

RESEARCH ARTICLE

Nurse preferences of caring robots: A conjoint experiment to explore most valued robot features

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Abstract

Aim: Due to the COVID pandemic and technological innovation, robots gain increasing role in nursing services. While studies investigated negative attitudes of nurses towards robots, we lack an understanding of nurses' preferences about robot characteristics. Our aim was to explore how key robot features compare when weighed together.

Methods: Cross-sectional research design based on a conjoint analysis approach. Robot dimensions tested were: (1) communication; (2) look; (3) safety; (4) self-learning ability; and (5) interactive behaviour. Participants were asked to rank robot profile cards from most to least preferred.

Results: In order of importance, robot's ability to learn ranked first followed by behaviour, look, operating safety and communication. Most preferred robot combination was 'robot responds to commands only, looks like a machine, never misses target, runs programme only and behaves friendly'.

Conclusions: Robot self-learning capacity was least favoured by nurses showing potential fear of robots taking over core nurse competencies.

KEYWORDS

attributes, nurse, preferences, robots; robotics, conjoint analysis, features, characteristics

1 | INTRODUCTION

Both the COVID epidemic and increasing innovation have led to the growing involvement of robotic caregivers in nursing services. With the potential revolution in the computational power of artificial intelligence, Metzler et al. (2016) and Locsin (2017) have envisioned a future in which robots could become true professional collaborators of nurses. However, one of the main criticisms of the development of such skilled robots is that nurses seem to have very limited (or no) say in the development of robots for nursing (Archibald and

Barnard, 2018; Eriksson et al., 2017). This may be explained by the limited expertise of nurses and the limited research on robotics.

Glasgow et al. (2018) argued that nurses are missing critical opportunities to be involved in the design and development of future technology that could dramatically improve patient care. Even though nurses have historically been excluded from high-level decision-making, Robert (2019) affirmed that nurse participation in the design and deployment of telehealth robots is critical for the best use of the technology. Studying nurses' attitudes towards nursing robots is key because understanding nurses' preferences

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for robot features will help inform future robot design and development. Examples of nursing robots include Robear, the Japanese nursing robot, Grace, the humanoid nursing robot, Pepper, the geriatric robot, or Venous Pro, the blood collection robot (BBC, 2021; The Guardian, 2015; VascuLogic, 2022; WION, 2021).

Of those who have studied nurse preferences for caring robots, Broadbent et al. (2010) concluded that gender and age did not explain nurses' attitudes towards robots. Also, previous experience with robots was either positive or yielded mixed results (Broadbent et al., 2010; Papadopoulos et al., 2018; Papadopoulos et al., 2020; Turja et al., 2018). Patient safety was another main concern and a major barrier to robot utilization (Alaiad and Zhou, 2014; Broadbent et al., 2010; Papadopoulos et al., 2018). Robots appear to be more accepted to perform non-skilled nursing tasks (e.g. patient lifting, temperature control or medication administration), but the need for nurse control over robotic devices is clearly said (Lee et al., 2018; Liang et al., 2019; Turja et al., 2018). Rantanen et al. (2018) applied the Negative Attitudes towards Robots Scale in a large Finnish home care population. They concluded that robot rejection was only one aspect of nurses' attitudes towards robotics and that preferences should be explored as well. Reasons for rejecting robots included the limited analytical ability of robots and the ability of robots to self-acquire knowledge, which were thought to prevent robots from penetrating nursing practice (Papadopoulos et al., 2020). While some nurses prefer robots to be able to learn, others would keep a limited scope of performance and maintain close control (Lee et al., 2018; Papadopoulos et al., 2020).

Human-like feature was another attribute that generated a sharp debate in nursing, either being strongly supported or rejected by many nurses (Papadopoulos et al., 2020). Nurses were particularly concerned about how a machine could potentially harm nursing care provided by humans (Broadbent et al., 2010). Of those who opposed robotics, paediatric nurses were worried about how robots could mimic tactile sensations or display emotions, which are an essential part of the active healing process in paediatric nursing practice

(Liang et al., 2019). On the other hand, Jin and Kim (2020) discovered specific robot characteristics that paediatric nurses would greatly prefer, especially when the physical presence of nurses is not necessarily required. Lee et al. (2020) argued that nurses would prefer robots that can recognize different signs of emotion and are able to read facial expressions. Despite the growing body of research about integration of caring robots into nursing practice, Kangasniemi et al. (2019) and Maalouf et al. (2018) confirmed the need for research to guide the industry towards developing the most appropriate robot designs nurses feel comfortable with.

Our experiment, therefore, aimed to extend existing knowledge about nurses' preferences for caring robots by evaluating and jointly weighing multiple robot attributes. Different robot profiles were compared in parallel to assess which individual and combined attributes nurses preferred the most and the least. The main objective of this research was to assess what characteristics of caregiving robot's nurses like and dislike and to develop a model of the most and least preferred robot dimensions.

