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Optimizing the Operational Process of a Social Robot for Elderly Assistance: Enhancing Reliability and Readiness

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Abstract: Social robots designed to assist the elderly must function reliably in changing environments where usage conditions vary. Ensuring both reliability and readiness is crucial for effective daily interactions. This paper focuses on optimizing the operational processes of a social robot for elderly care. It presents a model that improves task planning and maintains consistent robot readiness. The study introduces an operational model that considers reliability, safety, and usability states. It applies Markov processes to predict transitions between usability states and assess readiness. It also proposes optimization methods to improve the robot's readiness index. By addressing these aspects, the study enhances the efficiency and dependability of social robots, ultimately improving the quality of life for elderly and disabled users.

Keywords: social robots; operational optimization; reliability; readiness assessment; elderly care



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1. Introduction

The aging population is one of the main factors contributing to the increasing proportion of people with reduced mobility in Poland's demographic structure. According to EUROSTAT data, by 2100, Poland will have the oldest population in the European Union, with the age dependency ratio rising from approximately 27% to 63%. One of the key challenges in this context, in addition to policies aimed at encouraging higher birth rates, is improving the quality of life for the elderly. A key way to address this challenge is to increase the use of automated and robotic systems that can support older people. The need to limit mobility and interpersonal contact (especially among the elderly), as experienced during the COVID-19 pandemic, highlights the importance of finding new solutions that minimize human involvement [1].

The use of social robots (including mobile and walking robots) to assist the elderly and people with reduced mobility has been studied by scientists for quite some time. Researchers have developed various concepts of mobile robotic platforms designed to perform specific tasks based on the needs of the individuals they support. These robot designs also consider potential hazards and the likelihood of interference with R2X model wireless communication, which is expected to increase as technology advances [2]. Rychlicki et al. (2020) [3] reviewed the literature on the application of artificial intelligence in user

access authentication, monitoring dangerous behavior, and detecting invalid traffic. From this, they identified communication risks and proposed a conceptual human-in-the-loop cybersecurity model. Meanwhile, Siva and Poellabauer (2019) [4] conducted a review of techniques, implementation strategies, and validation methods for Intrusion Detection Systems (IDS) in the Internet of Things (IoT). Their work also includes a classification of IoT attacks and addresses research challenges related to mitigating such attacks.

It is also important to highlight scientific studies that address the social significance of companion robots designed to assist elderly individuals. This aspect is particularly evident in the works of Broekens et al. (2009) [5], Santhanaraj and Ramya (2021) [6], and Martinez-Martin and del Pobil (2018) [7]. In these studies, alongside a comprehensive review of various robotic technologies, special attention is given to issues related to enhancing communication capabilities for the elderly, improving their safety, and reducing feelings of loneliness.

An aging population presents a significant challenge for medical professionals. It leads to a growing demand for medical and care-related services, thus increasing the need for healthcare workers. One concerning trend observed in Poland is the shortage of nurses in the domestic labor market. Poland has the lowest ratio of nurses (direct patient care) per 1000 citizens in Europe. In 2016, this figure was just 5.24, compared to 17.5 in Switzerland, 16.9 in Norway, 13.1 in Germany, 7.9 in the UK, and an average of 9.4 in OECD countries.

The nursing workforce is aging. The average age of a nurse in Poland was 44 years in 2008 and 52 years in 2018. Young nurses represent the smallest group, while the 45–54 age group is the most numerous. There are also still nurses who should have retired, i.e., those over 60 years old. The oldest working nurse in 2018 was 93. Data also show an increase in the number of nurses in the 55–64 and 65+ age groups. The fact that 13% of active nurses are over 65 years old is particularly alarming, while only 9.7% are under 35.

Forecasts for 2016–2030, presented in a report by the Supreme Council of Nurses and Midwives, are not optimistic. They predict an increase in the number of nurses with pension rights, a rise in the average age of active nurses, a lack of adequate replacement in the profession, and a decrease in the ratio of nurses per 1000 citizens.

Caring for sick, post-accident, or disabled patients is a physical burden for nurses. These patients often require assistance with lifting, carrying, and changing positions, as they frequently lack proper support equipment. In this context, robots could prove useful by physically relieving healthcare professionals. The International Standardisation Organisation (ISO) defines nursing robots as “mechanical, electric and control systems employed by trained operators in professional healthcare facilities that execute tasks in direct interaction with patients, nurses, doctors and other healthcare workers, which could modify behaviour based on what they register in their surroundings”.

It should be emphasized that a social robot is designed for use in a specific environment. However, despite this, these robots operate under varying conditions, which result, among other things, from different levels of usage. While previous research has explored the reliability and operational aspects of social robots, there remains a gap in addressing how these factors specifically impact human–robot interaction, particularly in the context of elderly care. This study aims to bridge that gap by focusing on both the reliability and operational efficiency of social robots, emphasizing their ability to adapt to diverse and unpredictable conditions. Previous observations of their operational processes lead to the conclusion that designers should focus not only on ensuring their reliability but also on optimizing their performance. The first area involves implementing solutions to improve the reliability of social robots by using appropriate reliability structures and components with sufficient dependability. The second area focuses on enhancing robot performance through maintenance-related activities.

The scope of these tasks includes three main research directions, which aim to do the following:

- Increase the reliability of social robots;
- Enhance the safety of services provided by social robots by introducing solutions that increase resistance to adverse factors;
- Improve the safety of social robots through proper operational process planning.

Unlike previous studies, which primarily focus on individual aspects of reliability or performance, this research introduces a comprehensive approach that integrates both factors to enhance human–robot interaction. A response to these limitations is the developed proprietary process for optimizing human–robot interaction for a social robot designed for the elderly. Designers can apply this method when developing new solutions aimed at increasing the safety of services provided to the elderly and people with disabilities. It will also be beneficial to define clearly which reliability and operational states of social robots are considered acceptable or unacceptable from a safety perspective.

The development of the reliability and operational model involved not only the states of fitness (safety) and unfitness (safety unreliability) but also the state of partial fitness (safety hazard). This approach allows for a more accurate representation of the actual functioning of social robots. Observations of robot operations reveal that transitions between these states occur randomly at previously unknown moments. Therefore, it is appropriate to apply a discrete-in-state and continuous-in-time Markov process to mathematically describe such processes.

The article has the following structure: introduction (1), state of the art (2), modeling of the operation process of a social robot dedicated to the elderly (3), and conclusions (4).

