determining or measuring each behavior are categorized as either quantitative or theoretical (Table 5). Most of the publications focused on quantitative approaches (*n*=205, 82.0%), which is understandable given that the search focused on quantifying the behaviors. For publications on the stability behavior, there was an almost even split between quantitative (n=42) and theoretical (n=43) approaches. However, publications on the robustness behavior were primarily focused on quantitative approaches. All (3) resilience publications applied quantitative approaches.

Table 5. Citations categorized by approach to determining or measuring behavior

Approach	Behavior	Citations	Total
Quantitative	Stability	[4, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 17, 18, 19, 20, 21, 23, 26, 27, 28, 29, 30, 31, 32, 34, 36, 38, 42, 43, 45, 50, 51, 53, 58, 59, 66, 70, 72, 73, 75, 78, 80]	42
	Robustness	[81-89, 92-104, 106-120, 122-196, 198-201, 203-222, 224-227, 229, 231-247, 249-250]	160
	Resilience	[1, 2, 3]	3
		Total Quantitative	205
Theoretical	Stability	[4, 5, 10, 13, 15, 16, 20, 22, 24, 25, 27, 33, 35, 36, 37, 39, 40, 41, 43, 44, 46, 47, 48, 49, 52, 54, 55, 56, 57, 60, 61, 62, 63, 64, 65, 67-69, 71, 74, 76-79]	44
	Robustness	[90, 91, 97, 105, 116, 121, 135, 145, 150, 165, 184, 185, 194, 195, 197, 200-202, 205, 206, 215, 216, 222, 223, 225-230, 233, 239, 240, 248, 250]	35
	Resilience	--	0
		Total Theoretical	79

If a document covered both quantitative and theoretical approaches, it was placed in both categories.

3.3.1 Types of Quantitative Approaches

Next, we further categorize the quantitative approaches into whether they are focused internal or external to the model (see Table 6). Internal quantitative approaches measure aspects within the model, e.g., its training and associated measures such as the value of rewards over time or the number of episodes until convergence. External quantitative approaches measure performance-related aspects of the model, e.g., variations in accuracy or throughput. Most (n=141, 63.2%) of the quantitative approaches were categorized as performance-related, or external, measures. Of these, most (n=103) were on robustness, with stability (n=36) next. The 3 papers on resilience focused on performance-related quantitative measures. Robustness also led the internal approaches (*n*=68) with stability following (*n*=14). These are primarily due to the large number of robustness papers (*n*=170) and paucity of resilience papers (*n*=3) overall. Of the robustness papers, 40.0% (*n*=68) contained internal quantitative measures and 60.6% contained external quantitative measures. For stability, these values are 18.2% and 46.8%, respectively.

Table 6. Quantitative approaches categorized by internal or external measures

Quantitative Approach	**Behavior**	**Citations**	**Total**
Internal	Stability	[7, 8, 9, 11, 13, 19, 20, 27, 29, 30, 43, 72, 75, 78]	14
	Robustness	[83, 84, 92, 94, 97, 101-103, 109, 114, 122, 130, 132, 134, 138, 143, 146, 149-151, 155-157, 163-164, 166, 174-176, 181-182, 185, 187-189, 191-193, 195, 198-200, 204-205, 208-209, 211-213, 215, 217, 220, 226, 229, 231-239, 241, 244-247, 250]	69
	Resilience	--	0
		Total Internal Measures	**83**
External	Stability	[6, 9, 10, 12, 13, 14, 15, 17, 18, 19, 20, 21, 23, 26, 27, 28, 31, 32, 34, 36, 38, 42, 45, 50, 51, 53, 58, 59, 66, 68, 70, 73, 75, 78, 80]	36
	Robustness	[81-83, 85-89, 93, 95-100, 102, 104, 106-120, 123-129, 131, 133, 135-145, 147-148, 152-154, 158-162, 165-173, 177-181, 183-184, 186, 190, 194-196, 201, 203-204, 206-207, 210, 214, 216, 218-219, 221-222, 224-227, 240, 242-243, 249]	103
	Resilience	[1, 2, 3]	3
		Total Performance-related Measures	**142**

If there were both internal and external quantitative approaches in a document, the document was placed in both categories.

3.3.2 Types of Internal Quantitative Approaches

Looking at the types of internal quantitative approaches, we see a fairly narrow set of aspects being considered in the papers (see Table 7). These are metrics specifically made to measure stability other than by the variance of the output. They essentially measure variation in training performance. The vast majority (*n*=75, 88.2%) of the internal quantitative approaches calculate reward- or score-based metrics. Other types of internal quantitative approaches include 2 each of policy entropy, variations in control strategy approximation weights, and the convergence rate, and 1 each of policy weight, calculation of the Lyapunov stability criteria and calculation of the Wasserstein function lower bound. The term *convergence*, in RL context, refers to the stability of the learning process (and the underlying model) over time [11].

Table 7. Internal Quantitative approaches categorized by metric

Internal Quantitative Metric	**Behavior**	**Citations**	**Total**
Reward or Score – magnitude, mean/ variance, variation in average reward, time to threshold, episode duration	Stability, Robustness	[7, 8, 9, 13, 30, 72, 75, 78] [83, 84, 92, 94, 97, 101-103, 109, 114, 122, 130, 132, 134, 138, 143, 146, 149-151, 155-157, 163-164, 166, 174-176, 181-182, 185, 188-189, 191-193, 195, 198-200, 204, 208-209, 211-213, 215, 217, 220, 226, 229, 231-239, 241, 244-247, 250]	75
Policy entropy	Stability	[11, 19]	2
Variations in control strategy approximation weights	Stability, Robustness	[20] [120]	2
Convergence rate	Stability	[27, 29]	2
Lyapunov stability criteria calculated	Stability	[43]	1
Policy weight	Robustness	[231]	1
Regret	Robustness	[187]	1
Wasserstein function bounds calculated	Robustness	[205]	1
		Total	**85**

If a document had metrics that fell in more than one category, the document was placed in each of the categories.

3.3.3 Types of External Quantitative Approaches

The external or performance-based quantitative approaches to measuring the behaviors primarily (*n*=39) used deviations or variation in performance-related metrics other than precision, accuracy or recall (see Table 8 and Figure 5). The next category (*n*=28) of quantitative metrics used error, failure and success rates. Statistics on the performance of the tracking or estimation error follows with *n*=23 papers. Papers in the network domain used network-related metrics (*n*=15) to measure the behavior. Statistics on precision, accuracy and recall (*n*=12) followed. Five papers used variance in loss or regret estimation, 3 papers used game-related performance measures to quantify behavior and 2 papers each used bounds on or the size of the stability region and terminal wealth and inventory. Eighteen (18) additional different types of external quantitative metrics categories were represented by a single paper each.

3.3.4 Quantitative Approach Objectives

An additional aspect reviewed was to what action or event were the quantitative approaches attempting to be stable, robust or resilient. We call this the *<behavior> objective*. The *<behavior>* objective category (see Table 9) with the highest number of citations was geared toward handling changes in the operational environment or a dynamic environment or network (*n*=41). Papers that did not specifically state their objective comprised the next most populous category (*n*=35). The objective of handling uncertainty and disturbances in the environment also contained *n*=35 papers. The remaining objectives included input variation/perturbations (*n*=20); differences between training and test or operational environments (*n*=19); differences or uncertainties in model parameters (*n*=16); adversarial attack (*n*=14); different domains, environments or settings (*n*=8); errors or failures in operational environment (*n*=5); differences in training data sets or initializations (*n*=5); high variability (*n*=2) and one paper each in systematic pressure, spamming, incomplete data, and unknown control coefficients.