2 | METHODS

A cross-sectional research design based on a full profile fractional factorial conjoint analysis approach was used. Researchers decided on five key robot characteristics to be tested and instructed the statistical software to develop ten feature cards to be presented to participants (Figure 1). The five dimensions were the following: (1) communication (responds to commands only/understands free speech); (2) look (machine/human-like); (3) safety (rare misses/always on target); (4) learning (runs programme only/self-learning); and (5) behaviour (mechanical/friendly, that is, robot makes no human-like gestures or can express some positive emotions). Participants were asked to rank order the cards from one to ten, where first place was assigned to the most preferred set of robot characteristics and the last place to the least preferred. We used rank ordering of cards

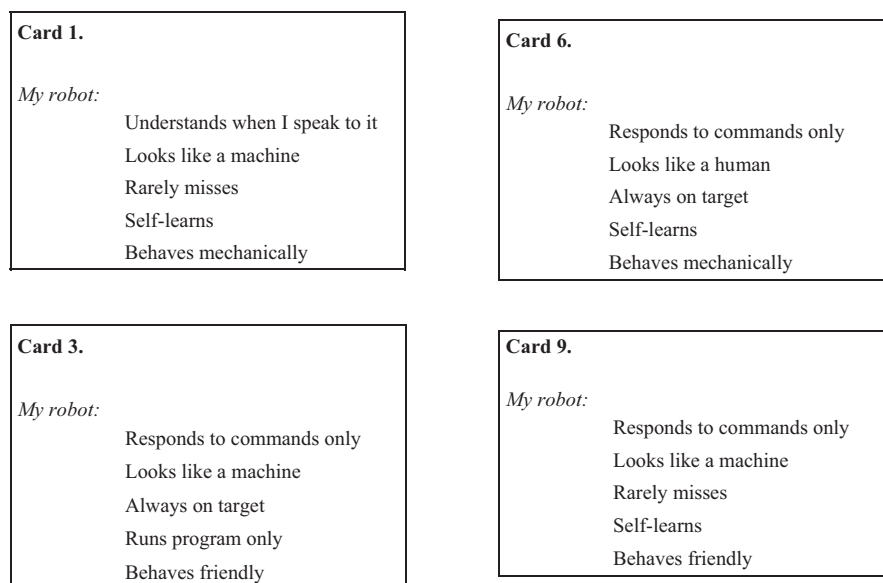


FIGURE 1 Sample profile cards

because it is assumed to produce more reliable outcomes when a smaller number of profiles are considered (Hair et al., 2014). For the purposes of this pilot, only 5 dimensions were developed because the full profile method is only recommended when factors do not exceed 6 or potentially are less (Hair et al., 2014). Also, each robot dimension contained only two levels in order to minimize the potential respondent bias by favouring factors with more levels (Hair et al., 2014). Researchers were aware that the relative position of a feature may increase by multiple factor levels. The number of attribute cards were also kept to a minimum as Hair et al. (2014) observed that over 20 evaluations responses tend to lose reliability. Of the 10 cards, cards 9 and 10 were used as 'holdout cards' for validation purposes.

To define a set of valid robot dimensions, nurse experts from the field were contacted. While the conjoint experiment is usually run by presenting the attribute cards in person, the electronic data collection instrument was carefully designed to avoid confusion about the task at hand. There is no specific power analysis available for conjoint analysis; however, a minimum of 200 participants is recommended as a threshold (Hair et al., 2014). Therefore, a sample size of at least 200 participants was sought to ensure reliability of the statistical analysis. While there was an attempt to identify conjoint reversals, to preserve representativeness of the sample (not to go below the suggested 200 subject threshold) no responses were deleted from the final model. There was no attempt to replace missing data, that is, any participant who failed to rank all profile cards were excluded from the analysis.

To prepare the paper the STROBE cross-sectional design checklist was applied (STROBE, 2007).

2.1 | Sample

In order to increase representativeness, participants were recruited from two large nurse training campuses of the four national university centres in Hungary. Participants were either nurses in their graduate training or who attended post-graduate courses and had already worked in health care. Only participants with Hungarian origin were included. A pool of five-hundred nurses were initially selected from campus registries and emailed the demographic form and robot attribute cards. Following the recommendation of Hair et al. (2014), a minimum sample of size of 200 participants was sought to ensure a tolerable margin of error.