2. State of the Art

Robotic solutions designed to assist elderly individuals are an interesting and frequently explored research topic across various fields and scientific disciplines. One of the key themes addressed in studies on this subject is the potential stimulants and barriers to implementing such solutions. Among the most significant works, the study by Hersh (2015) [8] stands out. In addition to the potential benefits discussed earlier in this article, the study also examines challenges related to social acceptance, robot safety, potentially high costs, and ethical concerns. Similar issues are explored in the works of Koh et al. (2021) [9], Papadopoulos (2020) [10], Servaty et al. (2020) [11], and Rigaud (2024) [12]. These studies highlight, among other things, the technological complexity of robotic solutions for elderly individuals, negative biases surrounding the use of robots in caregiving, and challenges related to integrating new technologies into daily caregiving practices. Noteworthy research findings were also presented by Luo et al. (2024) [13]. A unique aspect of their study was the recognition of different stakeholder groups' perspectives on implementing robotic solutions in elderly care. These groups included nurses, elderly individuals, nursing home managers, and robotics company employees. The authors emphasize that collaboration between stakeholders is essential for creating an environment conducive to adopting socially assistive robots, thereby maximizing their potential to improve the well-being of older adults.

An important research topic addressed in the literature is the preferences of older adults regarding the functionality of robots, their relationships with robots, and their general attitudes toward such devices. Several significant studies have explored this topic over the years. These include works by Sharkey and Sharkey (2011) [14], Kidd et al. (2006) [15], Sharkey and Sharkey (2012) [16], and Oh et al. (2020) [17]. These studies examine, among other things, the potential for companion robots to replace human caregivers and strongly advocate for a complementary role of robots in elderly

care. Furthermore, they emphasize the need to design robots whose actions are responsive to the current emotional state of the elderly person. The literature also includes studies on the openness of older adults to using companion robots for support [18], as well as research focused on quantifying the level of social awareness regarding the current and future role of companion robots for individuals with reduced mobility [19].

An interesting research topic is the role of robots in elderly care. In this context, a range of publications addressing this issue deserves mention. One such study is by Vercelli et al. (2018) [20], which highlights the challenges associated with the implementation of robots in elderly care. According to the authors, these challenges include the impact of robots on the emotions of older adults, their privacy, and their increasing dependence on mechanical devices. Similar issues are addressed in the studies by Chen et al. (2019) [21], Liang et al. (2022) [22], Santhanaraj et al. (2021) [23], and Bardaro et al. (2022) [23]. However, it is important to emphasize the various potential applications of companion robots identified and discussed in these studies. These include assistance with mobility, health monitoring, and support in the social interactions of older adults.

A frequently discussed research issue in the literature is the broadly understood safety of using robots designed to assist elderly individuals. In this context, the study by Fosch-Villaronga and Mahler (2021) [24] is worth mentioning. It examines issues related to cybersecurity and the risk of hacking. The paper advocates for a stronger link between cybersecurity and safety regulations, proposing a framework to address these challenges in the development and use of care robots in healthcare settings. The safety of companion robots for older adults has also been addressed in studies by Asgharian et al. (2022) [25], Arents et al. (2021) [26], Miyagawa et al. (2019) [27], and Ahn and Inhyuk (2023) [28]. These studies emphasize the importance of enhancing user safety and standardizing legal regulations and safety standards.

Despite the fact that scientists have been working on designing social robots to support the elderly and people with reduced mobility for years, the implementation of tasks requiring movement accuracy within a few centimeters remains a considerable challenge [29–31]. Several publications in the literature focus on robot navigation. One such work is the monograph edited by Matveeva, Savkina, Hoya, and Wang (2016) [10], which provides a comprehensive and unified review of the latest achievements in this field. The book also extends its scope to cover obstacles affecting general motion, including rotations and deformations (i.e., changes in shape and size), and places significant emphasis on reactive algorithms and rigorous mathematical studies related to proposed navigational solutions, demonstrating the correlation between mathematics and robotics. A similar approach is found in the work by Möller et al. (2021) [32], where the authors recognize that a robot serving the public and acting as a social agent must consider various research fields. The paper primarily focuses on robot navigation, offering an overview of existing solutions for specific research areas, along with perspectives on potential future directions. Autonomous navigation in a dynamic environment involving people, employees in different positions, schedules, and access restrictions requires, among other things, adapting to socially accepted rules. Similarly, the speed at which robots approach people, whether to establish communication or move around them, must be tailored to social conventions.

Current algorithms do not account for the social complexity of real-world environments and their relationship to the time of day or activities taking place in these scenarios. Calderit et al. (2021) [33] introduced a new robot navigation framework with the concept of time-dependent social mapping. The paper discusses how interaction areas change over time and how these changes affect human-aware navigation. Contributions from the literature also present various concepts of mobile robot platforms designed for specific

activities, depending on the age of the people they assist. Notable solutions in this area are outlined by Cavallo et al. (2014) [34], who review the ASTROMOBILE systems intended for assisting the elderly by directly delivering medication or reminders to take it. Additionally, Costa et al. (2018) [35] reviewed an interactive robot system called PHAROS, designed for monitoring physical exercise for the elderly. A broader approach to interactive social robots was presented by T. Kand (2017) [36].

The publications mentioned above discuss issues related to the application of social robots; however, they do not adequately address the concerns related to social robot reliability and operation. The following papers stand out in this field, with a particular focus on robot power supply issues.

The paper addresses the issue of energy usage in heterogeneous mobile robots. The authors analyzed electricity consumption by individual components of the mobile robots, allowing for a comparison across different models. A significant contribution of the authors is the table-form summary and comparison of around a dozen models designed to predict energy consumption in various robot types. This enables a comprehensive analysis of robot performance through the application of the appropriate model.

Another publication that also addresses the issue of robot power supply is [37]. It provides a detailed analysis of different types of robot power supplies, primarily focusing on battery usage. The paper also proposes algorithms for selecting the primary power supply source and electrical system for the robot. This approach could be applied when determining the social robot readiness index.

Another relevant paper that discusses robot power supply is [38]. It focuses on energy storage solutions and their impact on robot operational capabilities. The authors analyzed a power supply system consisting of an energy storage system made up of a battery and supercapacitor. Although the study was related to electric vehicles, the results obtained indicate a broad range of potential applications, such as for mobile devices. A similar approach was presented in [39], where the study involved a hybrid power supply system (fuel cell, ultracapacitor, and battery). To improve the operation of such a power supply system, the authors proposed a strategy for controlling energy flow between the three sources using fuzzy logic.

Another approach is presented in [40], which analyzes battery discharge characteristics. This significantly impacts the ability of a companion robot to perform its tasks. The obtained results were used to develop a model that enables forecasting future operational states based on the number of assigned tasks. Therefore, the discussed approach can be practically applied in maintenance support departments.

A perspective important in the context of a robot's ability to perform an assigned task is presented in [41]. The authors proposed a predictive control strategy for energy management, which positively influences the operating parameters of a companion robot related to mobility.

The authors of [42] reviewed the issue of rationalizing mobile robot control, aiming, among other things, to minimize energy consumption. Based on the conducted tests, they proposed a criterion that allows for the selection of optimal parameters for a robot motion control algorithm. This is beneficial from the perspective of minimizing energy consumption and reducing robot travel time.