Table 8. External Quantitative approaches categorized by metric

External Quantitative Metric	Behavior	Citations	Total
Deviations/variation in other (than precision, accuracy and recall) performance-related metrics	Stability, Robustness, Resilience	[9, 13, 15, 19, 20, 26, 27, 36, 38, 45, 50, 51, 58, 59, 68, 80] [85, 95, 97, 106, 107, 110, 111, 119, 126, 137-139, 141, 142, 152, 169, 178, 179, 181, 183, 184, 195] [2]	39
Error and failure rates/success rate	Stability, Robustness	[12] [86, 88, 100, 104, 112, 124, 129, 131, 133, 136, 140, 143, 153, 158, 160, 162, 166-168, 186, 204, 207, 221, 222, 225, 242, 249]	28
Performance of tracking/trajectories estimation error; mean absolute deviation, mean square error, mean absolute percentage error, margins and magnitude of correlation coefficient	Stability, Robustness	[10, 18, 23, 28, 31] [87, 88, 93, 96, 106, 116, 125, 144, 145, 147, 148, 158, 173, 186, 201, 224, 226, 240]	23
Network-related timing/delay, path and link metrics, connectivity, delivery ratio, routing loops, path optimality, visitation distribution, structural Hamming distance, Small base station-serving ratio, sum-rate and 5th percentile rate	Stability, Robustness	[6, 14, 32, 42, 53, 66, 73] [83, 89, 123, 127, 170, 180, 203, 214]	15
Mean/average and variation in accuracy, precision and recall, area under the receiver operating characteristic (ROC) curve (AUC)	Stability, Robustness, Resilience	[17, 34] [93, 99, 102, 108, 113, 154, 159, 161, 168, 227] [3]	12
Variance of the estimation of loss, regret	Robustness	[118, 159, 187, 216, 224]	5

Table 8. External Quantitative approaches categorized by metric

External Quantitative Metric	Behavior	Citations	Total
Game-related performance - scores of game playing, percent wins, exploitability	Robustness	[109, 120, 165]	3
Size of the stability region; bounds	Stability, Robustness	[21] [135]	2
Terminal wealth, terminal inventory, cost, Sharpe ratio	Robustness	[206, 218]	2
Average proportion of failed eavesdropping attempts and of jammed red-force nodes; Average throughput	Robustness	[81]	1
Hours of operation with some maintenance	Robustness	[82]	1
Response time, energy consumption, and execution time	Robustness	[98]	1
Spectral efficiency	Robustness	[243]	1
Time headway (sec)	Robustness	[210]	1
Covariance analysis as a metric	Robustness	[114]	1
Mutual information	Robustness	[177]	1
Fidelity	Robustness	[219]	1
Expected rank and Robust Measurements metric	Robustness	[115]	1
Singular value decomposition (SVD)-based controllability measure	Robustness	[117]	1
Time to find goal/destination	Robustness	[128]	1
Number of adversarial actions required to cause error	Resilience	[1]	1
Normalized Energy Stability Margin (NESM)	Stability	[70]	1
Voltage violation rate, active power loss	Robustness	[172]	1
Jensen-Shannon divergence (JSD)	Robustness	[171]	1
Number of successful steps	Robustness	[190]	1
Blood glucose responses, Insulin concentration	Robustness	[194]	1

Table 8. External Quantitative approaches categorized by metric

External Quantitative Metric	Behavior	Citations	Total
Likelihood (Mahalanobis Distance)	Robustness	[196]	1
		Total	**147**

If a paper contained quantitative approaches belonging to multiple categories, it was placed in each of the relevant categories.

