Human Interaction and Emerging Technologies (IHIET 2024), Vol. 157, 2024, 20–32
https://doi.org/10.54941/ahfe1005460

How Many Robots Is Too Many? Findings About Single-Human Multiple-Robot Systems

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ABSTRACT

Mobile robots are increasingly being used to perform tasks that are difficult for humans to reach. Due to their high degree of autonomy, a human can control multiple robots through a graphical user interface, which is called one-human multiple-robot (SHMR) system. However, information about them is scarce. The current literature review synthesizes the features of SHMR systems related to safety and health at work for the operator and system performance. A total of 658 records were identified through an exploratory search since 2000, and 35 were selected to meet the inclusion criteria. The characteristics were consolidated and provide valuable insights about field of application, team composition, and reported outcomes. Future research can focus on exploring these systems in industries that have not yet been studied, or it can examine the impact of individual operator characteristics on these systems.

Keywords: Human-robot interaction, Human-computer interaction, Multiple robots

INTRODUCTION

Mobile robots are automatic machines with locomotion mechanisms and a sense of position that enables to navigate a space with minimal intervention (Rubio et al., 2019, Siegwart and Nourbakhsh, 2004). As an example are zoomorphic robots that can be used for remote inspection (BostonDynamics, 2023). These robots are particularly useful in areas that are difficult for humans to reach, such as in a natural disaster (Casper and Murphy, 2003), or for progress monitoring, such as in construction (Kim et al., 2022), among other fields. In addition, these robots do not require a human operator on board to perform their intended tasks and can be remotely controlled (Huang, 2004). Depending on their purpose, they can navigate on the ground (Unmanned Ground Vehicle – UGV), in the water (Unmanned Surface/Underwater Vehicles – USV/UUV), or in the air (Unmanned Aerial Vehicle – UAV, also known as drone) (Balestrieri et al., 2021). A group of these robots is called a swarm, which typically follows a single command autonomously (Wilson et al., 2023).

Autonomy in robots is required to support effective performance (sense an environment, plan based on it, and act in it to reach a goal) without external control (Beer et al., 2014). However, even with the current level of artificial intelligence, these robots are not fully autonomous and still require humans to evaluate tasks, modify goals, or intervene when the system fails (Patel et al., 2022). With a high degree of autonomy, an operator can coordinate multiple robots, which is referred to as *Single-Human Multiple-Robots (SHMR) systems* (Wong et al., 2011). In general, SHMR systems are used for resource optimization, e.g., reduce labor costs, and improve system performance, e.g., more goals in less time (Wong and Seet, 2017). Among the levels of shared interaction, we focus on the collective structure on supervising multiple robots, where each robot has a task assigned directly by the operator (Yanco and Drury, 2002).

In order for humans to interact with multiple robots, a graphical user interface (GUI) is used as an intermediary (Lewis, 2013). This means that the relationship between humans and multiple robots is established through one or more screens. Therefore, it is important to consider the field of human-computer interaction (HCI) (Kawamura et al., 2003), especially to understand how this interaction affects human performance (Lewis, 2013). The use of robots interacting with human workers raises new safety and health concerns that must be addressed in order to ensure the safe use of robotic systems in the workplace (Murashov et al., 2016). In the case of SHMR systems, some scholars have found that the human workload may increase with each additional robot (Adams, 2009, Trouvain and Wolf, 2002, Velagapudi et al., 2008), and that switching attention from one robot to another may reduce supervisor's awareness (Prewett et al., 2009), leading to a greater tendency to fail to complete critical tasks (Wickens, 2008).