Ref. [43] discusses increasing mobile robot energy efficiency from a holistic perspective. The authors did not focus on a specific companion robot system but instead developed a model that considers energy consumption by three primary subsystems: the sensor system, control system, and motion system. The results lead to the conclusion that the developed energy model can be used to estimate energy consumption during robot

motion processes. This contributes to a more effective analysis of energy consumption characteristics in mobile robots.

A review of the literature shows that research on robots assisting the elderly focuses on social, functional and technical aspects. Many publications emphasize the importance of stakeholder collaboration and the need to adapt robots to the emotional and physical needs of seniors. Despite a wide range of studies, the operational reliability of robots in the context of long-term use, especially taking into account dynamic environmental conditions and energy constraints, has been insufficiently investigated. The research gap therefore relates to the development of integrated energy and reliability management models that take into account real-life scenarios of robots in elderly care.

This approach is presented by the authors in the following chapters of this paper.

3. Modeling the Operation Process of a Social Robot Dedicated to the Elderly

In the literature on assistive robot reliability, the most commonly used statistical models are:

- Weibull models, used to analyze time to failure, but which do not take into account the operational context of the robot.
- Markov processes, which allow for the modeling of robot transients, but are often based on a limited number of states and assume stationarity.
- Redundancy-based models, typical for critical systems, but difficult to apply to light mobile robotics.

In contrast to the above, our proposed model takes into account the following:

- classification of robot states based on the robot's actual activity in the user environment;
- the dynamics of transitions between states (activity–inactivity–failure);
- integration with an optimization function for operational decision-making.

This approach allows for a better representation of the real-world operating conditions of a robot assisting the elderly, where reliability includes not only the mechanical aspects of operation, but also the continuity of interaction with the user.

The implementation of all operational tasks requires specific social robots to have full functionality of assumed functionalities. Figure 1 shows the permissible space of technical states for a group of robots used to perform individual tasks (functionalities). The green color indicates technically permissible (safety) states, where all robots are in a state of complete fitness—they perform all functionalities. Safety states from S_{D1} to S_{Dn-1} are the so-called partial failure of only some robot functionalities (corresponding to them, green color with red filling). Individual failures of functionalities performed by different robots are also marked in red. The red color in Figure 1 indicates the state of complete failure, the so-called safety failure. All functions performed by the group of robots from S_{01} , S_{02} , ..., to S_{0n} are not performed. There is a complete incapacity of all functionalities (tasks) performed by the robot team. Only transitions between individual states of safety hazard (partial incapacity of the robot team) are permissible. In the implementation of ensuring all functionalities for robots at a given time, known technical principles are used, increasing reliability (evaporating damage), e.g., redundancy or safe failure. The initial state for the performance of all tasks by the robot team presented as in Figure 1 is always S_0 (technical state of full serviceability, the initial state sometimes called basic). In this state, all functionalities of the robot team are serviceable (green rectangle filling color, permitted-designed tasks from S_{011} to S_{0nn} can be performed—Figure 1). All these functionalities are implemented in a strictly defined time (axis $OX-t$ (time) under the figure). The influence of time on the repertoire of changes in technical states is always decisive, because in all technical objects, so-called aging occurs, causing damage.

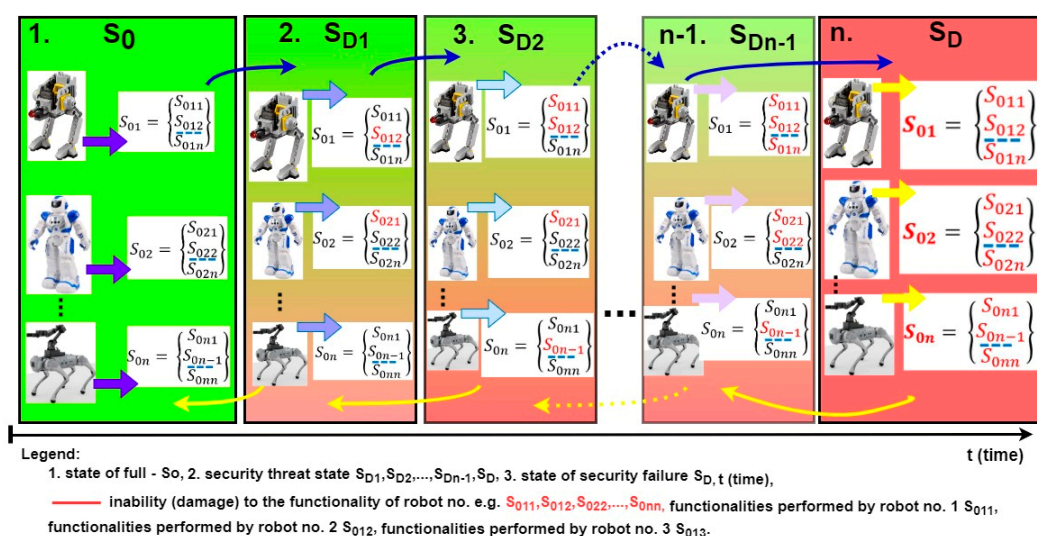


Figure 1. Physical interpretation of the technical states of robots employed in the course of care-related monitoring and assistance for patients in hospital settings, with the following definitions: S_0 —state of full fitness of all functionalities for robots No. $S_0, S_{D1}, S_{D2}, \dots, S_{Dn-1}, S_D$; S_{D1} —state of safety hazard No. 1 (unfitness of all functionalities of robots No. $S_0, S_{D1}, S_{D2}, \dots, S_{Dn-1}, S_D$, unfitness of functionalities No. S_{012}, S_{021} (marked in red); S_{D2} —state of safety hazard No. 2 (unfitness of selected functionalities of robots No. $S_0, S_{D1}, S_{D2}, \dots, S_{Dn-1}, S_D$; unfitness of functionalities No. $S_{011}, S_{012}, S_{021}, S_{0n-1}$ (marked in red), S_{Dn-1} —state of safety hazard No. $n-1$ for robots No. $S_0, S_{D1}, S_{D2}, S_{Dn-1}$; unfitness of selected functionalities No. $S_{011}, S_{012}, S_{01n}, S_{021}, S_{022}, S_{0n-1}$ (marked in red); S_D —state of safety unreliability for robots No. $S_0, S_{D1}, S_{D2}, S_{Dn-1}$; unfitness of all assumed functionalities No. $S_{011}, S_{012}, S_{01n}, S_{021}, S_{022}, S_{02n}, S_{0n1}, S_{0n-1}, S_{0nn}$ (marked in red for implementing selected care-related activities) [source: own study].

