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Nurses' Robot Use Self-Efficacy: Mediation Effect in The Relationship Between Robot Anxiety and Preference of Automation Levels

Hemşirelerin Robot Kullanımına Dair Öz Yeterliği: Robot Kaygısı ve Otomasyon Seviyesi Tercihleri İlişkisinde Aracılık Etkisi

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Keywords:

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Anahtar Sözcükler:

Otomasyon seviyesi; sağlık hizmeti; hemşire; robot kaygısı; öz-yeterlik.

ABSTRACT

Objective: Healthcare organizations may develop their employees' competencies to adapt to robot technologies by identifying potential challenges beforehand. The psychological characteristics of the employees are among these challenges. In the current study, we focused on the influence of nurses' robot anxiety on their preferred level of automation and also the role of robot use self-efficacy between these two variables.

Methods: 281 Nurses working in a university hospital answered paper-based surveys. These surveys included Robot Anxiety Scale, Robot Use Self-Efficacy in Healthcare Work (RUSH), and Preference of Automation Level (PAL). In data analysis, Pearson product-moment was used for correlation analysis and PROCESS macro was used for mediation analysis.

Results: The analysis showed that the main hypothesis was supported in the context of both robot anxiety and its sub-dimensions. Robot use self-efficacy had a full mediation effect between robot anxiety and preference of automation levels.

Conclusion: In order to achieve effective nurse-robot cooperation, identifying robot use self-efficacy during employee selection and training of current employees may ease the adoption process of this technology.

ÖZ

Amaç: Sağlık kuruluşlarında her geçen yıl robotik teknolojilerin kullanımı gittikçe artmaktadır. Bu süreçte kuruluşlar çeşitli problemlerle karşılaşabilirler. Sağlık kuruluşları, çalışanlarının robot teknolojilerine uyum sağlama yetkinliklerini geliştirerek bu konuda karşılaşabilecekleri olası problemlere dair önlem alabilirler. Bu çalışmada, hemşirelerin robot kaygısının tercih ettikleri otomasyon seviyesi üzerindeki etkisine ve ayrıca robot kullanımı öz yeterliğinin bu iki değişken arasındaki rolüne odaklanılmıştır.

Yöntem: Bir üniversite hastanesinde çalışan 281 hemşire kendilerine verilen anketleri yanıtlamıştır. Bu anketler arasında Robot Kaygısı Ölçeği, Sağlık Hizmetinde Robot Kullanımı Öz-Yeterliği (RUSH) ve Otomasyon Düzeyi Tercihi (PAL) ölçekleri yer almıştır. Veri analizinde, korelasyon analizi için Pearson momentler çarpımı, aracılık analizi içinse PROCESS macro kullanılmıştır.

Bulgular: Analiz hem robot kaygısı hem de alt boyutları bağlamında ana hipotezin desteklendiğini göstermiştir. Robot kullanımı öz-yeterliği, robot kaygısı ile otomasyon düzeylerinin tercihi arasında tam aracılık etkisi göstermiştir.

Sonuç: Etkili hemşire-robot iş birliğinin sağlanabilmesi için çalışan seçimi ve mevcut çalışanların eğitimleri sırasında robot kullanım öz yeterliklerinin belirlenmesi bu teknolojinin benimsenme sürecini kolaylaştırabilir.

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INTRODUCTION

There are many predictions about the coming Artificial Intelligence (AI) Revolution and its impact on all aspects of societies, institutions, and life (Makridakis, 2017). It is predicted that humans will gradually assign an increasing number of repetitive and dangerous service tasks to the next generation of robots. Robots will be able to contribute to the realization of a safe and peaceful society that helps people both physically and psychologically (Weng, Chen and Sun, 2009), and robots also can contribute to a healthier society as well.

As of July 2022, more than 575 million cases of coronavirus disease (COVID-19) have been reported worldwide, with approximately 6.4 million deaths from the disease (Worldometer). The emersion of COVID-19 in 2019 has negatively affected daily life all over the world. Due to the sudden and rapid spread of the epidemic, patients flocked to hospitals, and healthcare workers faced serious workload increases (Zeng et al., 2020). In some hospitals, thanks to robots, healthcare workers can, to some degree, serve patients without contact. Robot can play a different role, ranging from patient registration, scanning, receiving tele-consultancy from doctors, and connecting patients to their families through video (Kanade et al., 2021). With the inclusion of robots in healthcare institutions, healthcare professionals can remotely measure the body temperature of patients and the blood pressure and oxygen saturation of patients connected to the ventilator, thus they can cope with the crisis more easily. In addition, robots can also be used to bring food to those in quarantine (Fang et al., 2021). For example, 14 robots have been deployed in a hospital in China to clean and disinfect the hospital, measure patient temperatures, dispense medicine and food, and entertain and relax patients by communicating and dancing (Zeng et al., 2020).