Regarding system effectiveness, some scholars have proposed equations to estimate the number of robots an operator can effectively control. Olsen Jr. & Wood (2004) and Crandall et al. (2005) developed the fan-out equation, which is the ratio between the effective time a robot can operate without human intervention and the time required by the operator to interact with a robot. Crandall & Cummings (2007) and Cummings & Mitchell (2008) complemented the equation with the waiting times caused by the operator, including interaction with other robot, human decision-making queue, and loss of situation awareness. Later, Breslow et al. (2014) incorporated the time available for humans to solve a robot problem before a damage considering that several robots are likely to require human attention at the same time. Parallel, Boussemart and Cummings (2011) used a model with Markov chains to create a predictor of operator actions in the area of human-monitored automated systems. Understanding the threshold at which the number of robots becomes too large for a single operator to effectively manage is critical to the design and implementation of these systems. To this end, it is essential to examine the limits of the system considering the relevant user states, which include workload, engagement, situational awareness, attention, fatigue, and emotional state (Schwarz et al., 2014), in particular by interacting with the robots through a GUI.

Some reviews have been made so far. Prewett et al. (2009) and Lewis (2013) performed literature search that involved remote human supervision on multiple unmanned vehicles, its performances indices and human effects. However, the literature is outdated. A more recent meta-analysis is done by Hocraffer and Nam (2017), who evaluated the state of research of mobile robots, but they focus on unmanned aerial vehicle swarm only. One more specific is done by Moud et al. (2018) in the construction sector. And one more broadly is done by Chen and Barnes (2021), who cover the human-robot interaction in a detailed and comprehensive manner, without focusing on the SHMR systems of interest. Therefore, this literature review seeks to comprehend the features of SHMR systems that researchers have reported in any task or industry, excluding the military sector. This manuscript provides a synthesize of the main characteristics such as the field of application, the number and type of robots and outcome measurements related to the operator and system performance. The findings will help practitioners to develop effective SHMR systems.

METHODOLOGY

We conducted a literature review in September 2023 following the "Methodology for developing evidence-informed management knowledge" by Tranfield et al. (2003), divided into three stages. In the first stage, planning the review, we focused on the research question: *What are the characteristics of SHMR systems?* Here, characteristics refer to field of application, team composition and reported outcomes. Inclusion criteria were systems with one human and multiple highly automated robots, mobile robots coexisting with the human, and the human as operator or supervisor. Multiple humans, industrial manipulators, swarms with a common goal, interactions without a GUI, technical studies focused on algorithms, and the military sector were excluded.

In the second stage of conducting the review, we searched on the Ebsco Discovery Service databases (EBSCO, 2023) using the following keywords within our scope: *("Highly automated robot" OR "mobile robots" OR "Remotely operated vehicle" OR "Autonomous underwater vehicle" OR "Unmanned ground vehicle" OR "Unmanned aerial vehicle") AND ("Human–robot interaction" OR "Human–robot interface" OR "Human robot interaction" OR "Human robot interface") NOT (Militar*).* Only articles and conference proceedings published in English in peer-reviewed journals from the year 2000 onward that included experiments with more than two participants were included. We did not include short reports, conference posters, or abstracts.

A total of 444 records were found in the literature search directly from the EBSCO database. The references of the papers were checked and a further 214 records were identified. After the first scan, 134 documents were excluded as duplicates or irrelevant. After screening, 86 reviews on robotics, 32 articles on the military field, and 245 on other topics were discarded. This left 161 eligible manuscripts. After reading all the papers, 28 were excluded because they dealt with a single robot, 47 because they were technical, and 50 because they did not meet the criteria, leaving 16 journal articles and 19 proceedings to be included. Data from 35 documents were extracted and classified according to the following aspects:

- Field of application: industry where the SHMR system was tested;
- Team composition: number and type of robots (e.g. UGV, USV/UUV, UAV).
- Reported outcomes: operator and system performance (Steinfeld et al., 2006).

Finally, in the third, reporting and dissemination stage, we answer the research question in the next section, which provides a descriptive analysis of the findings, and then we critically evaluate the sources to identify and discuss strengths and weaknesses. Later, we consolidate the results of the literature review and derive a checklist for developing effective SHMRS. In the end, our conclusions provide insights into how humans can effectively manage multiple robots simultaneously.