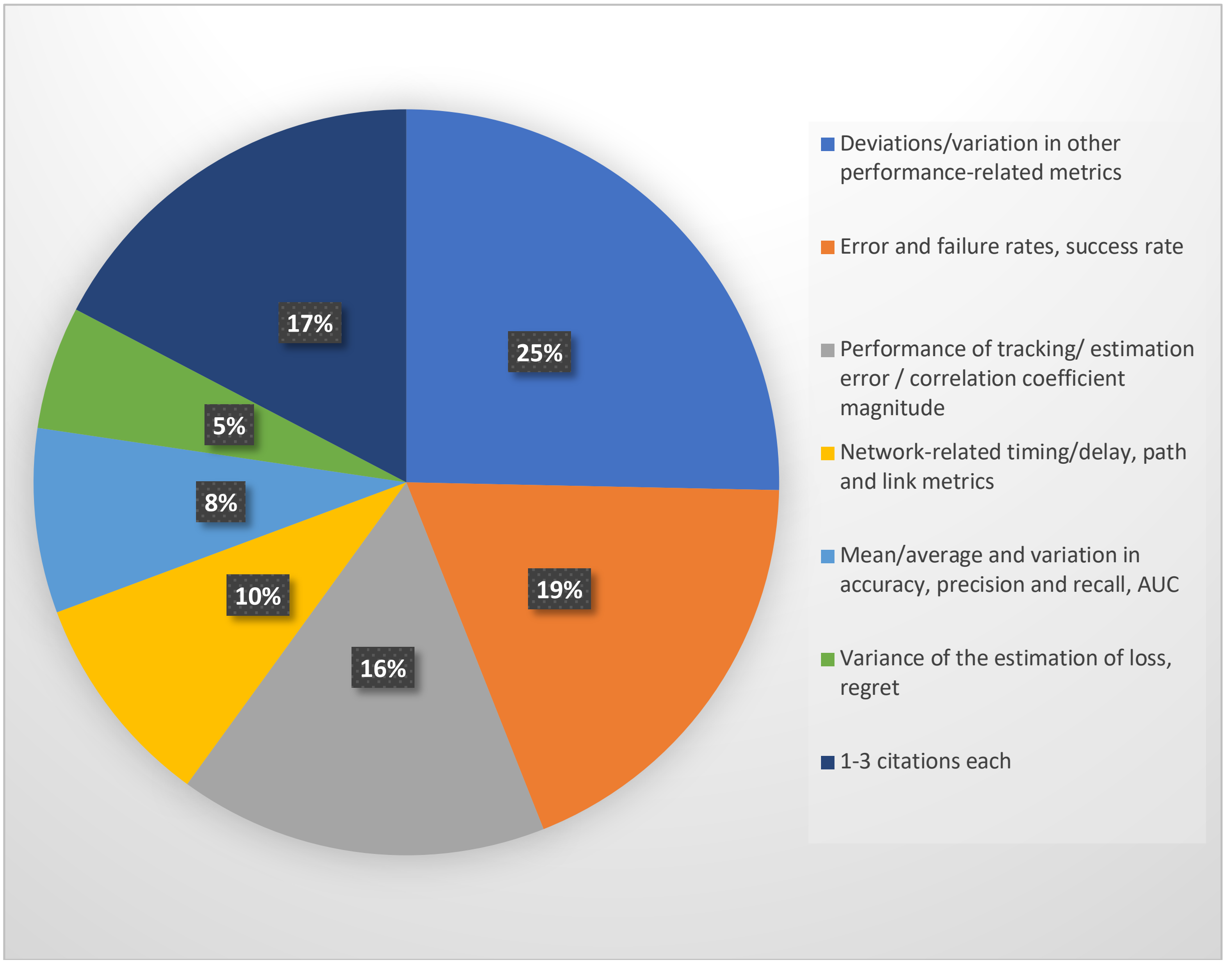


Figure 5. External quantitative metrics

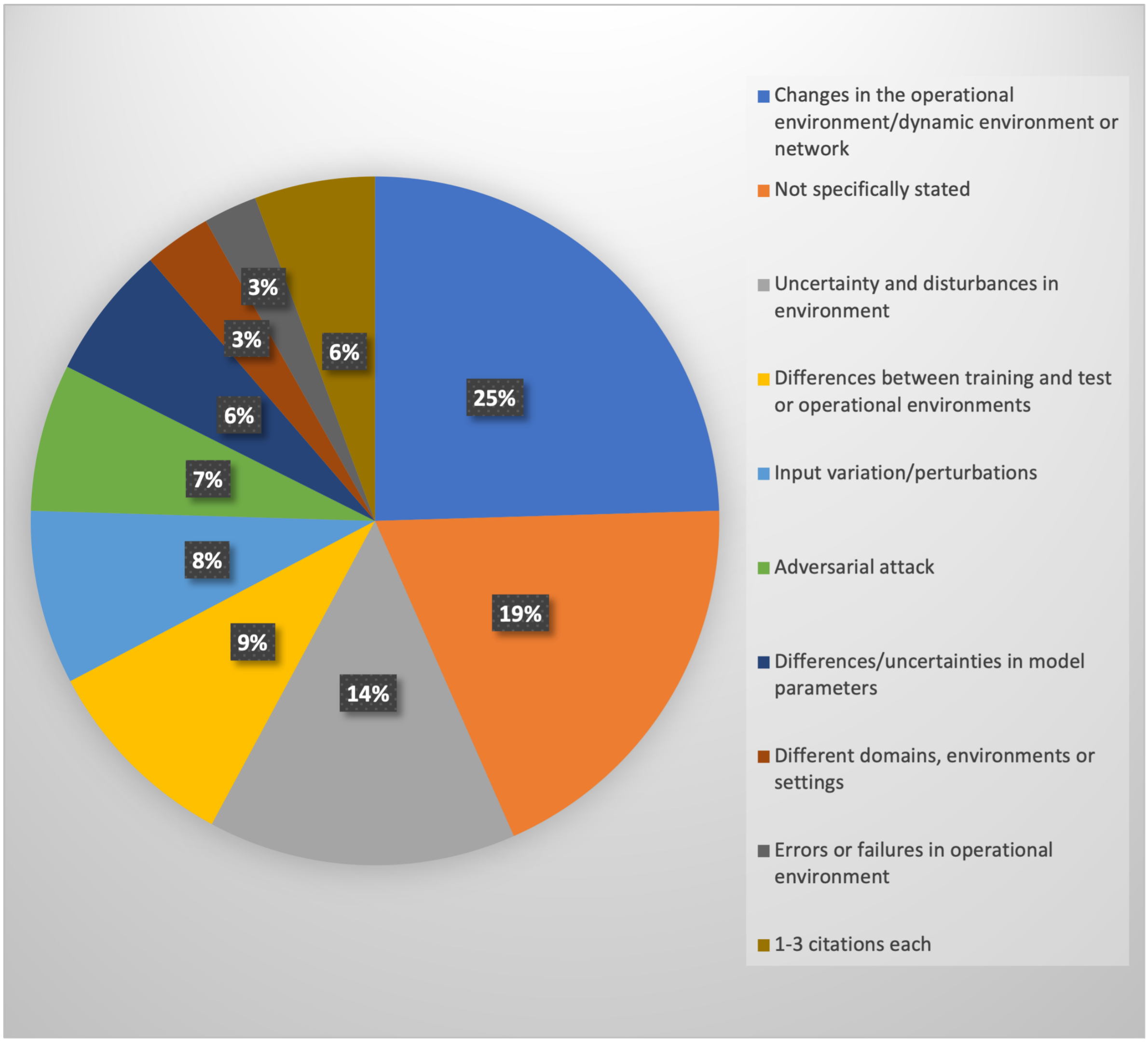


Figure 6. Quantitative <*behavior*> objectives

3.3.5 Types of Theoretical Approaches

A majority of the types of theoretical approaches in the papers reviewed were based on Lyapunov theory (n=50, 61.0%) (Table 10). The next highest types of theoretical approaches used are convergence to Nash equilibrium (n=10) and value-based guarantees such as error and output deviation bounds (n=8). Of the remainder, 3 papers used the Wasserstein distance to explore stability, 3 papers proved the methods were doubly robust, 2 papers proved the methods exhibited Lipschitz continuity, and stochastic stability theory to prove stability, stability guarantees, policy-based guarantees, regret bounds, minimization of the Jacobian on input, and per-episode Bellman-error regret guarantees/bounds were used by a single paper each to establish stability of the RL methods discussed.

Table 9. Quantitative <*behavior*> objectives

<***behavior***> **Objective**	**Behavior(s)**	**Citations**	**Total**
Changes in the operational environment/dynamic environment or network; distribution shift	Stability Robustness Resilience	[26, 27, 32, 45, 50, 66, 70, 73] [85, 86, 89, 93, 94, 96, 98, 99, 102, 107, 108, 111, 112, 114, 117, 118, 122, 123, 128, 131, 142, 154, 167, 171, 172, 177, 187, 194, 207, 214, 220, 243] [3]	41
Not specifically stated	Stability Robustness	[6, 8, 9, 10, 11, 13, 14, 15, 17, 18, 20, 21, 23, 28, 31, 38, 43, 51, 58, 59, 78] [113, 116, 125, 127, 130, 134, 165, 184, 198, 209, 216, 227, 240, 247]	35
Uncertainty and disturbances in environment, e.g., noisy sensor data, measurement noise, distractors, nuisances	Robustness	[133, 135, 138, 140, 141, 147, 148, 152, 153, 162, 169, 173, 175, 178, 186, 188, 190, 191, 193, 195, 196, 199, 208, 211, 217, 218, 219, 222, 224, 225, 234-236, 244, 249]	35
Input variation/perturbations, outliers	Stability Robustness	[7, 12, 19] [101, 103, 106, 132, 139, 143, 146, 149, 157, 158, 170, 187, 195, 208, 221, 226, 231]	20
Differences between training and test or operational environments	Stability Robustness	[31, 42] [82-84, 87, 95, 100, 109, 119, 120, 124, 129, 136, 149, 174, 191, 221, 245]	19

Table 9. Quantitative <*behavior*> objectives

<*behavior*> Objective	**Behavior(s)**	**Citations**	**Total**
Differences/uncertainties in model [hyper-]parameters, model error	Stability Robustness	[36, 53, 75] [92, 110, 126, 137, 164, 174, 181, 182, 192, 201, 225, 237, 241]	16
Adversarial attack	Stability Robustness Resilience	[29, 30] [81, 97, 156, 159, 163, 166, 204, 206, 210, 212] [1, 2]	14
Different domains, environments or settings	Stability Robustness	[80] [161, 164, 176, 203, 224, 232, 242]	8
Errors or failures in operational environment	Robustness	[104, 115, 145, 168, 189]	5
Differences in training data sets or initializations	Stability Robustness	[34] [88, 151, 213, 238]	5
High variability	Robustness	[144, 183]	2
Systematic pressure, e.g., sudden surge of requests	Robustness	[160]	1
Spamming	Robustness	[179]	1
Incomplete data	Robustness	[180]	1
Unknown control coefficients	Stability	[68]	1
		Total	**204**

If a technique had multiple robustness objectives, it was placed in each of those objectives.

Table 10. Theoretical approaches categorized by specific approach

Theoretical Approach	**Behavior**	**Citations**	**Total**
Lyapunov stability theory	Stability	[4, 5, 10, 15, 16, 20, 25, 35, 36, 39, 40, 41, 43, 44, 46, 47, 48, 49, 52, 54, 55, 56, 57, 60, 61, 62, 64, 65, 67, 69, 74, 76-79]	50
	Robustness	[90, 91, 97, 105, 116, 121, 135, 145, 194, 200, 222, 225, 230, 233, 248]	
Convergence to Nash equilibrium	Stability	[22, 24, 37, 63, 71]	10
	Robustness	[165, 197, 206, 215, 230, 239]	
Value-based guarantees, error bounds, output deviation bounds	Robustness	[195, 201, 226-228, 230, 233, 250]	8
Wasserstein distance	Robustness	[185, 201, 205]	3
Prove double robustness	Robustness	[184, 216, 240]	3
Prove Lipschitz continuity	Robustness	[201, 229]	2
Stochastic stability theory	Stability	[33]	1
Prove stability guarantees	Stability	[68]	1
Policy-based guarantees	Robustness	[201]	1
Regret bounds	Robustness	[202]	1
Minimize Jacobian on input	Robustness	[150]	1
Per-episode Bellman-error regret guarantees/bounds	Robustness	[223]	1
		Total	**82**

If a paper used multiple theoretical approaches, the was placed in each of those categories.