2.2 | Data collection

Data collection took place between May–July 2020. Due to the COVID-19 pandemic, cards were not printed but emailed to participants who volunteered for the study. E-mail was the preferred method of responding over web-based survey forms since researchers already had low response rate experience with the latter. Participants returned a table in a Word document where participants inserted the number of each card in the order of their individual

preferences. They also responded to a few items concerning their socio-demographic and professional profiles. Participants returned their electronic responses to a dedicated email account.

2.3 | Data analysis

We used descriptive statistics to summarize sample characteristics. For the main analysis, a conjoint technique based on the additive model was used. The main purpose was to evaluate the utility (i.e. part-worth) of each robot attribute and to determine their contribution to nurse preferences concerning an imaginary caring robot. We used Spearman's rho and Kendall's tau as goodness-of-fit measures of the conjoint model. All data analyses were performed by IBM SPSS Statistics version 27.0 for Mac.

3 | RESULTS

Of the 500 emails forwarded, we received 228 responses with complete data. Descriptive statistics of the distribution of sample characteristics is presented in Table 1. The average age of our sample was 36.4 (SD 10.5) years. Those who were employed had been working in health care/nursing for an average of 16.1 (SD 11.2) years preceding our study. A total of 13.5% of our respondents reported to have had some kind of experience with health-care/nursing robots before.

TABLE 1 Descriptive statistics

	%
Gender	
Female	87.0
Male	13.0
Status	
Student	46.2
Graduated/at work	58.3
Education programme	
BSc	70.6
MSc	27.9
PhD	1.5
Field of work	
Primary care	8.3
Outpatient care	11.3
Hospital care	80.4
Speaks foreign language	
No	58.5
Yes	41.5
Has experience with robot	
No	86.5
Yes	13.5

To assess the overall model's goodness-of-fit Kendall's tau was evaluated. Since rank-ordered data was studied, the Pearson correlation coefficient is not interpreted here as it is related to rating methods. Kendall's tau values both for the general sample and holdouts appeared to be high (Kendall's tau = 0.714, $p = .007$ and Kendall's tau holdout = 0.873) but not close to 100% where model fit may be questionable (Liang et al., 2019).

Table 2 displays utility (part-worth) scores for the different dimensions assessed. Since we used an additive model, total utility scores by adding part-worth estimates for each attribute level may be calculated. Total utility scores were then used to evaluate preferences for the various combinations of attribute levels. The two most extreme, negative (least preferred combination) and positive (most preferred combination) total utility scores are calculated as follows.

3.1 | Most preferred combination

The robot...responds to commands only (0.27)+looks like a machine (0.26)+always on target (0.15)+runs programme only (0.315) and +behaves friendly (0.24) [+ constant (4.497) = 5.732].

3.2 | Least preferred combination

The robot...understands free speech (-0.27)+looks like a human (-0.26)+rarely misses (-0.15)+self-learns (-0.315) and +behaves mechanically (-0.24) [+ constant (4.497) = 3.262].

Evidently, using the additive method, any other factor combinations may be calculated and compared in terms of their utility (preference) for each respondent following the technique above. For ease of evaluation, we showed the two most extreme cases of combinations.

Finally, Table 3 presents relative importance values of each attribute as they contribute to the overall preference (utility scores).

TABLE 2 Utility scores

		Utility estimate	Std. error
Communication	Responds to command only	.027	.054
	Understands free speech	-.027	.054
Look	Machine-like	.026	.054
	Human	-.026	.054
Safety	Rare misses	-.015	.054
	Always on target	.015	.054
Learning	Runs programme only	.315	.054
	Self-learning	-.315	.054
Behaviour	Mechanical	-.024	.063
	Friendly	.024	.063
(Constant)		4.497	.054

Averaged importance scores, therefore, explain the underlying preference structure of respondents. Table 3 shows these importance values. In the order of magnitude, ability to learn ranked highest, followed by robot behaviour, look, operating safety and communication being rated last. In brief, nurses favoured a robot that was controlled by command, did not have a human-like look, was operating with precision, did not have capacity for self-learning and exhibited a friendly behaviour towards nurses.

4 | DISCUSSION

The aim of our study was to describe how nurses perceived key features of current and future nursing robots. We confirmed that age and gender made no difference to nurses' perceptions of robot profiles (Broadbent et al., 2010). Due to the very low number of participants exposed to nursing robots, we were not able to conduct a separate analysis to support previous findings. Therefore, we could not confirm the positive views of nurses who had already worked with caring robots (Broadbent et al., 2010; Turja et al., 2018). About utility scores (preferences), higher absolute scores indicated higher preference. However, negative values indicated lower preferences. Learning ability, therefore, was on top of nurses' preference list, followed by communication, appearance, behaviour and operational safety.