The individual acronyms define the technical, partial states for the given robots. The technical states marked in Figure 1, e.g., for robot S_{01} , rectangle no. 1 as $(S_{011}, S_{012}, \dots, S_{01n})$ denote the implementation of the designed partial functionality—e.g., delivery of medicines, water, telephones, notification of health condition, delivery of a magazine or book, etc. The partial states are responsible for the implementation of the functionality for the given robot. The number of these technical states is also a function of the technical complexity of the given robot (how many given tasks can be designed and implemented). The implementation of individual partial tasks assigned to the given robots already at the design stage is also a function dependent on the energy consumption of the performed activities. Various available strategies can be used in robot control, e.g., adaptive, conditional, play-off, and other strategies, as well as those using logical functions for given partial states. However, priority is given to functions implemented for health protection. However, these functions always have maximum priority during the implementation of all tasks. Robots operate in difficult, complex operating environments, but the first steps to specifying the functional data always belong to the designer. This does not mean that there is a finite number of technical state data for a particular robot. Observation during operation, research, performance properties and the use of artificial intelligence for control can partially or completely change existing functionalities using different control and optimization rules. A given “scenario” of robot use developed by the designer can be completely changed when other input forces appear or when there are existing operational disturbances. Safety states occurring within a limited operational space of robots that supervise patients requiring hospitalization can be expressed as:

$$SB = \{S_{PZ}, S_{ZB}, S_B\}, \quad (1)$$

In this case, the SB is a set of the following operation states of robots used to supervise and assist, for example, in in-patient hospital settings. Operational states can be interpreted as follows, as shown in Figure 1, followed by a corresponding interpretation:

- $S_{PZ} (S_0)$ —state of full fitness of all robots employed within a limited space of a patient care facility. All assumed robot functionalities are implemented on an ongoing basis. Control and safety monitoring systems covering individual robots are functional. All primary and redundant power supply sources are fit for use and ready to accept the load associated with the operation of robots $S_{01}, S_{02}, \dots, S_{0n}$. Robot power supply systems are always diagnosed online due to the technical parameters of battery bank charging voltage.
- $S_{ZB} (S_{D1}, S_{D2}, \dots, S_{Dn-1})$ —state of safety hazard for the implementation of specific functionalities in robots used in relation to monitoring and care for hospitalized patients. Out of the available robot functionalities, only selected functions are implemented, which enable providing patient care at a pre-set safety level. This is marked in Figure 1 by distinguished, technically permissible, appropriate technical states; S_{D1} —state of safety hazard No. 1 (unfitness of selected functionalities in robots No. $S_0, S_{D1}, S_{D2}, \dots, S_{Dn-1}, S_D$), which is the unfitness of functionalities, No. S_{012}, S_{021} , respectively, (marked in red in Figure 1). In a state of safety hazard, S_{D2} No. 2 (unfitness of selected functionalities in robots No. $S_0, S_{D1}, S_{D2}, \dots, S_{Dn-1}, S_D$) is the respective unfitness of a greater number of functionalities in individual robots numbered $S_{011}, S_{012}, S_{021}, S_{0n-1}$ (red in Figure 1). The last permissible state in space S_{ZB} is S_{Dn-1} is the state of safety hazard n-1 in robots No. $S_0, S_{D1}, S_{D2}, S_{Dn-1}$). Is the unfitness for selected robots, marked, respectively, in the context of implementing functionalities as No. $S_{011}, S_{012}, S_{01n}, S_{021}, S_{022}, S_{0n-1}$, in red in Figure 1. Ensuring the continuity and quality of healthcare implemented by robot groups $S_0, S_{D1}, S_{D2}, \dots, S_{Dn-1}, S_D$ requires selecting only the most important function for implementation, to guarantee continued technical quality of the technical system. The available local maintenance personnel immediately takes repair action associated with recovering all robots implementing custom programmed functions, including the guarantee of electricity supply by power supply systems. In the case of extensive technical systems of such a type, remote services that are not located within the facility should be taken into account. Such personnel may be located at a remote center, monitoring the operation process. Remote service receives all information on unfitness and has a specified time to intervene to improve all functionalities, taking into account the priorities of implementing the entire healthcare process. Robot battery bank charging stations are always diagnosed online due to the technical parameters of battery bank charging output voltage. Such information on the unfitness states of stations for robots with specific functionalities is sent to a collective receiving center that manages the technical system.
- $S_B (S_D)$ —state of safety unreliability for the technical healthcare system in question implemented by robots. All states in Figure 1 were marked in red accordingly. Individual technical states within the healthcare system operation process graph that prevent the implementation of all system functionalities were marked. However, technical discussions are required to ensure the functionality of the care provided by robots designated to guarantee operational continuity in the aspect of its safety and implement assumed operational tasks, taking into account elemental and informational redundancy, including permissible failures in accordance with the safe-failure principle. Task implementation by individual robots within a technical system is independent. A state of safety unreliability, S_D , for the technical system in question is a function of many variables, with power supply being one of them. It is a very technical function due to the ability of all robots to implement operational tasks.

By carrying out the social robot functioning analysis, it can be stated that the relationships taking place in it, in reliability and operation terms, can be visualized as shown in Figure 2. The basic state for the considered operational graph is always the state of SPZ—full serviceability for the implementation of all functionalities by the robot group. The occurrence of a failure (damage) with intensity λ_{ZB1} causes the transition of the entire technical system to the state of threat to safety SZB1. If a local service is available at the place of use, it is possible to carry out immediate renewal with intensity μ_{ZB1} (restoration of the input state—full serviceability of SPZ at a given time). It is also possible to transition (Figure 2) in the technical system from the state of full serviceability SPZ to the state of safety unreliability SB with damage intensity λ_{B0} . However, this transition occurs for very small values of damage intensity λ_{B0} . The occurrence of this transition is unlikely, because appropriate technical and organizational solutions are used in technical systems that do not allow for such changes in the technical state. The use of element, information, structural, strength, and other redundancies prevents the implementation of such transitions as shown in the graph in Figure 2. In well-organized technical systems (functioning for a fairly long time) there are always intermediate states before the state SB (safety failure). These states are shown in Figure 2 as SZB1 and SZB2 (security threats); they refer to only partial inability to perform a given task or functionality. This principle has a special application, e.g., in electronic security systems.

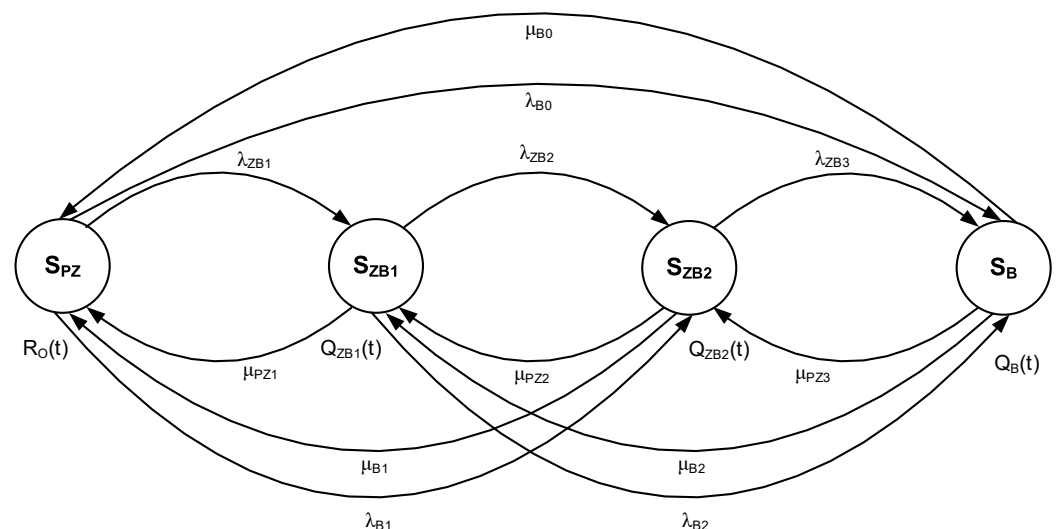


Figure 2. Reliability and operational relationships of a social robot [source: own study].