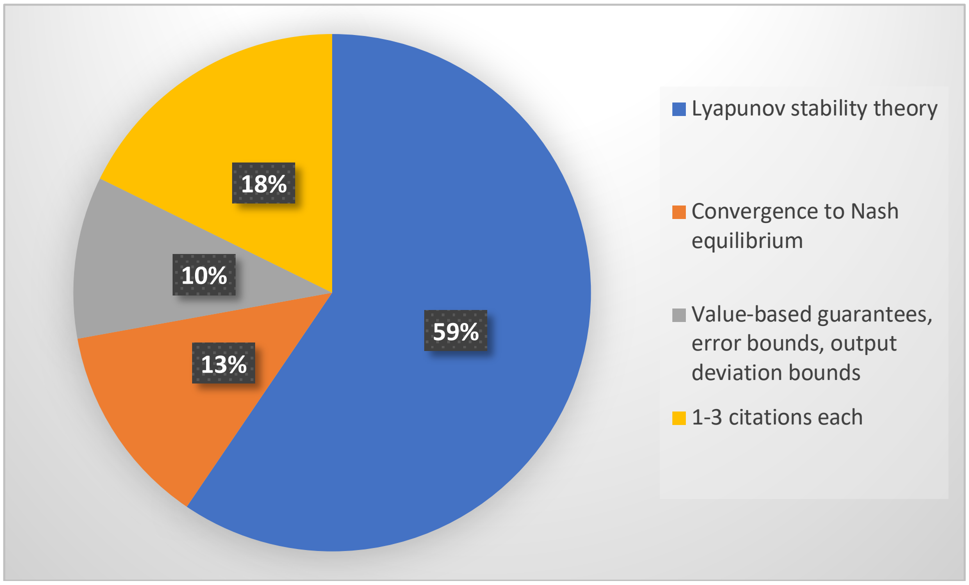


Figure 7. Theoretical Approaches

3.3.6 Theoretical Approach Objectives

We also reviewed the *<behavior> objective* for theoretical papers (Table 11). Most (n=42, 54.5%) papers on theoretical approaches did not state their objective. Of those few that did, changes or dynamics in the operational environment was the most frequent objective (n=10), followed by differences or uncertainties in model parameters (n=7), adversarial attack (n=6), error or failure (n=5), differences between training and test or operational environments (n=2), input variation (n=2), then 1 each for domain shifts, different function approximation architectures and differences in quantization levels.

4. Discussion

Our study was conducted to characterize published means of measuring or determining the stability, robustness or resilience of RL. Out of an initial collection of 16,015 items 248 papers met inclusion criteria and were systematically reviewed. Approaches to measuring or determining the behavior were classified as either quantitative or theoretical. Quantitative approaches were further classified as internal or external depending on whether they evaluated the training phase or the test or operational phases. For both categories of quantitative approaches, we categorized the metrics used, with internal approaches primarily using the reward or score (and statistics on same) and external approaches primarily using variations on performance-related metrics

Table 11. Theoretical <*behavior*> objectives

<*behavior*> Objective	**Behavior(s)**	**Citations**	**Total**
Not specifically stated	Stability Robustness	[4, 5, 10, 15, 16, 20, 22, 24, 25, 33, 37, 39, 41, 43, 44, 46, 47, 48, 49, 52, 54, 56, 57, 60, 61, 62, 63, 64, 65, 67, 74, 76, 78, 80] [90, 105, 116, 121, 165, 184, 197, 200, 216, 227, 240]	42
Changes in the operational environment/dynamic environment, environment uncertainties, environment disturbances	Stability Robustness	[35, 79] [135, 185, 194, 195, 222, 225, 228, 248]	10
Differences/uncertainties in model parameters	Stability Robustness	[36, 55, 68] [91, 201, 205, 225]	7
Adversarial attack, corruption, perturbations	Robustness	[150, 206, 215, 223, 230, 239]	6
Error, failure	Stability Robustness	[69, 71] [135, 145, 202]	5
Differences between training and test or operational environments	Stability Robustness	[40] [215]	2
Input variation or perturbation	Robustness	[195, 226]	2
Domain shifts	Robustness	[229]	1
Function approximation architecture	Robustness	[233]	1
Quantization level	Robustness	[250]	1
		Total	**77**

If a paper used multiple theoretical approaches, it was placed in each of those categories.

(though not precision, accuracy or recall). Theoretical approaches were dominated by the use of Lyapunov stability theory. We further characterized the objectives of the stability, robustness and resilience behaviors. Quantitative approaches to measuring the behavior focused on the ability to handle differences in the operational environment, whereas the vast majority of theoretical approaches to determining the behavior did not specifically state an objective. However, the objective of the theoretical approaches can be implied by the use of Lyapunov stability theory, that is, to prove the stability of the system. Lyapunov was used regardless of whether the article was on stability or robustness.

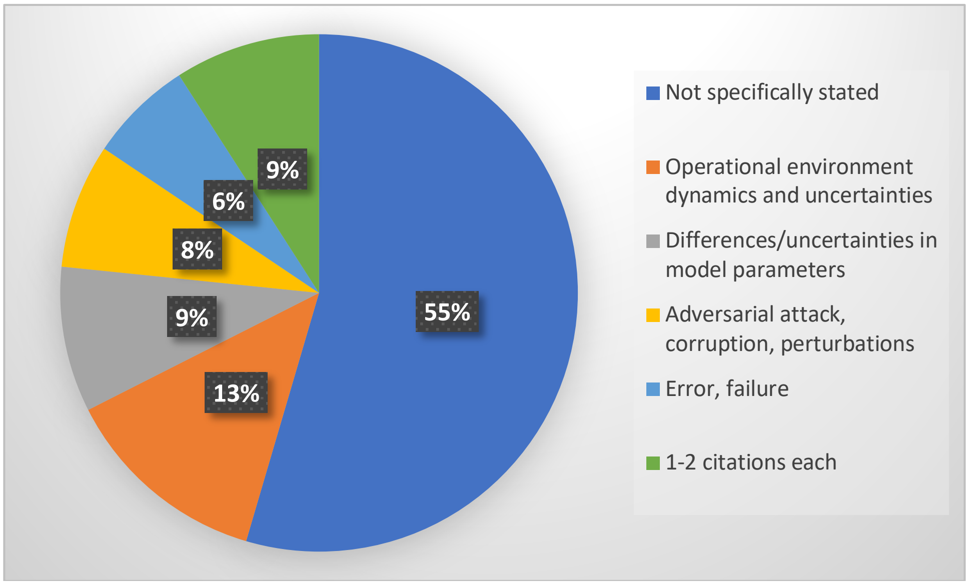


Figure 8. Theoretical <*behavior*> objectives

As an aid to deciding which metric to use, we developed a decision tree based on the information obtained in this literature review. It is a collapsible tree so that branches are not exposed unless selected and open branches can be closed or collapsed. There are several levels in the decision tree, starting with the i) behavior (stability, robustness or resilience); ii) the domain (see Table 3); iii) a list of quantitative and theoretical objectives (see Tables 9, 11); iv) the next level divides the metrics into external, internal and theoretical metrics (see Tables 5, 6); and v) the last level, i.e., the leaves, is the set of metrics for that branch of the decision tree (see Tables 7, 8). For example, suppose we want to find a suitable metric to measure robustness of a control system that is expected to face changes in the operational environment. From the metric decision tree shown in Figure 14, we see that the first selection is for a robustness metric. This selection displays the domains in which robustness metrics were described. Selecting the General Control domain reveals 5 quantitative objectives and 4 theoretical objectives, including the objective “Changes in the Operational Environment” in both the quantitative and theoretical objectives. An external metric found in the literature for this case is “blood glucose response” which is not applicable for this control system. The more appropriate metrics and approaches are Lyapunov stability theory and calculation, size of the stability region and value-based guarantees. One or all of these can be used to measure robustness of a general control system to changes in the operational environment.