Even before the coronavirus pandemic the healthcare sector was one of the most prominent areas in which robotic technologies have made great progress. In this sector, robots can do all the work for many services or facilitate the completion of tasks. Robots can work in rehabilitation for dementia patients (Sharkey and Sharkey, 2012), carry patients (Hu et al., 2011), take blood samples from patients (Chen et al., 2015), be involved in surgical operations as surgical robots (Sánchez et al., 2014) and assist in the general care of the patient (dressing, lifting from bed, taking to the toilet, bathing, washing) as a nurse robot (Pérez-Vidal et al., 2012; Pino et al., 2015). Robots can also work as entertainment robots in healthcare facilities (Coeckelbergh, 2011). Therefore, the main reason for technology adoption in healthcare is to increase the efficiency of care provided to patients (Strudwick, 2015). Nevertheless, organizations may invest in technology, but they cannot guarantee that employees will use those technologies (Beedholm et al., 2015).

Studies based on the healthcare workers' perspective on robots that can work in healthcare are not sufficient (Turja et al., 2018). For example, there are challenges employees need to overcome about the robots that can interact with people (Olaronke et al., 2017). In healthcare, acceptance of robots is still accepted challenge (Savela et al., 2018). Even though some nurses see robots as assistive tools and monitoring devices, they may also think robots are not suitable for jobs that require social interaction (Jenkins and Draper, 2015). Telepresent robots (Koceski and Koceska, 2016) and robots that can be remotely controlled by health professionals (Savela et al., 2018) are seen more suitable than autonomous ones. Furthermore, another group of healthcare workers, caregivers, want robots only to lift heavy things, to turn the lights on and off (Broadbent et al., 2012), to remind patients to take their medication (Alaiad and Zhou, 2014), and prefer a moderate level of automation (Erebak and Turgut, 2019). Since this scenario points to machines exhibiting human interaction features, these robots containing AI may have varying degrees of adaptability, learning ability, and connectivity. For example, robots working on hospital floors can be suitably designed to perform mechanical tasks such as vacuuming the floor routinely and making the bed consistently, rather than chatting interactively with patients. In this case, these robots designed with a low level of learning ability can only be reprogrammed occasionally.

The production and the use of human-centered technology need more precise management, especially in the case of robotic technologies. To benefit from the robotic technology used at the targeted level, the psychological characteristics of the people working with the robots should be taken into consideration. The healthcare sector is important in this context; because the service that is offered directly affects the quality of life of patients. Therefore, the technology used in the healthcare sector may affect patients as well as professionals. Laboratory-based studies on human-robot interaction (HRI) have been conducted, but the number of job-specific studies in these research projects is not yet sufficient. Therefore, we conducted the current study with nurses in order to present a job-specific approach and to better understand the psychological factors affecting people in anticipated HRI. In this way, we may contribute to the understanding of potential psychological challenges so that the necessary precautions can be taken.

Self-efficacy

Self-efficacy, one of the factors guiding human activities, is the belief that an individual has the ability to perform a specific task (Bandura, 2010). According to Bandura, self-efficacy strongly determines performance outcomes and does not require the person to have skills related to that task. Self-efficacy influences the extent of the struggle for the difficulties that individuals face when exhibiting any behavior. For example, we cannot engage in a task that we think we can fail (Bandura, 2010).

Robot anxiety

Emotions are an essential part of human behaviors (Mehrabian and Russell, 1974); because emotions can play an important role in the needs and goals of individuals (Izard, 2013). In other words, emotions have a crucial place between cognition and human behavior (Stock and Nguyen, 2019). If emotions affect human behavior (Izard, 2013), they can also affect HRI (de Graaf and Allouch, 2013). Although robots are expected to be part of our daily routines, there is not enough information about the emotions that robots evoke in humans (de Graaf and Allouch, 2013).

Since negative emotions are not pleasant, people may try to stay away from the behaviors and situations in which negative emotions occur (Izard, 2013). The most prominent emotion in HRI is anxiety (Stock and Nguyen, 2019) because those who are concerned about robots refrain from interacting with robots (de Graaf and Allouch, 2013). Therefore, negative emotions such as anxiety in HRI should be examined more (Nomura et al., 2006). Considering this, Nomura and his colleagues (2006) have identified the feelings of fear or anxiety as *robot anxiety* which would prevent people from communicating with robots in HRI. Robot anxiety can be associated with many factors such as robot behavior, context avoidance, distance setting, and mental reactions (Bartneck et al., 2007; Nomura et al., 2011).

Automation levels

In a production system, tasks can be divided into routine and adaptations (Chen et al., 2015). Automation is a full or partial operation performed by machines (Parasuraman et al., 2000). When and to what extent a task needs to be performed with automation depends on the automation adaptation system. This means that the task must be performed at a certain level and at the proper time by competent operators (Chen et al., 2015). It enhances both the performance and reliability of the system (Hilburn, 2017). The distribution of tasks between the operator and the machine can be at various levels. Therefore, the ratio of each task transferred to automation is defined as the level of automation (Parasuraman et al., 2000). Levels of automation have a crucial role in the design of the automation adaptation system.