The Kolmogorov–Chapman equation system was used to describe the graph of relations presented in Figure 2. Observations of the robot group operation process allow us to state that transitions between distinguished states occur randomly, at previously unknown moments. Therefore, it is reasonable to use a discrete Markov process-in-states and continuous-in-time processes for the mathematical description of such processes. For the purposes of reliability and operation modeling of robots, the intensities of transitions between distinguished states were used. Assuming that the failure intensity is constant in time, an exponential distribution was adopted for further analysis. Thus, when considering the homogeneous Markov process, all transition intensities have finite values. Therefore, such a process satisfies the Kolmogorov–Chapman equations. Failure intensity is the probability of failure occurrence within a unit of working time under specific conditions. Repair intensity is the probability of completing maintenance activities (repair) within a unit of working time under specific conditions. For the exponential distribution, the unit of intensity is $[1/h]$ and results, among others, from the exponential law of reliability.

Designations in Figure:

$R_O(t)$ —probability function of the robot staying in a state of full fitness S_{PZ} ;

$Q_{ZB1}(t)$ —probability function of the robot staying in a state of safety hazard S_{ZB1} ;

$Q_{ZB2}(t)$ —probability function of the robot staying in a state of safety hazard S_{ZB2} ;

$Q_B(t)$ —probability function of the robot staying in the S_B state of safety unreliability;

λ_{ZB1} —intensity of a transition from a state of full fitness S_{PZ} to a state of safety hazard S_{ZB1} ;

λ_{ZB2} —intensity of a transition from a state of safety hazard S_{ZB1} to a state of safety hazard S_{ZB2} ;

λ_{ZB3} —intensity of a transition from a state of safety hazard S_{ZB2} to a state of safety unreliability S_B ;

μ_{ZB1} —intensity of a transition from a state of safety hazard S_{ZB1} to a state of full fitness S_{PZ} ;

μ_{ZB2} —intensity of a transition from a state of safety hazard S_{ZB2} to a state of safety hazard S_{ZB1} ;

μ_{ZB3} —intensity of a transition from a state of safety unreliability S_B to a state of safety hazard S_{ZB2} ;

λ_{B0} —intensity of a transition from a state of full fitness S_{PZ} to a state of safety unreliability S_B ;

μ_{B0} —intensity of a transition from a state of safety unreliability S_B to a state of full fitness S_{PZ} ;

λ_{ZB1} —intensity of a transition from a state of full fitness S_{PZ} to a state of safety hazard S_{ZB2} ;

μ_{B1} —intensity of a transition from a state of safety hazard S_{ZB2} to a state of full fitness S_{PZ} ;

λ_{B2} —intensity of a transition from a state of safety hazard S_{ZB1} to a state of safety unreliability S_B ;

μ_{B2} —intensity of a transition from a state of safety unreliability S_B to a state of safety hazard S_{ZB1} .

A state of full fitness S_{PZ} is a state wherein a social robot operates correctly. A state of safety hazard Q_{ZB1} is a state wherein a social robot implements most functions, including these most important from the operational perspective. A state of safety hazard Q_{ZB2} is a state wherein a social robot implements the functions that are most important from the operational perspective. A state of safety unreliability Q_B is a state wherein a social robot is unfit.

A transition from a state of full fitness S_{PZ} to a state of safety hazard S_{ZB1} at an intensity of λ_{ZB1} follows a robot failure and the absence of implementing some function. If a robot is in a safety hazard state S_{ZB1} , it is possible to switch to a state of full fitness S_{PZ} , provided that actions are taken aimed at restoring robot fitness.

A transition from a state of safety hazard S_{ZB1} to a state of safety hazard S_{ZB2} at an intensity of λ_{ZB2} follows a robot failure leading to the inability to implement functions (except for the most important ones from the operational perspective). A transition from a state of safety hazard S_{ZB2} to a state of safety hazard S_{ZB1} is possible upon taking actions that involve restoring the capability of implementing some robot functionalities.

A transition from a state of safety hazard S_{ZB2} to a state of safety unreliability S_B at an intensity of λ_{ZB3} follows a robot failure, leading to the inability to implement the functions most important from the operational perspective. A transition from a state of safety unreliability S_B to a state of safety hazard S_{ZB2} is possible upon taking actions that involve restoring the capability of implementing the functions most important from an operational perspective.

A transition from a state of full fitness S_{PZ} to a state of safety unreliability S_B at an intensity of λ_{B0} follows a robot failure leading to the inability to implement the functions most important from the operational perspective.

A transition from a state of safety unreliability S_B to a state of full fitness S_{PZ} at an intensity of μ_{B0} follows the restoration of robot fitness.

A transition from a state of full fitness S_{PZ} to a state of safety hazard S_{ZB2} at an intensity of λ_{B1} follows a robot failure leading to an inability to implement some functions (except for the most important ones from the operational perspective).

A transition from a state of safety hazard S_{ZB2} to a state of full fitness S_{PZ} at an intensity of μ_{B1} follows restoring robot fitness.

A transition from a state of safety hazard S_{ZB1} to a state of safety unreliability S_B at an intensity of λ_{B2} follows a robot failure leading to the inability to implement the functions most important from the operational perspective.

A transition from a state of safety unreliability S_{ZB} to a state of safety hazard S_{ZB1} at an intensity of μ_{B2} follows the restoration of the robot's capability to implement the functions most important from the operational perspective.