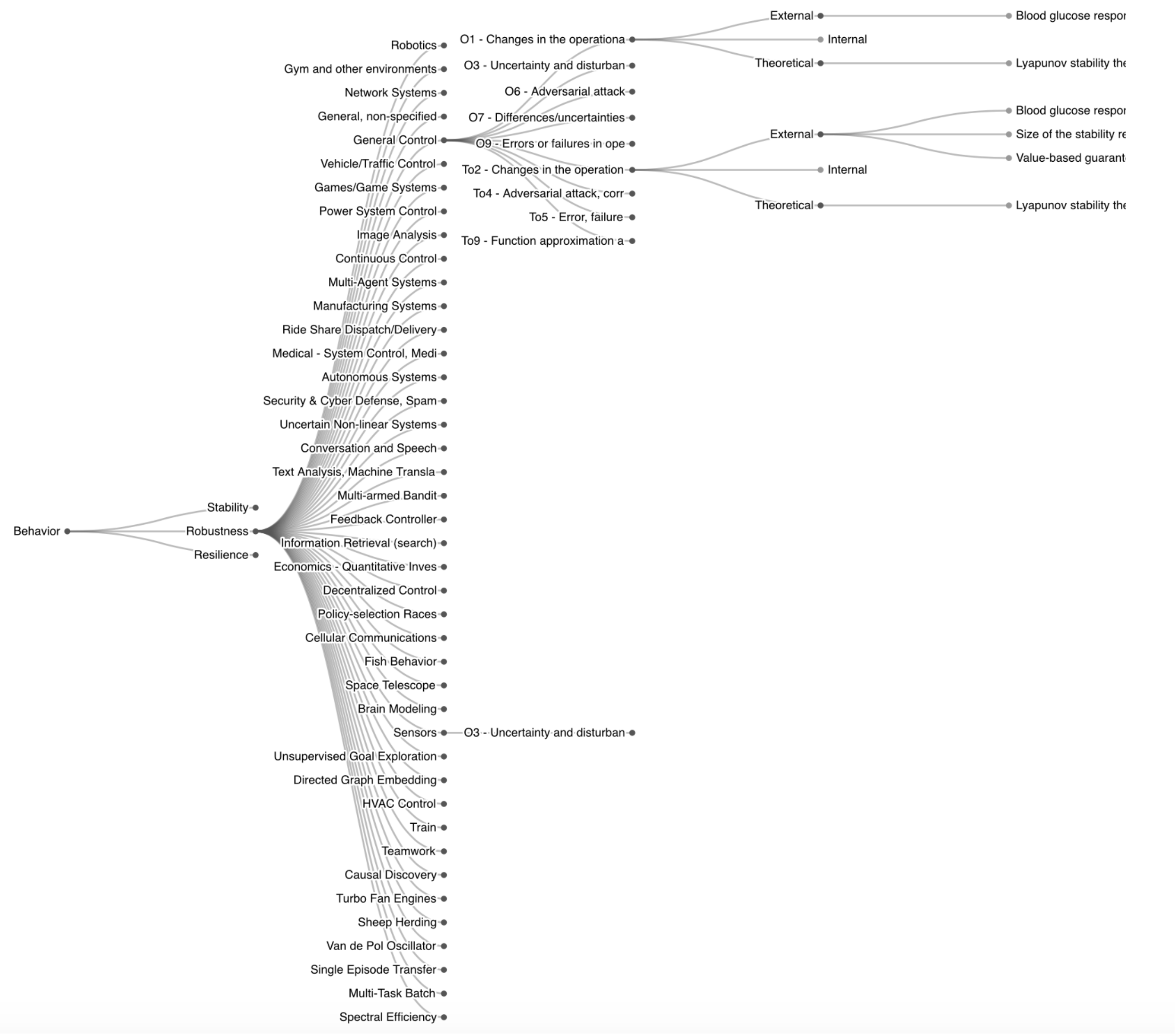


Figure 9. Metric Selection Decision Tree

5. Supporting Information

The databases in Table 12 were readily available to the author through Oak Ridge National Laboratory library subscriptions. Databases selected for this study are international in scope and ensure we investigate relevant studies that are global and cover a wide range of application domains, thereby eliminating the risk of bias from the author subject matter expertise and a Western perspective. However, we are bound by the content of these databases.

Many abstracting and indexing databases have very broad coverage, which results in individual databases duplicating content found in others. Duplicated bibliographic records were identified and removed. After duplicate entries were removed, the remaining citations were reviewed for completeness in terms of information needed to obtain the document from a library. If the citation did not include this information (e.g., author name(s), article title, and journal name), the missing information was obtained from the source database or other online sources and the citation was manually corrected.

Table 12. Information sources used in study

Database	**Dates of Coverage**	**Type of Database**
arXiv	1991-present	Publicly Available / Open Access
Scopus	1823-present	Subscription
Web of Science	1900-present	Subscription