A task can be carried out fully by a human or automation. In the range of distribution of work from full automation to full human operation, there are various levels have been proposed for the between these two extremes (Riley, 1989; Sheridan and Verplank, 1978). One of the prominent ones, in which automation levels are matched with the functions for the realization of a task, was developed by Parasurman, Sheridan and Wickens (2000). The automation levels used are information acquisition, information analysis, decision/action selection, and action implementation. Thus, the tasks are initially categorized, and it is easier to analyze the support of the automation needed in each section.

The hypothesis

In the processes of adoption of robots to workplaces, human satisfaction may not be given much importance; but it is essential to keep employee's feelings positive and motivating; because they can contribute to this process with their knowledge and creativity. Therefore, it can be helpful to establish a human-centered adaptation system taking into account the automation level preferences of employees (Chen et al., 2015). However, for a variety of psychological factors, employees may focus on lower levels of automation for robots. This can also lead to a non-efficient HRI while trying to provide human-centric technology adaptation; which, in this case, damages the final purpose of the work. Therefore, learning what factors that influence automation level preferences of employees can help to change the preferences of users at an individual level to help the HRI become efficient.

Since self-efficacy is related to the perception of an individual about a specific activity, the measurement should also be linked to a specific task or situation (Bandura, 2006). Hence, self-efficacy has been associated with several technologies: computer (Marakas et al., 1998), software (Hasan, 2006), the internet (Hsu and Chiu, 2004), health technology (Rahman et al., 2016), and robotics (Turja et al., 2017). Studies show that self-efficacy can have a direct effect on technology usage in the context of healthcare (Ma and Liu, 2005). For example, health technology self-efficacy (the belief that the person can use tools which can be used to monitor treat, and diagnose health status) (Rahman et al., 2016) and robot use self-efficacy in healthcare work (healthcare workers' confidence in themselves for using robots) (Turja et al., 2017) are different from one another.

If computer self-efficacy works, we can find a similar effect in HRI (Rosenthal-von der Pütten et al., 2017). This may not mean that the same effects may be seen in other areas. Nevertheless, self-efficacy can be effective in terms of the usage trends of the person in HRI. If employees are given the chance to shape the system according to their preferences, self-efficacy can increase in individuals and thus acceptance rates can increase (Rosenthal-von der Pütten et al., 2017).

Self-efficacy of most of the employees in the healthcare sector may not take its sources from past performance, vicarious experience, or verbal persuasion since very few robots (requiring social interaction, having some anthropomorphic features) work in the healthcare sector. Thus, emotional cues' effectiveness in determining self-efficacy may be further strengthened. Therefore, robot anxiety can affect an individual's robot use self-efficacy in healthcare work. Since self-efficacy influences technology usage positively (Ma and Liu, 2005), we expect that nurses' self-efficacy can predict their preferences about the automation level. So, we proposed the following hypothesis:

Hypothesis: Nurses' robot use self-efficacy in healthcare work have a mediation effect between their robot anxiety and preferred levels of automation. That is, robot anxiety influences preferred levels of automation through robot use self-efficacy in healthcare work (see Figure 1).

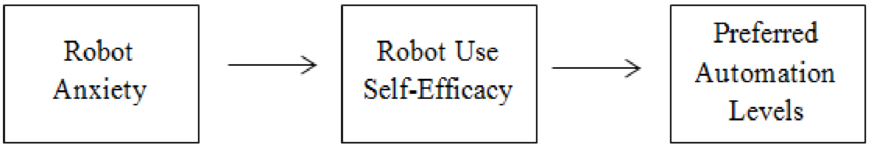

Figure 1. The Mediation Model for the Hypothesis

METHODS

Research Design

The research was designed to investigate the relationship between nurses' robot anxiety, robot use self-efficacy in healthcare work (RUSH), and their preferences for the level of automation in healthcare settings (Preference of Automation Level or PAL). The study employed a cross-sectional survey design to collect data from nurses working in various departments of a university hospital. The data collection took place during the spring of 2019, approximately nine months before the onset of the coronavirus pandemic in Türkiye.

Population and Sample

A total of 281 out of 307 nurses working in the hospital accepted to respond the survey. These nurses were from Surgery, Internal Medicine, Emergency, Pediatrics and Dialysis departments.

Data Collection

The researcher went to the hospital of the university during the day and night shift and distributed paper-based surveys to the nurses. Data were collected through these paper-based surveys distributed to nurses.

Data Collection Tools

Robot Anxiety Scale: Developed by Nomura and his colleagues (2006) and adapted to Turkish by Erebak and Turgut (2019), the Robot Anxiety Scale has three sub-dimensions: anxiety about communication capabilities of robots (RA-communication), behavioral characteristics of robots (RA-behavioral), and the discourse with robots (RA-discourse). This scale contains 11 items. Respondents read the items and described how much anxiety they might have about the given situation or scenario using a 6-point Likert-type scale (1 = I do not feel anxiety at all and 6 = I feel anxiety very strongly) about. Examples of an item from RA-communication was "Robots may talk about something irrelevant"; from RA-behavioral was "How robots will act"; and from RA-discourse was "How I should talk with robots". We performed a confirmatory factor analysis (CFA) and the results indicated that the three-factor structure of robot anxiety had acceptable goodness of fit indices, [($\chi2$ / df = 2.640, CFI = 0.977, GFI = 0.939, RMSEA = 0.077, and SRMR = 0.032)].