The relations between a social robot and the infrastructure related to communication security have been described by the following Kolmogorov–Chapman equations:

$$\begin{aligned} R'_0(t) &= -\lambda_{ZB1} \cdot R_0(t) + \mu_{PZ1} \cdot Q_{ZB1}(t) - \lambda_{B0} \cdot R_0(t) + \mu_{B0} \cdot Q_B(t) - \lambda_{B1} \cdot R_0(t) + \mu_{B1} \cdot Q_{ZB2}(t) \\ Q'_{ZB1}(t) &= \lambda_{ZB1} \cdot R_0(t) - \mu_{PZ1} \cdot Q_{ZB1}(t) - \lambda_{ZB2} \cdot Q_{ZB1}(t) + \mu_{PZ2} \cdot Q_{ZB2}(t) - \lambda_{B2} \cdot Q_{ZB1}(t) + \mu_{B2} \cdot Q_B(t) \\ Q'_{ZB2}(t) &= \lambda_{ZB2} \cdot Q_{ZB1}(t) - \mu_{PZ2} \cdot Q_{ZB2}(t) - \lambda_{ZB3} \cdot Q_{ZB2}(t) + \mu_{PZ3} \cdot Q_B(t) + \lambda_{B1} \cdot R_0(t) - \mu_{B1} \cdot Q_{ZB2}(t) \\ Q'_B(t) &= \lambda_{ZB3} \cdot Q_{ZB2}(t) - \mu_{PZ3} \cdot Q_B(t) + \lambda_{B0} \cdot R_0(t) - \mu_{B0} \cdot Q_B(t) + \lambda_{B2} \cdot Q_{ZB1}(t) - \mu_{B2} \cdot Q_B(t) \end{aligned} \quad (2)$$

Assuming the following initial conditions:

$$\begin{aligned} R_0(0) &= 1 \\ Q_{ZB1}(0) &= Q_{ZB2}(0) = Q_B(0) = 0 \end{aligned} \quad (3)$$

and applying defined Laplace transforms, the following system of linear equations is obtained (labels are consistent with those adopted for the relation graph shown in Figure 2):

$$\begin{aligned} s \cdot R_0^*(s) - 1 &= -\lambda_{ZB1} \cdot R_0^*(s) + \mu_{PZ1} \cdot Q_{ZB1}^*(s) - \lambda_{B0} \cdot R_0^*(s) + \mu_{B0} \cdot Q_B^*(s) - \lambda_{B1} \cdot R_0^*(s) + \mu_{B1} \cdot Q_{ZB2}^*(s) \\ s \cdot Q_{ZB1}^*(s) &= \lambda_{ZB1} \cdot R_0^*(s) - \mu_{PZ1} \cdot Q_{ZB1}^*(s) - \lambda_{ZB2} \cdot Q_{ZB1}^*(s) + \mu_{PZ2} \cdot Q_{ZB2}^*(s) - \lambda_{B2} \cdot Q_{ZB1}^*(s) + \mu_{B2} \cdot Q_B^*(s) \\ s \cdot Q_{ZB2}^*(s) &= \lambda_{ZB2} \cdot Q_{ZB1}^*(s) - \mu_{PZ2} \cdot Q_{ZB2}^*(s) - \lambda_{ZB3} \cdot Q_{ZB2}^*(s) + \mu_{PZ3} \cdot Q_B^*(s) + \lambda_{B1} \cdot R_0^*(s) - \mu_{B1} \cdot Q_{ZB2}^*(s) \\ s \cdot Q_B^*(s) &= \lambda_{ZB3} \cdot Q_{ZB2}^*(s) - \mu_{PZ3} \cdot Q_B^*(s) + \lambda_{B0} \cdot R_0^*(s) - \mu_{B0} \cdot Q_B^*(s) + \lambda_{B2} \cdot Q_{ZB1}^*(s) - \mu_{B2} \cdot Q_B^*(s) \end{aligned} \quad (4)$$

Applying the Laplace transform to the system of Equation (3), we obtain the probability function for a system staying in a state of full fitness in symbolic terms, expressed by the relationship (4). This function was determined because it is most important to determine the probability of the robot's fitness, because then it fully performs the designated activities. Mathematical operations aimed at determining the dependencies (5) consist of solving the system of Equation (4), taking into account the numerical values given in Example 1.

$$R_0(s) = \frac{0.476001 + 1.835 \cdot s + 2.35 \cdot s^2 + s^3}{0.476002 \cdot s + 1.83501 \cdot s^2 + 2.35001 \cdot s^3 + s^4} \quad (5)$$

For the purposes of the calculations above, the authors adopted the intensities of transitions between distinguished system states, as per the values adopted for the calculations in Example 1.

Simulation and computer methods and studies provide an opportunity to determine the influence of changes in reliability and maintenance parameters of particular elements on the values of indices describing the entire system relatively fast [44–46].

With the help of computer assistance, it is possible to determine the probabilities of robots staying in the states of full fitness R_O , safety hazard Q_{ZB1} , safety hazard Q_{ZB2} , and safety unreliability Q_B . Such a sequence of actions is shown in Example 1.

Example 1:

Let us assume the following values describe the analyzed social robot:

- Research duration—1 year (time in hours [h]):

$$t = 8760[h]$$

- Intensity of a transition from a state of full fitness S_{PZ} to a state of safety hazard S_{ZB1} :

$$\lambda_{ZB1} = 0.0000018[1/h]$$

- Intensity of a transition from a state of safety hazard S_{ZB1} to a state of safety hazard S_{ZB2} :

$$\lambda_{ZB2} = 0.0000016[1/h]$$

- Intensity of a transition from a state of safety hazard S_{ZB2} to a state of safety unreliability S_B :

$$\lambda_{ZB3} = 0.000001[1/h]$$

- Intensity of a transition from a state of full fitness S_{PZ} a state of safety unreliability S_B :

$$\lambda_{B0} = 0.0000001[1/h]$$

- Intensity of a transition from a state of full fitness S_{PZ} to a state of safety hazard S_{ZB2} :

$$\lambda_{B1} = 0.0000004[1/h]$$

- Intensity of a transition from a state of safety hazard S_{ZB1} to a state of safety unreliability S_B :

$$\lambda_{B2} = 0.0000002[1/h]$$

- Intensity of a transition from a state of safety hazard S_{ZB1} to a state of full fitness S_{PZ} :

$$\mu_{PZ1} = 0.8[1/h]$$

- Intensity of a transition from a state of safety hazard S_{ZB2} to a state of safety hazard $ZB1$,

$$\mu_{PZ2} = 0.6[1/h]$$

- Intensity of a transition from a state of safety unreliability S_B to a state of safety hazard S_{ZB2} :

$$\mu_{PZ3} = 0.4[1/h]$$

- Intensity of a transition from a state of safety unreliability S_B to a state of full fitness S_{PZ} :

$$\mu_{B0} = 0.1[1/h]$$

- Intensity of a transition from a state of safety hazard S_{ZB2} to a state of full fitness S_{PZ} ,

$$\mu_{B1} = 0.25[1/h]$$

- Intensity of a transition from a state of safety unreliability S_B to a state of safety hazard S_{ZB1} :

$$\mu_{B2} = 0.2[1/h]$$

A solution to Equation (5) in the time domain is seen in expression (6).