Robots with a human look were less liked in our sample. This adds additional proof to existing observations that human-like features are not universally appreciated by nurses (Papadopoulos et al., 2020). Self-learning was another attribute that nurses did not support. This indicated that nurses were not ready to hand over nursing tasks involving cognitive skills to robots. It also confirmed that nurses regard professional control over robots a high priority (Lee et al., 2018). Many nurses considered robots that 'respond to commands only' their preferred choice. The most preferred combination that identified in our analysis was a robot that followed only instructions (commands), did not self-learn, had 100% operational safety, was friendly and had machine-like features. Nurses preferred a robot that would 'always be on target', confirming earlier findings about patient safety being a top priority (Alaiad and Zhou, 2014; Broadbent et al., 2010; Papadopoulos et al., 2018). However, Table 3 showed patient safety only fourth in terms of its relative importance to other variables. This finding was in direct contrast to prior research in which patient safety concerns were the most frequently cited barriers in the way of robot utilization (Broadbent et al., 2010;

TABLE 3 Importance (preference) values

Learning	23.66
Behaviour	21.25
Look	20.47
Safety	17.70
Communication	16.91

Note: Averaged importance score.

Papadopoulos et al., 2018). Authors, therefore, recommend further research to explore reasons behind this controversy.

Self-learning capacity was on top of nurses' preference list, but in an opposite sense. Nurses did not want robots to achieve a level of intelligence, which allows robots to entirely replace nurses. This outcome was aligned with findings of Pepito and Locsin (2018) who documented that nurses became frustrated by machines outperforming them in several areas of clinical practice. Our outcomes also supported findings by Jackson et al. (2021) who argued that cognitive work, especially critical thinking or decision-making, are central and unique aspects of nursing practice. Our results are aligned with nurses' fears that artificial intelligence will supersede human cognition and will challenge the core values of nursing.

Communication with robots would be considered a key feature; however, this dimension was the least important for nurses. We succeeded in this research to describe the order of importance of five key robot characteristics and showed what robot profile nurses preferred today. Authors, however, acknowledge that these preferences will change as robots become more available and improved, especially when nurses begin to collaborate with them on a larger scale. When nurses have gained more experience with task delegation to robots, different nurse attitudes and preferences will emerge from what we presented above.

The main conclusion of this research was that out of all dimensions we presented to our participants, self-learning capability identified as key priority. The skill of a robot to acquire self-knowledge was the least favoured function by nurses today. Authors suggest extending factor levels (e.g. look = human-like/machine-like/animal-like etc.) in future research to allow for more representative illustrations of today's nursing robots. Authors also recommend the replication of this research with nursing students and nurses who had already experienced working with caring robots.

4.1 | Limitations

Authors acknowledge that while the current sample exceeded minimum requirements, larger and more representative samples will be required in future research to make results generalizable. Authors admit that both the number of cards and the order in which robot profiles were listed may have influenced respondents' evaluations. Authors made no attempt to remove participants with extreme high and low utility scores to preserve sample representativeness. Finally, face-to-face presentation of profiles is the suggested method for conjoint experiments, we are uncertain how the email assessment impacted on respondent choices.

5 | CONCLUSIONS

Using the conjoint technique, authors successfully developed a representation of nurses' preferences about a set of robot features. Authors also contributed to a better understanding of what

combination of robot characteristics, and in what order, nurses would prefer when those features are mutually weighed. However, future research is necessary to explain the rationale behind the choices of respondents as our current research technique was not designed to answer such questions.

AUTHOR CONTRIBUTIONS

MZ involved in study design, data analysis, manuscript writing, manuscript revision and reviewers' response. AP and ÚAS involved in study design and data collection. KL involved in study design. DV and JB involved in study design and manuscript revision. AO involved in study design, manuscript revisions and reviewers' response. All authors listed below have substantially contributed to read and approved the manuscript.

CONFLICT OF INTEREST

Authors report no conflict of interest.

DATA AVAILABILITY STATEMENT

The datasets generated during the current study are not in the public domain but will be made available from the corresponding author on reasonable request.

ETHICAL APPROVAL

Participation was voluntary, and participants were ensured the anonymity of their responses. Participants were instructed to email back the Word file without saving any personal ID in the file. A single email address was setup where all responses were collected. A research assistant downloaded attached files, assigned an individual ID code and aggregated data and cleared emails to avoid later identification. The research plan was reviewed and received prior Research Ethics Committee approval from the local scientific research in health ethics committee. Although responding to instruments was based on voluntary participation and anonymity (no email or IP addresses were collected), participants had to read and accept an electronic consent informing about the study goal, data collection and handling. Those who did not accept and return the consent form could not participate despite submitting the completed questionnaire.

CONSENT STATEMENT

The research involved no patients and any invasive intervention on human participants for whom a special ethical consent was required. However, all participants had to agree to and return an electronic consent form by completing and submitting the research instrument to be considered for participation.

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