Robot Use Self-Efficacy in Healthcare Work (RUSH): Developed by Turja, Rantanen, and Oksanen (2017), the Robot Use Self-Efficacy in Healthcare Work scale measures how much healthcare workers believe in their ability to use robots. There are six items on this scale for technological skills, self-confidence in learning to use robots, and guiding others to use robots. Items 2, 4, and 5 are available for the short version of the scale. An example of an item from the scale was "I'm confident in my ability to learn how to use care robots if they were to become part of my unit".

The scale was originally validated in Finnish (Turja et al., 2017). The non-validated English version is specified in the original study. These English items were translated into Turkish by an expert and then back into English by another expert. The semantic differences between the two translations have been corrected by experts and the authors of this study. Respondents replied on a 6-point Likert-type scale (1 = strongly disagree, 6 = strongly agree).

To ensure the reliability of the Turkish version of the scale, we randomly divided the entire sample into two. To evaluate the construct validity of RUSH, KMO and Bartlett Sphericity test was applied, the results showed that the data was applicable for factor analysis. One half of the sample was used for explanatory factor analysis (EFA) (N = 140; F = 106, M = 34; mean age = 34; mean tenure = 11), and the other half was used for confirmatory factor analysis (CFA) (N = 141; F = 94, M = 47; mean age = 35; mean tenure = 13). EFA results showed that items were collected under a single factor and had factor loading above .58 (α = .89). This single factor accounted for 68% of total variance, and CFA results showed that this single factor structure had acceptable goodness of fit indices [($\chi2$ / df = 1.559, CFI = 0.995, GFI = 0.983, RMSEA = 0.063, and SRMR = 0.029)].

Preference of Automation Level (PAL): The level of automation that nurses prefer in healthcare has been measured through the Preference of Automation Level scale developed by Erebak and Turgut (2019) (see Appendix 1). In this scale, the preferences of the participants were determined through the automated functions (data collection, data analysis, decision making, and decision implementation) developed by Parasuraman, Sheridan, and Wickens (2000).

Appendix 1. Items for the Preference of Automation Levels

Automated Functions	Items
Information Acquisition	I would assign the robot to collect information on whether or not there is any need of the patient.
Information Analysis	I would assign the robot to analyze the collected information.
Decision Selection	After the analysis of the information, I would assign the robot to decide what to do.
Action Implementation	I would assign the robot to implement the decision.

By reading the example below, nurses scored each function adapted to patient care using a 6-point Likert-type scale (1 = strongly disagree, 6 = strongly agree).

"Imagine that a robot is working as an assistant in your workplace and remember what your tasks are in general. Specify the degree to which you can get your robot to work, taking into account the work that the robot can do."

An item for the data analysis was such as "I assign the robot to evaluate the information collected about the patient". The EFA results showed that these 4 items with factor loads above .85 were grouped under a single factor and accounted for 74% of the total variance (α = .89).

Data Analysis

The collected data were subjected to various statistical analyses to test the research hypothesis and explore the relationships between key variables. The analysis involved the following steps:

Descriptive statistics: Demographic information, including age and tenure, was summarized using descriptive statistics such as means and standard deviations.

Pearson product-moment correlations: Correlations were computed to examine the relationships between variables. Specifically, the correlations explored the associations between RUSH, PAL, and robot anxiety, as well as the impact of demographic variables (age and tenure) on these key constructs.

Mediation analysis: The researchers used the PROCESS macro by Hayes (2012) to test the mediation hypothesis. The fourth model within the PROCESS macro was selected for the analysis. This model allowed for an examination of the mediation effect of RUSH on the relationship between robot anxiety (including its sub-dimensions: RA-communication, RA-behavioral, and RA-discourse) and PAL.

Ethical Considerations

After the ethical approval of Erzincan Binali Yıldırım University Human Research Ethics Committee (Decision number: 01/03 on 16 January 2019), permission was obtained from the university hospital administration. All nurses were given informed consent.

RESULTS

Since the hospital was founded about 10 years ago and there were nurses graduated from the medical vocational high school (those who start working there as nurse at the age of 18), the mean age of the nurses was relatively low (M=34 years; SD = 8, ranging from 18 to 55 years) and the average tenure was 12 years (SD = 9, ranging from 1 year to 37 years). See Table 1 for other demographic information.

Table 1. Demographic Data

		Frequency	%
Education	High School	45	16.0
	College	70	24.9
	Bachelor's Degree	142	50.5
	Master's degree	24	8.5
	Total	281	100.0
Gender	Female	200	71.2
	Male	81	28.8
	Total	281	100.0

Pearson product-moment correlations were examined to understand the relationships between variables. The results showed that RUSH had a weak and positive relationship with Pal and robot anxiety. Also, no relationship was found between PAL and robot anxiety (see Table 2). Regarding demographic information, there was no relationship between nurses' age and robot anxiety; however, there was a weak negative relationship between nurses' age and RUSH and PAL. There was no relationship between the tenure of the nurses and robot anxiety; however, there was a weak negative relationship between their tenure and RUSH and PAL.