RESULTS

Team Composition

Table 1 shows the team composition that the different authors have explored, including the number and type of robots. Around 63% of the studies used UGV only, 17% drones only, and 11.4% a combination of both. Just two authors were found to used different mobile robots: Glas et al. (2012) who tested social robots for monitoring guides in a shopping mall and Sellner et al. (2006a), (2006b) who used a combination of Roving eye, UGV and a Crane robot to simulate remote assembly in construction sites.

About 49% of the records investigated the influence of the operator-robot ratio on system performance. Adams (2009), Humphrey et al. (2007), Velagapudi et al. (2008) evaluated robot team composition to see the effects on task and operator performance. Chandarana et al. (2021) used four combinations to simulate costs in different scenarios. Crandall and Cummings (2007) tested the usefulness and appropriateness of different metrics for SHMR. Other authors conducted mixed designs to evaluate performance of the SHMR system, varying the number of robots and different factors such as coordination techniques (Glas et al., 2012), exploration modes (Vilela et al., 2013, Wang et al., 2009b), operation modes (Hong et al., 2019), different task conditions (Lewis et al., 2010), different environments (Trouvain et al., 2003, Trouvain and Wolf, 2002), interaction modes (Villani et al., 2020), video displays (Wang et al., 2009a), automation and latency level (Khasawneh et al., 2019), and automation reliability and scheduling discipline (Chien et al., 2013).

Table 1. Team composition in the experiments per each author.

ID	Author	Number of robots	Type of robots
[1]	Adams (2009)	1H: 1,2,4R	UGVs
[2]	Brooks et al. (2011)	1H:12R	UGVs
[3]	Chandarana et al. (2021)	1H: 5,8,10,15R	UGVs
[4]	Chien et al. (2013)	1H:3,6R	UGVs
[5]	Crandall and Cummings (2007)	1H:2,4,6,8R	UGVs + UAVs

(Continued)

Table 1. Continued

ID	Author	Number of robots	Type of robots
[6]	Crandall et al. (2005)	1H:3R	UGVs
[7]	Dietz et al. (2017)	1H:10R	UGVs
[8]	Donmez et al. (2010)	1H:5R	UGVs + UAVs
[9]	Fooladi Mahani et al. (2021)	1H:3R	UAVs
[10]	Frische and Ludtke (2013)	1H:3R	UAVs
[11]	Fuchs et al. (2014)	1H:4R	UAVs
[12]	Glas et al. (2012)	1H:2,3,4R	Social robots
[13]	Goodrich et al. (2007)	1H:3R	UGVs
[14]	Hong et al. (2017)	1H:4R	UAVs
[15]	Hong et al. (2019)	1H:5,10,15,20R	UGVs
[16]	Humphrey et al. (2007)	1H:6,9R	UGVs
[17]	Khasawneh et al. (2019)	1H:1,2R	UGVs
[18]	Lewis et al. (2010)	1H:4,8,12R	UGVs
[19]	Lewis et al. (2014)	1H:6R	UGVs
[20]	Olsen Jr and Wood (2004)	1H:18R	UGVs
[21]	Ratwani et al. (2010)	1H:5R	UAVs
[22]	Roldán et al. (2017)	1H:2R	UGVs + UAVs
[23]	Rosenfeld et al. (2017)	1H:3R	UGVs
[24]	Ruiz et al. (2015)	1H:3R	UAVs
[25]	Sellner et al. (2006a)	1H:3R	Roving eye + UGV + Crane
[26]	Sellner et al. (2006b)	1H:3R	Roving eye + UGV + Crane
[27]	Setter et al. (2015)	1H:5R	UGVs
[28]	Trouvain and Wolf (2002)	1H:2,4,8R	UGVs
[29]	Trouvain et al. (2003)	1H:1,2,4R	UGVs
[30]	Velagapudi et al. (2008)	1H:4,8,12R	UGVs
[31]	Vilela et al. (2013)	1H:1,2,3,4R	UGVs
[32]	Villani et al. (2020)	1H:2,3,12R	UGVs + UAVs
[33]	Wang and Lewis (2007)	1H:3R	UGVs
[34]	Wang et al. (2009a)	1H:4,8,12R	UGVs
[35]	Wang et al. (2009b)	1H:4,8,12R	UGVs

Fields of Application

Most studies focused on search and rescue (SARs) and urban search and rescue (USARs), in particular for victim detection. Others authors researched on fire fighters, assembly in construction, inspections, surveillance, aviation, guide service and logistics. Eight studies did not specify the application of domain (see also Figure 1).