$$\begin{aligned} R'_0(t) &= -\lambda_{ZB1} \cdot R_0(t) + \mu_{PZ1} \cdot Q_{ZB1}(t) - \lambda_{B0} \cdot R_0(t) + \mu_{B0} \cdot Q_B(t) - \lambda_{B1} \cdot R_0(t) + \mu_{B1} \cdot Q_{ZB2}(t) \\ Q'_{ZB1}(t) &= \lambda_{ZB1} \cdot R_0(t) - \mu_{PZ1} \cdot Q_{ZB1}(t) - \lambda_{ZB2} \cdot Q_{ZB1}(t) + \mu_{PZ2} \cdot Q_{ZB2}(t) - \lambda_{B2} \cdot Q_{ZB1}(t) + \mu_{B2} \cdot Q_B(t) \\ Q'_{ZB2}(t) &= \lambda_{ZB2} \cdot Q_{ZB1}(t) - \mu_{PZ2} \cdot Q_{ZB2}(t) - \lambda_{ZB3} \cdot Q_{ZB2}(t) + \mu_{PZ3} \cdot Q_B(t) + \lambda_{B1} \cdot R_0(t) - \mu_{B1} \cdot Q_{ZB2}(t) \\ Q'_B(t) &= \lambda_{ZB3} \cdot Q_{ZB2}(t) - \mu_{PZ3} \cdot Q_B(t) + \lambda_{B0} \cdot R_0(t) - \mu_{B0} \cdot Q_B(t) + \lambda_{B2} \cdot Q_{ZB1}(t) - \mu_{B2} \cdot Q_B(t) \end{aligned} \quad (6)$$

Figure 3 shows the waveform of a probability function (6) related to a social robot staying in a state of full fitness.

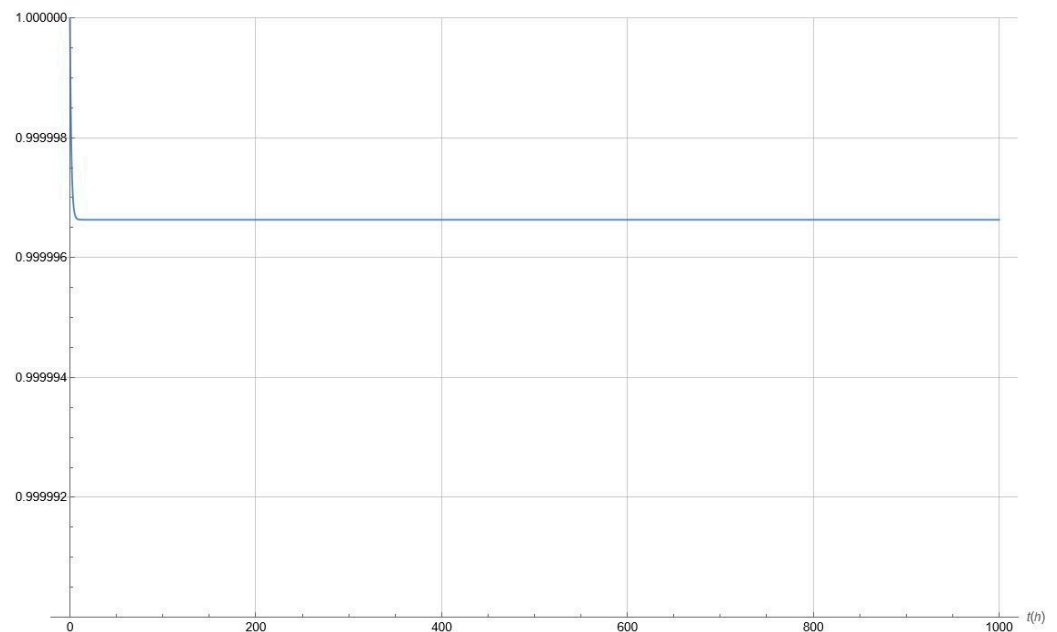


Figure 3. Waveform of the $R_0(t)$ function for the probability of a social robot staying in a state of full fitness [source: own study].

Verifying the specific probability of staying in a state of full fitness is an important issue related to operating a social robot. From an operational perspective, this is impacted by the time to restore a state of full fitness. Further considerations were based on the adopted analysis of the impact of the transition μ_{PZ1} from a state of safety hazard S_{ZB1} to a state of full fitness S_{PZ} . It is a value rather significantly affected by the user through properly ensuring an adequate operation process.

Figure 4 shows the waveform of a probability function (5) related to a social robot staying in a state of full fitness, for the following transition intensity values:

- $\mu_{PZ1} = 0.5[1/h]$;
- $\mu_{PZ1} = 0.25[1/h]$;
- $\mu_{PZ1} = 0.125[1/h]$;
- $\mu_{PZ1} = 0.1[1/h]$.

The following relationships are a solution to a time domain Equation (4) for the intensities of transition μ_{PZ1} from a state of safety hazard S_{ZB1} to a state of full fitness S_{PZ} :

- for $\mu_{PZ1} = 0.5[1/h]$:

$$R_0(t) = 0.999995 - 1.12045 \cdot 10^{-7} \cdot e^{-0.850005 \cdot t} - 7.61892 \cdot 10^{-7} \cdot e^{-0.699999 \cdot t} + 5.85711 \cdot 10^{-6} \cdot e^{-0.500001 \cdot t} \quad (7)$$

- for $\mu_{PZ1} = 0.25[1/h]$:

$$R_0(t) = 0.999991 + 2.07521 \cdot 10^{-13} \cdot e^{-0.850005 \cdot t} - 4.76197 \cdot 10^{-8} \cdot e^{-0.699998 \cdot t} + 9.33325 \cdot 10^{-6} \cdot e^{-0.250002 \cdot t} \quad (8)$$

- for $\mu_{PZ1} = 0.125[1/h]$:

$$R_0(t) = 0.999982 + 2.70459 \cdot 10^{-8} \cdot e^{-0.850005 \cdot t} + 7.66029 \cdot 10^{-8} \cdot e^{-0.699998 \cdot t} + 0.0000177868 \cdot e^{-0.125003 \cdot t} \quad (9)$$

- for $\mu_{PZ1} = 0.1[1/h]$:

$$R_0(t) = 0.999978 + 3.13732 \cdot 10^{-8} \cdot e^{-0.850005 \cdot t} + 9.52363 \cdot 10^{-8} \cdot e^{-0.699998 \cdot t} + 0.0000220661 \cdot e^{-0.100003 \cdot t} \quad (10)$$

Figure 4 shows the waveform of a probability function (6) related to a social robot staying in a state of full fitness, for the transition intensities adopted for the analysis.