Table 2. The Correlations among the Variables

	1	2	3	4	5
1 Robot Anxiety	-	.221**	.034	-.053	-.020
2 RUSH		-	.180**	-.225**	-.217**
3 PAL			-	-.184**	-.152*
4 Age				-	.859**
5 Tenure					-

Note. [a] PAL: Preference of Automation Level. [b] **. Correlation is significant at the 0.01 level (2-tailed). [c] * Correlation is significant at the 0.05 level (2-tailed).

We executed PROCESS macro (Hayes, 2012) to test our simple mediation hypothesis. We chose the fourth model and analyzed robot anxiety and its sub-dimensions as predictor variables, the RUSH as a mediator, and PAL as the outcome variable. Results indicated that RUSH had a full mediation effect between the robot anxiety, its sub-dimensions (RA-communication, RA-behavioral, and RA-discourse), and PAL (see Figure 2 and Table 3); hence, our main hypothesis was supported.

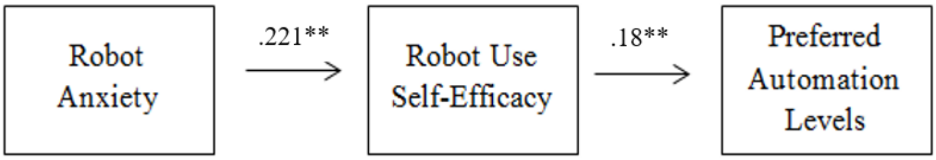

Figure 2. The Mediation Model with Findings

Note. **. Correlation is significant at the 0.01 level (2-tailed).

Table 3. The Mediation Effect of the RUSH

Independent Variable	**Point Estimate**	**Bootstrapping**		
			Percentile 95% CI	
		SE	**Lower**	**Upper**
Robot Anxiety	**Direct Effects**			
	-0.0078	0.0818	-0.1688	0.1533
	Indirect Effects			
	0.0541	0.0272	0.0110	0.1169
RA - Communication	**Direct Effects**			
	0.0838	0.0710	-0.0559	0.2236
	Indirect Effects			
	0.0410	0.0225	0.0051	0.0925
RA - Behavioral	**Direct Effects**			
	-0.0733	0.0770	-0.2248	0.0782
	Indirect Effects			
	0.0526	0.0265	0.0110	0.1146
RA - Discourse	**Direct Effects**			
	-0.0164	0.0707	-0.1556	0.1229
	Indirect Effects			
	0.0374	0.0197	0.0057	0.0809

Note. [a] Bootstrap sample size = 5.000. [b] Dependent variable: PAL.

DISCUSSION

In the process of recruiting an employee, human resource specialists often consider whether the candidate can adapt to their potential coworkers. When robots are adopted to perform a task with people, the process can be executed differently. The robot may need to work in harmony with humans and humans may need to have the ability to work with the robot. Therefore, if the aim is to ensure maximum human-robot co-operation, it can be useful for organizational behaviorists as well as robot producers to pay attention to the HRI process.

If the behavioral characteristics of people who will work with robots are predicted, organizations can prepare their human resources better for the HRI process. Therefore, in this study, we focused specifically on healthcare organizations and nurses. We investigated whether nurses' robot anxiety affects their self-efficacy and whether their self-efficacy helps to determine their preferred level of automation. Our hypothesis was supported in the context of both robot anxiety and its subdimensions. RUSH showed a full mediation effect between robot anxiety and PAL.

Studies that focus on the relationship between a specific type of self-efficacy and anxiety indicate different results; for example, while one study found a positive relationship between computer self-efficacy and computer anxiety (Achim and Al Kassim, 2015), another study found a negative relationship (Talebi et al., 2012). However, there was a positive correlation between robot anxiety and RUSH in this mediation model. Currently, there have been no studies found that proposed any relationship between robot anxiety and RUSH to compare these results. This positive correlation may be due to the fact that people can be more knowledgeable or aware of the challenges they may face and their potential to get over them. Anyway, this relationship was positive but weak. To better understand this relationship, participants could be asked about the challenges of robot usage in new studies.

In the process of nurse-robot cooperation, two questions may also be important: Should the nurse be left to determine the extent to which the robot will be used or should that be determined in advance? Especially in routine and repetitive tasks that do not require interaction with patients and do not involve risk, the nurse's authority over the use of robots can be restricted. Because the psychological characteristics of the nurse, such as low self-efficacy, can reduce the use of the robot. However, in the context of situational awareness, the flexibility of nurses to use robots can be increased, especially in risky sensitive situations that require interaction with the patient.

When robotic technology is introduced to healthcare organizations, it is important to understand in advance who will work within the organization with this technology. Using the RUSH scale by recruiters can help them in the selection process of these people. In addition, as a strategy of training management, trainings can be planned to increase the self-efficacy of the employees in general. Therefore, nurses who have higher robot use self-efficacy can be recruited and nurses who work in the hospital can be trained in order to increase their robot-use self-efficacy.