Reported Outcomes

According to Steinfeld et al. (2006), common metrics for human-robot interaction assess the performance rather for the operator, the system or the robot. From a human factor perspective, operator performance in human-robot interaction is influenced by a combination of cognitive, physical, and psychological factors (Hopko et al., 2022). The outcomes are listed in Table 2.

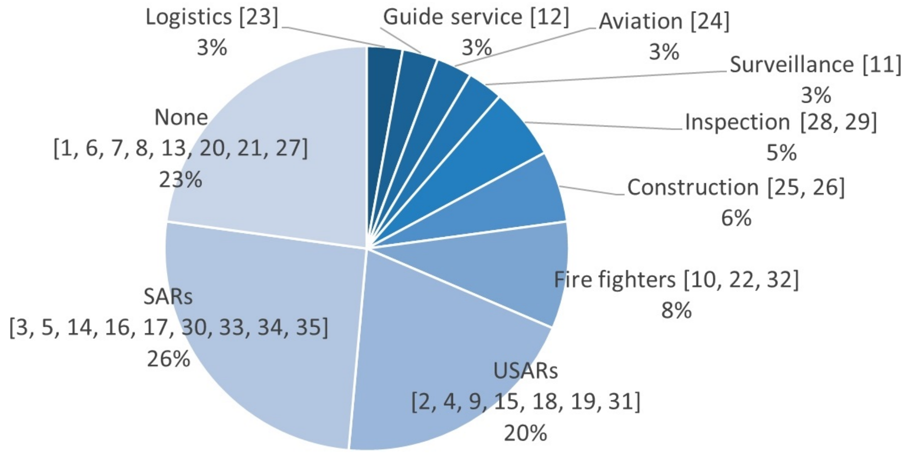

Figure 1: Distribution of field of domains [IDs] can be found in Table 1.

As expected, the most common operator performance measures were workload and situational awareness (SA). Of the 22 authors who measured workload, 18 used NASA-TLX, while others measured workload with robot attention demand, the operator utilization rate, the ZEIS rating method by Pitrella (1989), or the heart rate. In the case of SA, some scholars used standardized methods such as the SAGAT by Endsley (1988) or the 3D SART by Taylor (1990, 2017), while others used eye movement or tracking, navigation or perception metrics, and operator response or waiting times. In addition, attention was measured in three studies using vehicle wait times due to operator attentional inefficiencies. Other studies investigated the trust in automation or in the robots. Only one author considered emotional state using the SAM questionnaire by Bradley and Lang (1994).

Table 2. Operator performance outcomes.

Outcome	Measuring instrument	IDs
Workload	NASA-TLX	[1, 2, 3, 4, 13, 16, 17, 18, 19, 22, 23, 24, 25, 27, 29, 30, 34, 35]
	Other instruments	[6, 8, 28, 32]
Situational awareness	SAGAT and 3D SART	[16, 22, 24]
	Eye movement or tracking	[10, 21]
	Other instruments	[5, 14, 25, 26]
Attention	Waiting times	[8, 13, 33]
Trust	Trust in automation	[4, 17]
	Trust in the system	[9]
Emotional state	SAM questionnaire	[7]

System performance measures, on the other hand, are those that assess how well the human and robots perform as a team (Steinfeld et al., 2006). The compilation of these outcomes is listed in Table 3. In summary, in search and rescue, including fire fighters, most authors considered the number of victims found (performance rate) or missed or (error rate) as an effectiveness measure, and the time to complete the mission and the area covered or missed by the robots as efficiency measures. Just three authors considered the mean fan-out depending on the workload or SA.