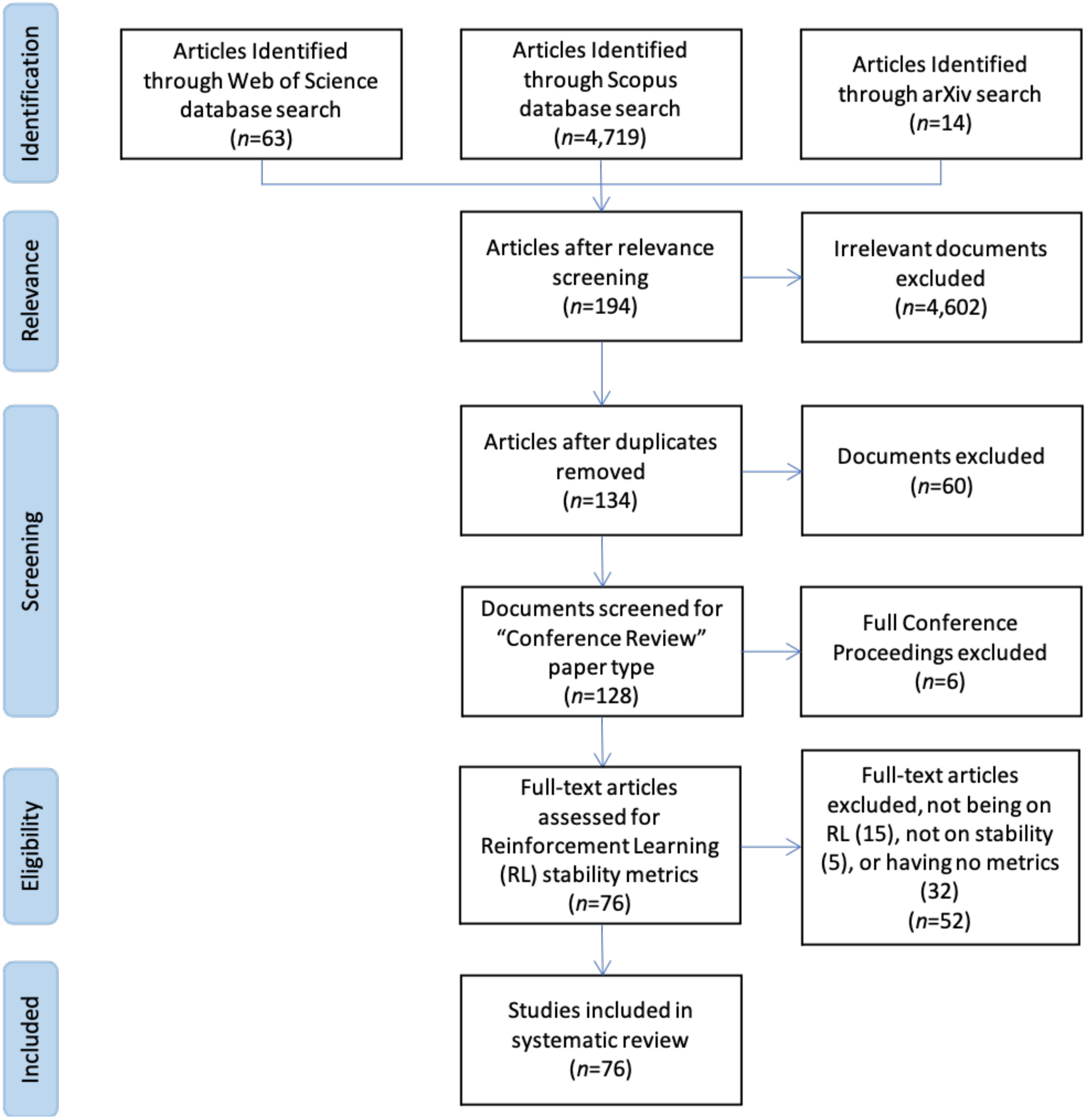

Identification
Articles Identified through Web of Science database search (*n*=63)
Articles Identified through Scopus database search (*n*=4,719)
Articles Identified through arXiv search (*n*=14)
Relevance
Articles after relevance screening (*n*=194)
Irrelevant documents excluded (*n*=4,602)
Screening
Articles after duplicates removed (*n*=134)
Documents excluded (*n*=60)
Documents screened for "Conference Review" paper type (*n*=128)
Full Conference Proceedings excluded (*n*=6)
Eligibility
Full-text articles assessed for Reinforcement Learning (RL) stability metrics (*n*=76)
Full-text articles excluded, not being on RL (15), not on stability (5), or having no metrics (32) (*n*=52)
Included
Studies included in systematic review (*n*=76)

Figure 10. The PRISMA Flow Diagram for Stability

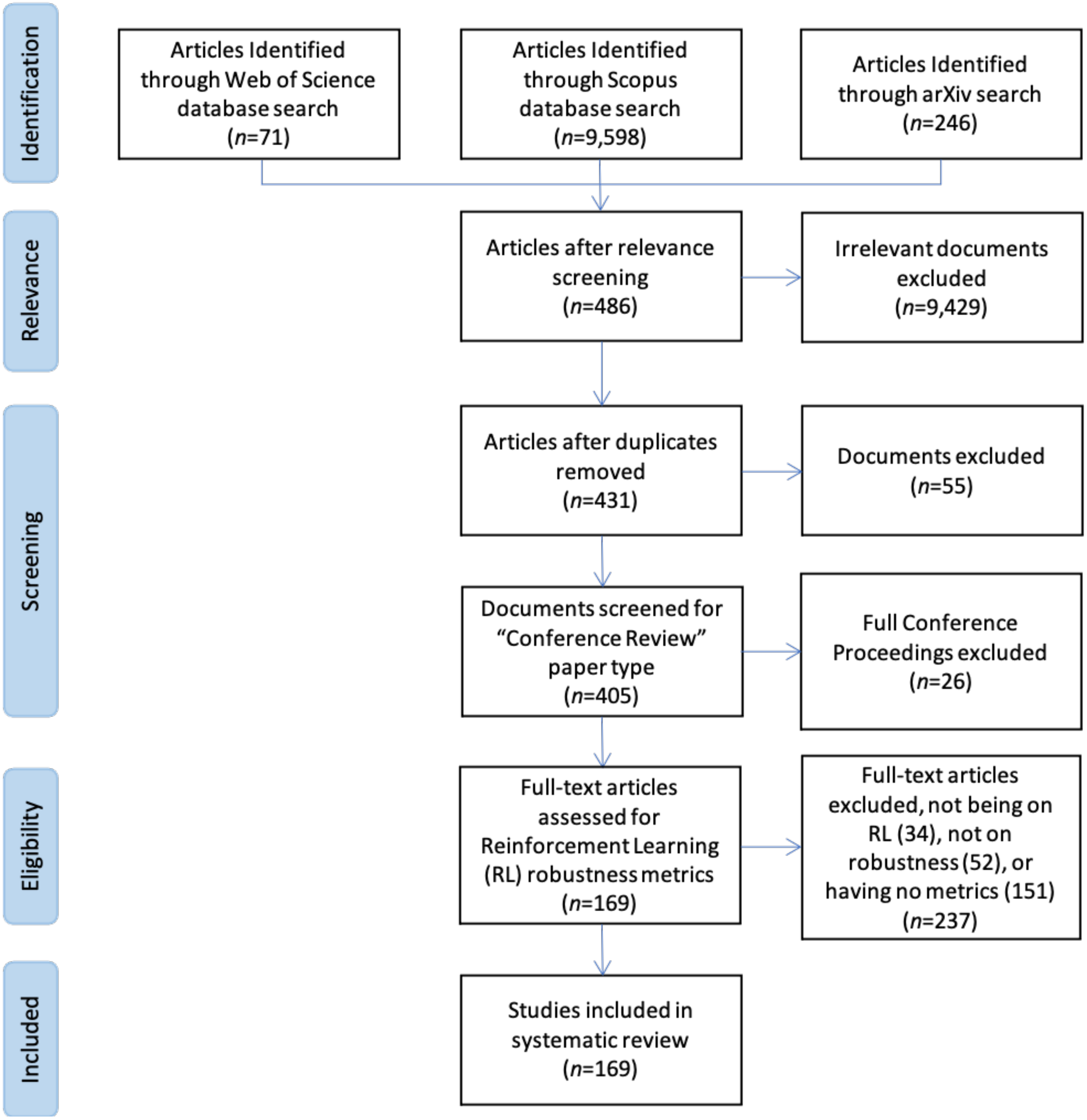

Identification
Articles Identified through Web of Science database search (n=71)
Articles Identified through Scopus database search (n=9,598)
Articles Identified through arXiv search (n=246)
Relevance
Articles after relevance screening (n=486)
Irrelevant documents excluded (n=9,429)
Screening
Articles after duplicates removed (n=431)
Documents excluded (n=55)
Documents screened for “Conference Review” paper type (n=405)
Full Conference Proceedings excluded (n=26)
Eligibility
Full-text articles assessed for Reinforcement Learning (RL) robustness metrics (n=169)
Full-text articles excluded, not being on RL (34), not on robustness (52), or having no metrics (151) (n=237)
Included
Studies included in systematic review (n=169)