Considering the large investments of the robotics industry in the field of nursing, robotics in nursing can be considered as a very large area of opportunity for big companies. Developments in this area point to a further increase in efficiency in the field of health care. However, the level of efficiency that robots will increase will be determined by one of the primary users, nurses (Frazier, et al., 2019). So, firstly, curriculum reform in nursing education programs in academic institutions and clinical practice settings is necessary to prepare nursing students and nurses to work safely and efficiently in the age of AI. In addition, nurse educators should adopt new and evolving curriculum involving artificial intelligence to support students better at all educational levels (Buchanan et al., 2021). Moreover, nurses should adopt AI technology as it will reduce nurse workload and cognitive overload and increase patient-nurse interaction. When nurses use AI at the bedside, they can focus less on the tasks that AI can handle and more on care. In addition, artificial intelligence prediction algorithms can also ease the administrative tasks of staff (Watson et al., 2020).

AI has sometimes been used in homes and long-term care facilities. However, few studies have examined how this technology can be used in a hospital setting. For example, although the use of such systems is increasing, there is a lack of scientific literature on how the applied robotic systems can be used to support inpatients. Before AI can be better integrated into healthcare, research must consider several factors to help users adopt and use robots (Lee et al., 2020). Therefore, there is a need to collect specific information on these issues. Thus, predictions about how nurses will use robots more efficiently can become clearer.

Robots can be programmed to measure and record how much they are used. Thus, it is possible to learn how much automation level is allowed by the person who is expected to co-operate with the robot, and therefore necessary measures may be taken in the process. In this way, the return of investment can be assessed more effectively.

New studies may be designed that overcome the limits of the present study. When nurses were asked about their level of automation, they were asked to prefer an automation level that they assign robots to do some nursing tasks for them. However, this preference could be asked for each task in which the nurse is responsible for the unit; therefore, more systematic information about the preference of automation level could be obtained. Additionally, an explanation could be requested to clarify the reasons behind the preferences. Thus, it helps to know whether the preferences of nurses are related to technical issues or psychological factors.

CONCLUSION

Robotics is developing rapidly. Experts expect to see robots working in various work areas outside factories. During the coronavirus pandemic healthcare institutions understood that they should further improve the service they offer through robots. However, it is essential to adopt robot technology to the healthcare organization with a human-centered technology perspective. Nurses are an important part of the workforce in healthcare organizations. Some psychological characteristics of nurses affect the adoption and efficient use of this technology. As the main contribution of this study, we found that RUSH could affect the level of use of robots and that RUSH can have a mediation effect between robot anxiety and PAL. Nurses' perception of robots, in general, affect the nurse-robot cooperation process. As the influences of individual characteristics are better predicted, more accurate decisions may be made in the selection of personnel who will work with the robot.

Author Contributions

Concept and design: S.E, N.K. Data collection: N.K. Data analysis and interpretation: S.E., N.K. Writing manuscript: S.E. Critical review: N.K.

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REFERENCES

Achim, N., Kassim, A. A. (2015). Computer usage: the impact of computer anxiety and computer self-efficacy. *Procedia - Social and Behavioral Sciences*, *172*, 701–708. https://doi.org/10.1016/j.sbspro.2015.01.422

Alaiad, A., Zhou, L. (2014). The determinants of home healthcare robots adoption: An empirical investigation. *International Journal of Medical Informatics, 83*(11), 825-840. https://doi.org/10.1016/j.ijmedinf.2014.07.003

Bandura, A. (2006). Guide for constructing self-efficacy scales. *Self-Efficacy Beliefs of Adolescents, 5*(1), 307-337.

Bandura, A. (2010). Self-efficacy. *In the corsini encyclopedia of psychology* (eds I. B. Weiner and W. E. Craighead). doi:10.1002/9780470479216.corpsy0836

Bartneck, C., Suzuki, T., Kanda, T., Nomura, T. (2007). The influence of people's culture and prior experiences with Aibo on their attitude towards robots. *Ai & Society, 21*(1-2), 217-230. https://doi.org/10.1007/s00146-006-0052-7

Beedholm, K., Frederiksen, K., Frederiksen, A. M. S., Lomborg, K. (2015). Attitudes to a robot bathtub in Danish elder care: A hermeneutic interview study. *Nursing & Health Sciences, 17*(3), 280-286. https://doi.org/10.1111/nhs.12184

Broadbent, E., Tamagawa, R., Patience, A., Knock, B., Kerse, N., Day, K., MacDonald, B. A. (2012). Attitudes towards health-care robots in a retirement village. *Australasian Journal on Ageing, 31*(2), 115-120. https://doi.org/10.1111/j.1741-6612.2011.00551.x

Buchanan, C., Howitt, M. L., Wilson, R., Booth, R. G., Risling, T., Bamford, M. (2021). Predicted influences of artificial intelligence on nursing education: Scoping review. *JMIR Nursing, 4*(1), e23933.