In other fields, scholars focused more on number of successful task completions or task completion time, number of errors or false alarms, waiting time or interaction time. Other outcomes included percentage of collisions or robot damage, robot‘s detection accuracy, progress, speed, or synchronization, maneuverability, force mapping, path and perceived usefulness.

Table 3. System performance outcomes.

Field	Outcome	IDs
Search and rescue (including fire fighters)	Victim detection	[2, 4, 10, 14, 15, 17, 18, 19, 33, 34, 35]
	Task completion time	[3, 10, 15, 16, 19, 30]
	Area explored	[3, 4, 15, 19, 31, 33, 34, 35]
	Fan-out	[5, 30, 35]
	Others	[9, 14, 15, 22]
Other fields	Task success	[1, 8, 12, 21, 23, 25, 28]
	Task completion time	[1, 6, 8, 13, 20, 25, 28, 29]
	Errors or false alarms	[1, 26]
	Others	[7, 11, 27, 29]

DISCUSSION

The objective of this literature review was to comprehend the characteristics of SHMR systems and provide a synopsis of the most important features. We found that SHMRs are mainly used for search and rescue operations. In this domain, robots assist the operator during natural disasters by entering a hard-to-reach disaster area and understanding the environment in order to save lives (Kruijff-Korbayová et al., 2015). About 80% of the identified records used only one type of mobile robot. Combining different types of robots might bring advantages (e.g., increased area coverage), especially in emergency situations where the landscape is mixed (Magid et al., 2022), or in construction sites where the structure is constantly changing (Kim et al., 2022).

Studies have primarily focused on evaluating mental workload using the NASA TLX, and to a lesser extent, situational awareness using various techniques. Therefore, cognitive factors have been studied but with questionnaires that seem to show less sensitivity to task changes (Barajas-Bustillos et al., 2023, Rubio et al., 2004). Besides, when interacting with robots through a GUI, it is necessary to consider all multidimensional user states (Schwarz et al., 2014), including motivation, which has not been studied. Hence, there is a need to explore physical and psychological factors of the operator when interacting with multiple robots using one or multiple screens.

Among the system performance outcomes, some studies have shown that the more robots are used, the more problems may occur, such as robot damage or low task performance. This is due to increased operator workload (Adams, 2009) or decreased operator's attentional capacity (Crandall and Cummings, 2007). Finally, researchers have tested different robot team combinations, but few authors have explored the robot threshold at which system performance is no longer improved by adding additional robots. Wang et al. (2009b) and Velagapudi et al. (2008) proposed a fan-out of 9 robots, while Crandall and Cummings (2007) explained that there seems to be a plateau at 6 robots. Regarding robot automation, some authors argued that it might reduce operator workload by managing attention, reducing robot demands, and improving task performance (Goodrich et al., 2007, Hong et al., 2019). On the contrary, others explained that a higher level of automation does not necessarily improve system performance (Chien et al., 2013, Khasawneh et al., 2019).

Although we conducted an exploratory search, it is likely that we did not find more documents related to the topic of interest given our keywords, and therefore we obtained more records from other authors' references than directly from the database. Nevertheless, the synthesis presented here offers an overview of the current state of the systems. In summary, SHMR systems have the potential to enhance task performance, but their effect on the operator has not been sufficiently explored. Future research could focus on exploring these systems in industries that have not yet been studied (e.g., energy industry, gas or electricity), and analyzing the impact of individual characteristics, such as age or gender, on these systems.

FUNDING

The author(s) declare that they have received financial support for the research, writing, and/or publication of this article. This work is part of the project F2557 "Human Centered Technologies for a Safer and Greener European Construction Industry" (HumanTech), which is funded by the European Union's research and innovation program Horizon Europe under grant agreement N° 101058236) and the project F2569 "Optimized Work Design for Network Control Centers of Critical Infrastructure" (Beautiful), which is funded by the Federal Ministry of Education and Research (Bundesministerium für Bildung und Forschung, BMBF) (funding code: 03SF0694) and is coordinated by the Project Management Agency Jülich (PTJ).

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