Figure 11. The PRISMA Flow Diagram for Robustness

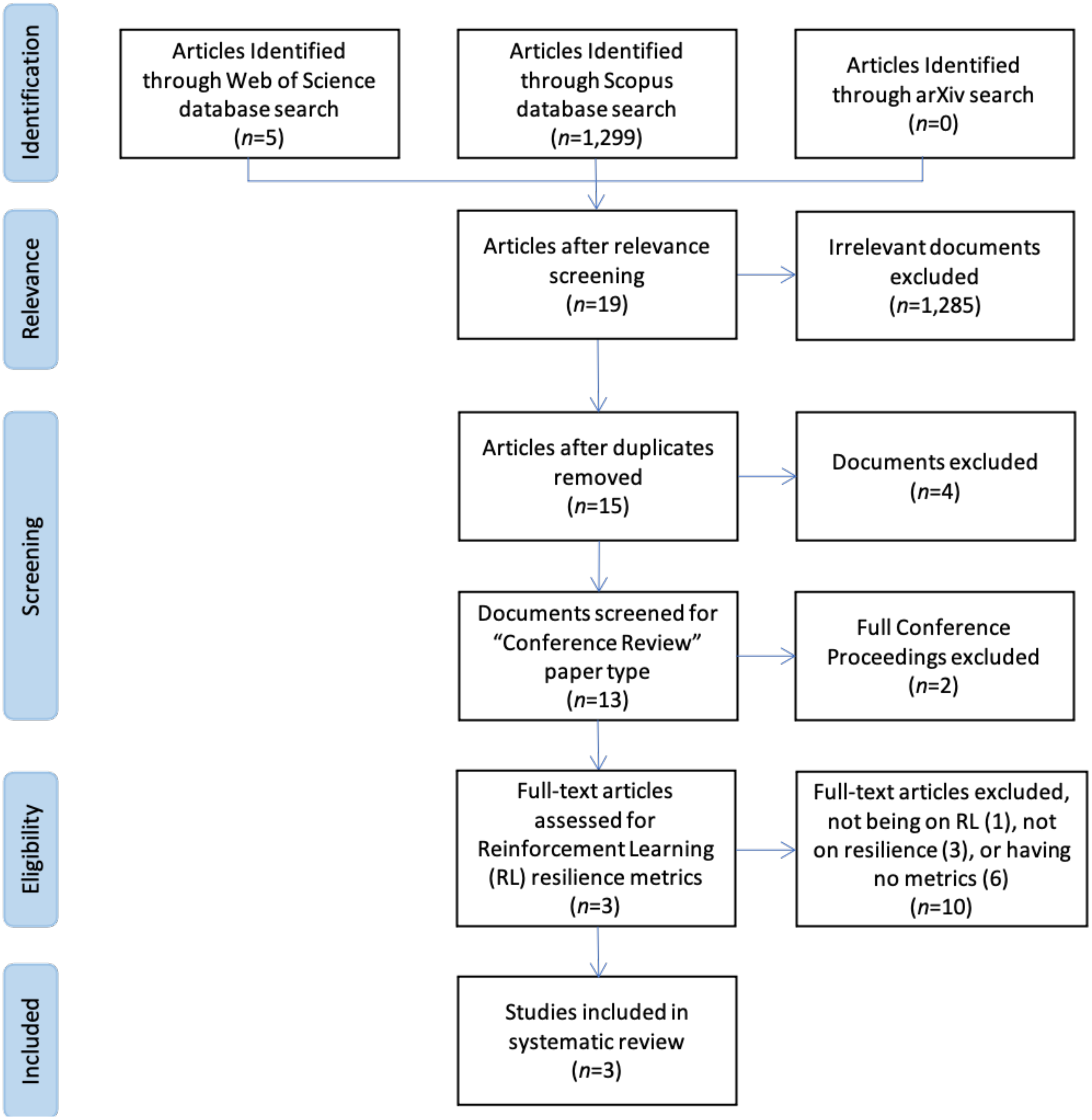
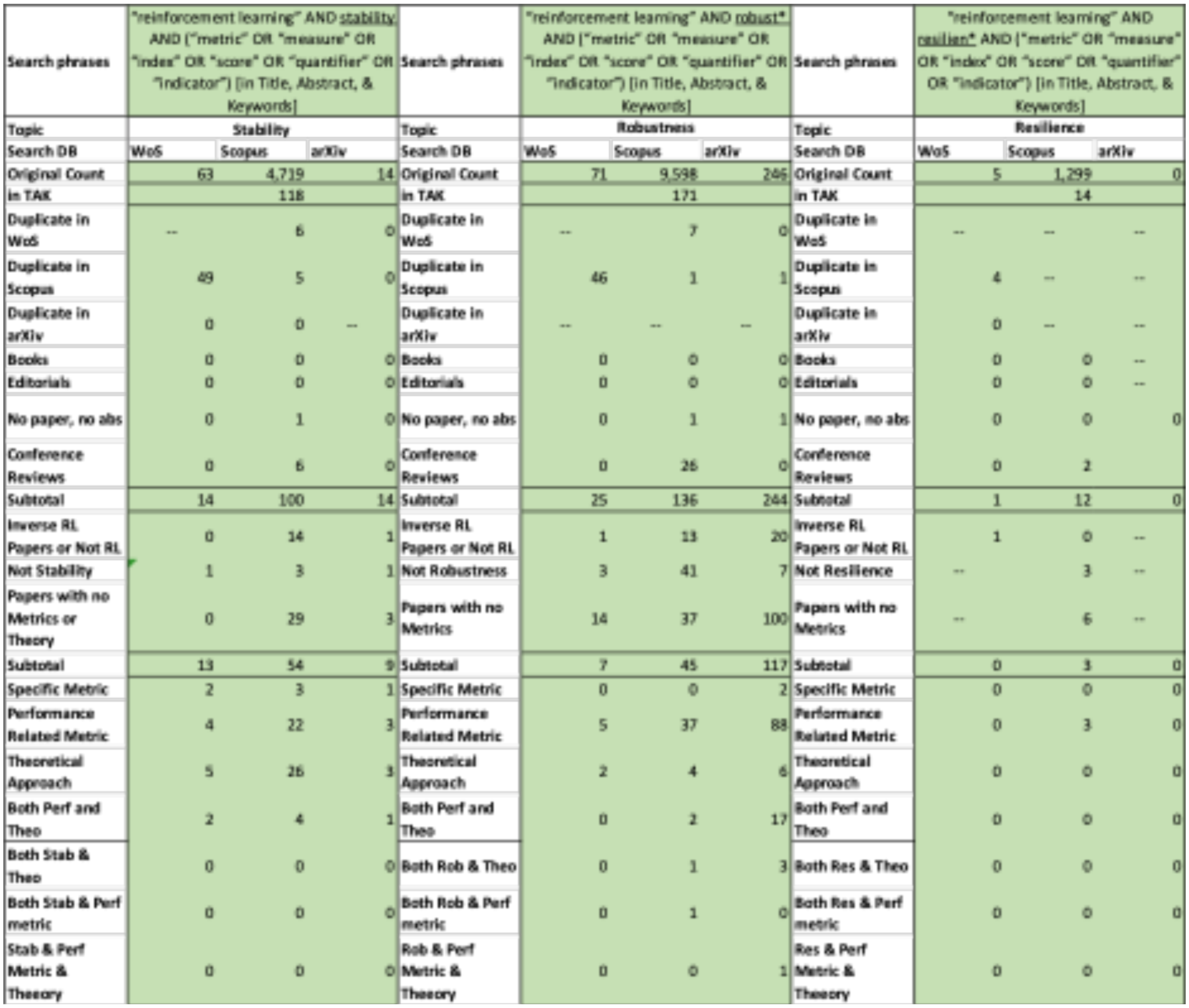

Identification
Articles Identified through Web of Science database search (n=5)
Articles Identified through Scopus database search (n=1,299)
Articles Identified through arXiv search (n=0)
Relevance
Articles after relevance screening (n=19)
Irrelevant documents excluded (n=1,285)
Screening
Articles after duplicates removed (n=15)
Documents excluded (n=4)
Documents screened for "Conference Review" paper type (n=13)
Full Conference Proceedings excluded (n=2)
Eligibility
Full-text articles assessed for Reinforcement Learning (RL) resilience metrics (n=3)
Full-text articles excluded, not being on RL (1), not on resilience (3), or having no metrics (6) (n=10)
Included
Studies included in systematic review (n=3)