Chen, A. I., Balter, M. L., Maguire, T. J., Yarmush, M. L. (2015). *Real-time needle steering in response to rolling vein deformation by a 9-DOF image-guided autonomous venipuncture robot.* Paper presented at the 2015 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS). https://doi.org/10.1109/iros.2015.7353736

Coeckelbergh, M. (2011). Human development or human enhancement? A methodological reflection on capabilities and the evaluation of information technologies. *Ethics and Information Technology, 13*(2), 81-92. https://doi.org/10.1007/s10676-010-9231-9

de Graaf, M. M., Allouch, S. B. (2013). *The relation between people's attitude and anxiety towards robots in human-robot interaction.* Paper presented at the 2013 IEEE RO-MAN. https://doi.org/10.1109/roman.2013.6628419

Erebak, S., Turgut, T. (2019). Caregivers' attitudes toward potential robot coworkers in elder care. *Cognition, Technology & Work, 21*(2), 327–336. https://doi.org/10.1007/s10111-018-0512-0

Fang, B., Mei, G., Yuan, X., Wang, L., Wang, Z., Wang, J. (2021). Visual SLAM for robot navigation in healthcare facility. *Pattern Recognition*, 107822.

Frazier, R. M., Carter-Templeton, H., Wyatt, T. H., Wu, L. (2019). Current Trends in Robotics in Nursing Patents—A Glimpse into Emerging Innovations. *CIN: Computers, Informatics, Nursing, 37*(6), 290-297.

Hasan, B. (2006). Delineating the effects of general and system-specific computer self-efficacy beliefs on IS acceptance. *Information & Management, 43*(5), 565-571. https://doi.org/10.1016/j.im.2005.11.005

Hayes, A. F. (2012). PROCESS: A versatile computational tool for observed variable mediation, moderation, and conditional process modeling [White paper]. Retrieved from http://www.afhayes.com/public/process2012.pdf

Hilburn, B. (2017). Dynamic decision aiding: the impact of adaptive automation on mental workload. *Engineering Psychology Cognitive Ergonomics: Volume 1: Transportation Systems*. https://doi.org/10.4324/9781315094496-19

Hsu, M.-H., Chiu, C.-M. (2004). Internet self-efficacy and electronic service acceptance. *Decision Support Systems, 38*(3), 369-381. https://doi.org/10.1016/j.dss.2003.08.001

Hu, J., Edsinger, A., Lim, Y.-J., Donaldson, N., Solano, M., Solochek, A., Marchessault, R. (2011). *An advanced medical robotic system augmenting healthcare capabilities-robotic nursing assistant.* Paper presented at the 2011 IEEE International Conference on Robotics and Automation. https://doi.org/10.1109/icra.2011.5980213

Izard, C. E. (2013). *Human emotions*. Springer Science & Business Media.

Jenkins, S., Draper, H. (2015). Care, monitoring, and companionship: Views on care robots from older people and their carers. *International Journal of Social Robotics, 7*(5), 673-683. https://doi.org/10.1007/s12369-015-0322-y

Kanade, P., Akhtar, M., David, F. (2021). Remote monitoring technology for COVID-19 patients. *European Journal of Electrical Engineering and Computer Science, 5*(1), 44-47.

Koceski, S., Koceska, N. (2016). Evaluation of an assistive telepresence robot for elderly healthcare. *Journal of Medical Systems, 40*(5), 121. https://doi.org/10.1007/s10916-016-0481-x

Lee, H., Piao, M., Lee, J., Byun, A., Kim, J. (2020). The purpose of bedside robots: Exploring the needs of inpatients and healthcare professionals. *CIN: Computers, Informatics, Nursing, 38*(1), 8-17.

Ma, Q., Liu, L. (2005). The role of Internet self-efficacy in the acceptance of web-based electronic medical records. *Journal of Organizational and End User Computing, 17*(1), 38-57. https://doi.org/10.4018/9781605660509.ch115

Makridakis, S. (2017). The forthcoming Artificial Intelligence (AI) revolution: Its impact on society and firms. *Futures*, 90, 46-60.

Marakas, G. M., Yi, M. Y., Johnson, R. D. (1998). The multilevel and multifaceted character of computer self-efficacy: Toward clarification of the construct and an integrative framework for research. *Information Systems Research, 9*(2), 126-163. https://doi.org/10.1287/isre.9.2.126

Mehrabian, A., Russell, J. A. (1974). *An approach to environmental psychology*. Cambridge, MA, US: The MIT Press

Nomura, T., Kanda, T., Yamada, S., Suzuki, T. (2011). *Exploring influences of robot anxiety into HRI.* Paper presented at the 2011 6th ACM/IEEE International Conference on Human-Robot Interaction (HRI). https://doi.org/10.1145/1957656.1957737

Nomura, T., Suzuki, T., Kanda, T., Kato, K. (2006). Measurement of negative attitudes toward robots. *Interaction Studies, 7*(3), 437-454.