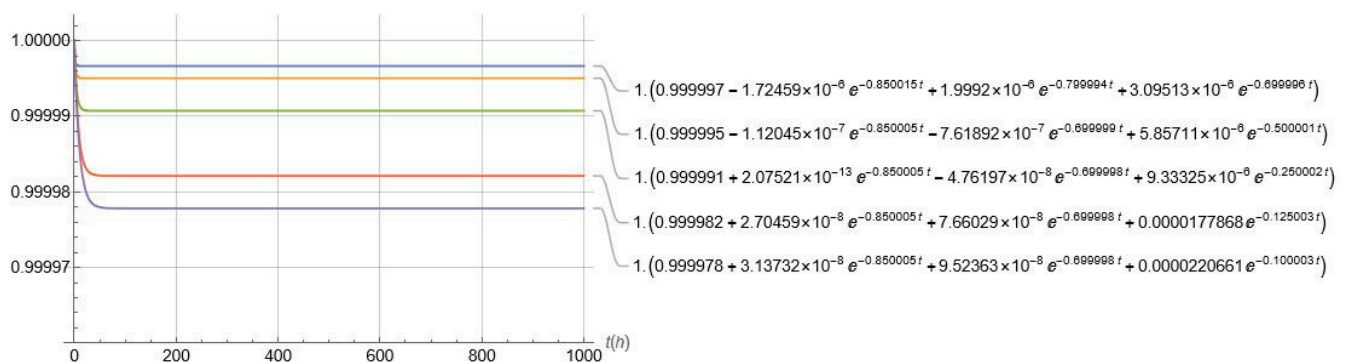


Figure 4. Waveform of a probability function $R_0(t)$ related to a social robot staying in a state of full fitness, for different intensities of transition from a state of safety hazard S_{ZB1} to a state of full fitness S_{PZ} [source: own study].

To increase the robustness of the proposed model, the following strategies are proposed:

- Multimodal data validation (sensor fusion)—combining data from different sources (camera, microphone, LIDAR, tactile sensors) allows the detection of inconsistencies typical of adversary attacks;
- Real-time anomaly detection—the use of statistical monitoring methods (e.g., deviation from patterns) allows early detection of suspicious changes in robot behavior;
- Estimating the level of confidence in the input data—by analyzing the stability of the signals and their compatibility with the operational context (e.g., location of the robot vs. expected area of operation);
- Resilient learning methods (adversarial training)—future versions of the model may be extended to include mechanisms for resilient learning (e.g., augmentation of data with simulated errors).

This approach may provide a starting point for the further development of system frameworks that are resilient to cyber threats and erroneous input data, which is particularly relevant for care and home applications.

4. Discussion About the Practical Application of Research

The practical application of the considerations above enables rational planning of a social robot's operation process, ensuring it can perform activities at an assumed readiness level. The research was conducted not only in a controlled environment but also in a real-world setting—specifically, a seniors' home—where the robot's performance was assessed under actual usage conditions. Our work focused on modeling robotic behavior in the context of assisting seniors. The main reason for this decision was the need to provide a formal basis for evaluating potential interaction strategies before their widespread implementation. The meeting was conducted at the "RAZEM" senior citizens' home in

Stawiguda (Warmińsko-Mazurskie Voivodeship, Poland) over a period of 3 h. Thirty people took part in the study, of which five actively used the robot. Tests included the robot's navigation in the real environment, its response to the users' commands and interactions between the robot and the seniors (Figure 5).



Figure 5. Meeting in seniors home with Spot robot [source: own library].

To ensure practical relevance, the probability function graphs and mathematical models used to describe robot state transitions were analyzed in terms of their real-world impact. These models allow for the prediction and optimization of operational states, directly contributing to improved reliability, better maintenance planning, and enhanced safety.

It is important to acknowledge key limitations and risks associated with using companion robots for elderly care. These include challenges in achieving precise movement, shortcomings in current navigation algorithms regarding complex social environments, and difficulties in integrating robotic solutions with daily caregiving practices. Additionally, cybersecurity concerns and the lack of standardized legal regulations remain significant barriers to large-scale adoption.

From an operational perspective, challenges such as power efficiency, energy storage, and the unpredictable nature of state transitions impact the long-term usability of companion robots. Addressing these issues through advanced predictive modeling and optimized maintenance strategies can significantly improve their practical application.

When considering the practical application of companion robots for the elderly, it is essential to take into account ethical considerations and the social acceptance of such technological solutions. Key challenges include the technological complexity of robotic systems for older adults, negative biases toward the use of robots in caregiving, and difficulties in integrating new technologies into daily care practices. A crucial aspect of this discussion is whether companion robots should replace human caregivers or merely serve a complementary role.

Furthermore, based on interactions between older adults and robots, it is important to emphasize the need for robots that can adapt their actions to the user's current emotional state. The attitudes of potential users—particularly older adults, women, and residents of small towns—may significantly influence the adoption of companion robots. Research indicates that these groups most frequently identify key barriers limiting the use of such technology in everyday life [19].

5. Conclusions

The research paper discusses the reliability and operational analysis of social robots. The authors focus not only on issues related to the reliability of social robots but also on the proper planning of their operational processes. Only this combined approach will lead to an increase in the social robot's readiness index, which significantly contributes to the successful implementation of assigned tasks.

The heuristic selection of fixed parameters in the readiness index in future studies may include reaction time threshold, weighting of social interaction and penalization for downtime. These values can be selected experimentally, but their selection can also be systematized using the following heuristics:

- Acceptable response time determined by the average response time observed in human–robot interaction;
- Social interaction weighting based on user surveys: the higher the expectation towards the interactivity of the robot, the more weight should be given to this component;
- An inactivity penalty estimated based on the frequency and length of inactivity episodes during testing.

In addition, we propose the future use of an adaptive calibration method, i.e., dynamically tuning these parameters during actual use of the robot, based on user feedback and operational performance.

The conducted functional analysis of the social robot, followed by the proposed proprietary functional model, allowed for a mathematical analysis to determine the relationships that enable the calculation of the probabilities of the social robot remaining in a state of full fitness. This, in turn, made it possible to compare the impact of the time required to restore full fitness on the readiness index value. As a result, it is now possible to optimize the human–robot interaction operation process for a social robot dedicated to the elderly, based on the established criteria. In future research, the authors plan to conduct analyses that will also consider the financial expenditure required for the periodic restoration of the social robot's operational potential.

The scientific novelty presented in the article includes, among other aspects:

- Development of a dedicated operational model for social robots that considers reliability, safety, and partial usability states, providing a more accurate representation of real-world operating conditions;
- Integration of Markov processes to mathematically model transitions between usability states, enabling precise predictions of a robot's operational readiness;
- Proposal of optimization methods for the operation process to improve the readiness index of social robots, specifically tailored to the needs of elderly and disabled users.

Some general conclusions that can be drawn from the research conducted for this article focus on the following facts:

- Aging populations demand innovative solutions, such as social robots, to address healthcare personnel shortages and enhance the quality of life for older adults [47,48];
- The operational readiness of social robots is heavily influenced by well-planned maintenance and operational processes, highlighting the critical importance of both design reliability and maintainability [49,50];
- Mathematical modeling of operational states and downtime facilitates the development of strategies that minimize disruptions and enhance the reliability of services provided by social robots [51–53].

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