Figure 12. The PRISMA Flow Diagram for Resilience

Table 13. Data Reduction Summary



Search phrases	"reinforcement learning" AND stability AND ("metric" OR "measure" OR "index" OR "score" OR "quantifier" OR "indicator") [in Title, Abstract, & Keywords]			Search phrases	"reinforcement learning" AND robust* AND ("metric" OR "measure" OR "index" OR "score" OR "quantifier" OR "indicator") [in Title, Abstract, & Keywords]			Search phrases	"reinforcement learning" AND resilien* AND ("metric" OR "measure" OR "index" OR "score" OR "quantifier" OR "indicator") [in Title, Abstract, & Keywords]		
Topic	Stability			Topic	Robustness			Topic	Resilience		
Search DB	WoS	Scopus	arXiv	Search DB	WoS	Scopus	arXiv	Search DB	WoS	Scopus	arXiv
Original Count	63	4,719	14	Original Count	71	9,598	246	Original Count	5	1,299	0
in TAK	118			in TAK	171			in TAK	14		
Duplicate in WoS	--	6	0	Duplicate in WoS	--	7	0	Duplicate in WoS	--	--	--
Duplicate in Scopus	49	5	0	Duplicate in Scopus	46	1	1	Duplicate in Scopus	4	--	--
Duplicate in arXiv	0	0	--	Duplicate in arXiv	--	--	--	Duplicate in arXiv	0	--	--
Books	0	0	0	Books	0	0	0	Books	0	0	--
Editorials	0	0	0	Editorials	0	0	0	Editorials	0	0	--
No paper, no abs	0	1	0	No paper, no abs	0	1	1	No paper, no abs	0	0	0
Conference Reviews	0	6	0	Conference Reviews	0	26	0	Conference Reviews	0	2	
Subtotal	14	100	14	Subtotal	25	136	244	Subtotal	1	12	0
Inverse RL Papers or Not RL	0	14	1	Inverse RL Papers or Not RL	1	13	20	Inverse RL Papers or Not RL	1	0	--
Not Stability	1	3	1	Not Robustness	3	41	7	Not Resilience	--	3	--
Papers with no Metrics or Theory	0	29	3	Papers with no Metrics	14	37	100	Papers with no Metrics	--	6	--
Subtotal	13	54	9	Subtotal	7	45	117	Subtotal	0	3	0
Specific Metric	2	3	1	Specific Metric	0	0	2	Specific Metric	0	0	0
Performance Related Metric	4	22	3	Performance Related Metric	5	37	88	Performance Related Metric	0	3	0
Theoretical Approach	5	26	3	Theoretical Approach	2	4	6	Theoretical Approach	0	0	0
Both Perf and Theo	2	4	1	Both Perf and Theo	0	2	17	Both Perf and Theo	0	0	0
Both Stab & Theo	0	0	0	Both Rob & Theo	0	1	3	Both Res & Theo	0	0	0
Both Stab & Perf metric	0	0	0	Both Rob & Perf metric	0	1	0	Both Res & Perf metric	0	0	0
Stab & Perf Metric & Theeory	0	0	0	Rob & Perf Metric & Theeory	0	0	1	Res & Perf Metric & Theeory	0	0	0

Table 13. The PRISMA Checklist [251]

Section/topic	#	Checklist item	Reported in Section
TITLE			
Title	1	Identify the report as a systematic review, meta-analysis, or both.	Introduction
ABSTRACT			
Structured summary	2	Provide a structured summary including, as applicable: background; objectives; data sources; study eligibility criteria, participants, and interventions; study appraisal and synthesis methods; results; limitations; conclusions and implications of key findings; systematic review registration number.	Introduction
INTRODUCTION			
Rationale	3	Describe the rationale for the review in the context of what is already known.	Introduction
Objectives	4	Provide an explicit statement of questions being addressed with reference to participants, interventions, comparisons, outcomes, and study design (PICOS).	Introduction
METHODS			
Protocol and registration	5	Indicate if a review protocol exists, if and where it can be accessed (e.g., Web address), and, if available, provide registration information including registration number.	Introduction
Eligibility criteria	6	Specify study characteristics (e.g., PICOS, length of follow-up) and report characteristics (e.g., years considered, language, publication status) used as criteria for eligibility, giving rationale.	Methods and Supporting Information (SI)
Information sources	7	Describe all information sources (e.g., databases with dates of coverage, contact with study authors to identify additional studies) in the search and date last searched.	Methods and SI
Search	8	Present full electronic search strategy for at least one database, including any limits used, such that it could be repeated.	SI
Study selection	9	State the process for selecting studies (i.e., screening, eligibility, included in systematic review, and, if applicable, included in the meta-analysis).	Methods

Table 13. The PRISMA Checklist [251]

Section/topic	#	Checklist item	Reported in Section
METHODS (Continued)			
Data collection process	10	Describe method of data extraction from reports (e.g., piloted forms, independently, in duplicate) and any processes for obtaining and confirming data from investigators.	Methods
Risk of bias in individual studies	12	Describe methods used for assessing risk of bias of individual studies (including specification of whether this was done at the study or outcome level), and how this information is to be used in any data synthesis.	Methods and SI
Summary measures	13	State the principal summary measures (e.g., risk ratio, difference in means).	Methods
Synthesis of results	14	Describe the methods of handling data and combining results of studies, if done, including measures of consistency (e.g., I^2) for each meta-analysis.	Methods
Risk of bias across studies	15	Specify any assessment of risk of bias that may affect the cumulative evidence (e.g., publication bias, selective reporting within studies).	Methods
Additional analyses	16	Describe methods of additional analyses (e.g., sensitivity or subgroup analyses, meta-regression), if done, indicating which were pre-specified.	Methods
RESULTS			
Study selection	17	Give numbers of studies screened, assessed for eligibility, and included in the review, with reasons for exclusions at each stage, ideally with a flow diagram.	Results and SI
Study characteristics	18	For each study, present characteristics for which data were extracted (e.g., study size, PICOS, follow-up period) and provide the citations.	Results
Risk of bias within studies	19	Present data on risk of bias of each study and, if available, any outcome level assessment (see item 12).	Results
Results of individual studies	20	For all outcomes considered (benefits or harms), present, for each study: (a) simple summary data for each intervention group (b) effect estimates and confidence intervals, ideally with a forest plot.	Results
Synthesis of results	21	Present results of each meta-analysis done, including confidence intervals and measures of consistency.	Results
Risk of bias across studies	22	Present results of any assessment of risk of bias across studies (see Item 15).	Results

Table 13. The PRISMA Checklist [251]

Section/topic	#	Checklist item	Reported in Section
RESULTS (Continued)			
Additional analysis	23	Give results of additional analyses, if done (e.g., sensitivity or subgroup analyses, meta-regression [see Item 16]).	Results
Data items	11	List and define all variables for which data were sought (e.g., PICOS, funding sources) and any assumptions and simplifications made.	Methods
Section/topic	**#**	**Checklist item**	**Reported in Section**
DISCUSSION			
Summary of evidence	24	Summarize the main findings including the strength of evidence for each main outcome; consider their relevance to key groups (e.g., healthcare providers, users, and policy makers).	Discussion
Limitations	25	Discuss limitations at study and outcome level (e.g., risk of bias), and at review-level (e.g., incomplete retrieval of identified research, reporting bias).	Discussion
Conclusions	26	Provide a general interpretation of the results in the context of other evidence, and implications for future research.	Discussion
FUNDING			
Funding	27	Describe sources of funding for the systematic review and other support (e.g., supply of data); role of funders for the systematic review.	Acknowledgements

6. Acknowledgements

The author would like to acknowledge Rama Vasudevan, PhD of Oak Ridge National Laboratory for intellectual discussions and collaborative research on reinforcement learning. The author would also like to thank Nathan Martindale for assistance making the decision tree more readable and thus usable.

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Acronyms

A2C	Advantage Actor Critic
AODV	Ad-hoc On-demand Distance Vector
ARVI	Anytime Reduced Value Iteration
ATTN	Active Tracking Target Network
AUC	Area Under the receiver operating characteristic (ROC) Curve (AUC)
BMI	Brain Machine Interface
CLAC	Lyapunov-based Actor Critic
CPPO	Constraint-controlled Proximal Policy Optimization
DB	Database
DDPG	Deep Deterministic Policy Gradient
DOE	Department of Energy
DrAC	Data-regulated Actor-Critic
HVAC	Heating, Ventilation, and Air Conditioning
JSD	Jensen-Shannon Divergence
Max	Maximum
Min	Minimum
MOOSE	Model-based Offline policy Search with Ensembles
NESM	Normalized Energy Stability Margin
Perf	Performance
PPO	Proximal Policy Optimization
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
RL	Reinforcement Learning
Res	Research
Rob	Robustness
ROC	Receiver Operating Characteristic

sec	seconds
Stab	Stability
SVD	Singular Value Decomposition
TAK	Title, Abstract and Keywords
Theo	Theoretical
US	United States
WoS	Web of Science

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Resilience

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