Olaronke, I., Oluwaseun, O., Rhoda, I. (2017). State of the art: A study of human-robot interaction in healthcare. *International Journal of Information Engineering and Electronic Business, 9*(3), 43-55. https://doi.org/10.5815/ijieeb.2017.03.06

Parasuraman, R., Sheridan, T. B., Wickens, C. D. (2000). A model for types and levels of human interaction with automation. *IEEE Transactions on systems, man, and cybernetics-Part A: Systems and Humans, 30*(3), 286-297.

Pérez-Vidal, C., Carpintero, E., Garcia-Aracil, N., Sabater-Navarro, J., Azorín, J. M., Candela, A., . . . Systems, A. (2012). Steps in the development of a robotic scrub nurse. *Robotics and Autonomous Systems, 60*(6), 901–911. *https://doi.org/10.1016/j.robot.2012.01.005*

Pino, M., Boulay, M., Jouen, F., Rigaud, A.-S. (2015). "Are we ready for robots that care for us?" Attitudes and opinions of older adults toward socially assistive robots. *Frontiers in Aging Neuroscience, 7*, 141. https://doi.org/10.3389/fnagi.2015.00141

Rahman, M. S., Ko, M., Warren, J., Carpenter, D. (2016). Healthcare Technology Self-Efficacy (HTSE) and its influence on individual attitude: An empirical study. *Computers in Human Behavior, 58*, 12-24. https://doi.org/10.1016/j.chb.2015.12.016

Riley, V. (1989). A general model of mixed-initiative human-machine systems. *Proceedings of the Human Factors Society Annual Meeting, 33*(2), 124–128. https://doi.org/10.1177/154193128903300227

Rosenthal-von der Pütten, A. M., Krämer, N. C., Hoffmann, L., Sobieraj, S., Eimler, S. C. (2013). An experimental study on emotional reactions towards a robot. *International Journal of Social Robotics, 5*(1), 17-34. https://doi.org/10.1007/s12369-012-0173-8

Saadé, R. G., Kira, D. (2009). Computer anxiety in e-learning: The effect of computer self-efficacy. *Journal of Information Technology Education: Research, 8*, 177-191. https://doi.org/10.28945/3386

Sánchez, A., Poignet, P., Dombre, E., Menciassi, A., Dario, P. J. R., Systems, A. (2014). A design framework for surgical robots: Example of the Araknes robot controller. *Robotics and Autonomous Systems*, *62*(9), 1342-1352. https://doi.org/10.1016/j.robot.2014.03.020

Savela, N., Turja, T., Oksanen, A. (2018). Social acceptance of robots in different occupational fields: A systematic literature review. *International Journal of Social Robotics, 10*(4), 493-502. https://doi.org/10.1007/s12369-017-0452-5

Sharkey, A., Sharkey, N. (2012). Granny and the robots: Ethical issues in robot care for the elderly. *Ethics and Information Technology, 14*(1), 27-40. https://doi.org/10.1007/s10676-010-9234-6

Sheridan, T. B., Verplank, W. L. (1978). *Human and computer control of undersea teleoperators*. Massachusetts Inst of Tech Cambridge Man-Machine Systems Lab. https://doi.org/10.21236/ada057655

Stock, R., Nguyen, M. A. (2019). *Robotic psychology. What do we know about human-robot interaction and what do we still need to learn?* Paper presented at the Proceedings of the 52nd Hawaii International Conference on System Sciences. https://doi.org/10.24251/hicss.2019.234

Strudwick, G. (2015). Predicting nurses' use of healthcare technology using the technology acceptance model: An integrative review. *Comput Inform Nurs, 33*(5), 189-198; quiz E181. https://doi.org/10.1097/01.ncn.0000465413.54230.e1

Talebi, S., Zare, H., Sarmadi, M. R., Saeedipour, B. (2012). Presenting the causal model of psychological variable (Computer experience, subjective norm, computer anxiety and computer self efficacy) on actual use of information technology on the basis of Davis's model. *Life Science Journal*, *9*(4), 3263-3266.

Turja, T., Rantanen, T., Oksanen, A. (2017). Robot use self-efficacy in healthcare work (RUSH): Development and validation of a new measure. *AI & Society*, 1-7. https://doi.org/10.1007/s00146-017-0751-2

Turja, T., Van Aerschot, L., Särkikoski, T., Oksanen, A. (2018). Finnish healthcare professionals' attitudes towards robots: Reflections on a population sample. *Nursing Open, 5*(3), 300-309. https://doi.org/10.1002/nop2.138

Watson, D., Womack, J., Papadakos, S. (2020). Rise of the robots: Is artificial intelligence a friend or foe to nursing practice?. *Critical Care Nursing Quarterly, 43*(3), 303-311.

Worldometer (2021). COVID-19 coronavirus pandemic. https://www.worldometers.info/coronavirus/

Weng, Y. H., Chen, C. H., Sun, C. T. (2009). Toward the human–robot co-existence society: On safety intelligence for next generation robots. *International Journal of Social Robotics, 1*(4), 267.

Zeng, Z., Chen, P. J., Lew, A. A. (2020). From high-touch to high-tech: COVID-19 drives robotics adoption. *Tourism Geographies, 22*(3), 724-734.