More Than a Choice: Evaluating the Impact of Trainer Customization in HUGO, a NAO-Based Cognitive Training Platform⋆

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Abstract

In recent years, Socially Assistive Robotics (SAR) has attracted increasing attention for its potential to promote cognitive, emotional, and physical wellbeing across various populations [1] [2]. Among SAR platforms, the humanoid robot NAO has been extensively employed in educational and clinical [3] contexts due to its versatile motor and social interaction features. Building on previous findings that cognitive training can improve working memory in older adults [4] [5] this pilot study investigates whether a human-robot interaction (HRI) protocol can modulate key psychological and usability related variables. This study aims to explore whether HRI, particularly when including a minimal user-customization element such as a pre-interaction choice, influences perceived enjoyment, self-efficacy, anxiety, technophobia, and usability. Based on existing literature on human-computer and human-robot interaction [6] [7], we hypothesized that participants in the experimental group would report greater enjoyment and self-efficacy, lower anxiety and technophobia, and increased perceived usability compared to those in the control condition. To evaluate these outcomes, we implemented a pre-post design using validated questionnaires derived from the Technology Acceptance Model 3 (TAM3) [8], the System Usability Scale (SUS) [9], and the Technophobia assessment [10]. The results indicated general improvements across both groups on several psychological dimensions, with a notable increase in perceived external control in the experimental group compared to the control group.

Keywords

Socially Assistive Robotics (SAR), Human-Robot Interaction (HRI), Technology Acceptance Model (TAM3), Technophobia, NAO robot, System Usability Scale (SUS), Cognitive Training,

1. Introduction

In recent years, the growing diffusion of digital technologies and the demographic shift toward aging populations have brought new challenges to cognitive intervention and well-being support among older adults. Cognitive training programs have gained traction to preserve mental functioning and quality of life [11]. However, traditional interventions often lack motivational engagement and personalization two factors known to influence adherence and outcomes in elderly populations [12]. In this context, Socially Assistive Robotics (SAR) has emerged as a promising field, offering motivational, cognitive, and emotional support through structured human–robot interaction [13] [2]. Recent advancements in digital neuropsychological tools have highlighted the potential of combining tangible interfaces, augmented reality, and machine learning for the assessment and training of cognitive functions [14][15][16][17].These approaches align with the broader goals of socially assistive robotics, which aim to combine interaction and assessment in real life contexts. SAR systems are physically embodied agents designed to assist users via social rather than physical interaction, thereby enhancing learning, rehabilitation, or therapy. Among SAR platforms, the humanoid robot NAO has gained considerable attention due to its versatility

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and multimodal interaction capabilities. With 25 degrees of freedom, touch sensors, cameras, and multilingual speech recognition, NAO has been successfully employed in educational, clinical, and rehabilitation contexts [1]. Research has demonstrated NAO's effectiveness in promoting engagement in children with autism [18], supporting physical therapy [19], and facilitating cognitive training in older adults [5]. Despite promising findings on user engagement and emotional benefits, little is known about how subtle variations in robot behavior such as offering users a choice of interaction style affects perceptions of usability, agency, or emotional engagement, particularly in aging populations. Prior work has shown that even superficial customization can shape users' feelings of control, trust, or frustration [12] [7]. Understanding these dynamics is crucial in designing meaningful interactions in Human–Robot Interaction (HRI). Despite growing adoption, relatively little is known about how subtle variations in robot interactions such as allowing users to customize behavior affect perceptions of usability and emotional engagement in older adults. To address this, we designed an exploratory study where participants engaged in a memory training administered by HUGO, a robotic cognitive trainer based on NAO humanoid robot.

2. Materials and Methods

2.1. Participants

The study involved a total of 26 participants, divided into two age-based subgroups: 12 older adults ($M = 65.42$ years, $SD = 6.35$) and 14 university students ($M = 21.64$ years, $SD = 1.08$). The participants were evenly assigned to two experimental conditions: 13 in the experimental group, who were allowed to choose the robot's interaction style (friendly or uthoritarian) and 13 in the control group, who interacted with a neutral version of the robot without any choice. In experimental conditions, participants were presented with a brief explanation stating that the robot hUGO could interact in different styles, either *friendly or authoritative*, and were asked to choose their preferred mode. The *friendly* style was described as warmer and encouraging, while the *authoritative* style was presented as more direct and instructional. However, this manipulation was illusory: in reality, the robot's behavior was kept identical across all conditions, with no actual difference in verbal style, tone, or gestures. This design allowed us to explore the impact of perceived customization rather than real behavioral changes, isolating the psychological effect of offering a choice in the absence of genuine personalization. Participants were not informed that the styles were simulated and reported their subjective experience as if their choice had been implemented.

2.2. Training Procedure

Participants underwent a cognitive memory training protocol inspired by Borella and collaborators [20] [21] and adapted for socially assistive robotics, following the implementation described in Gigliotta et al. [4] and in the development of the platform hUGO (Hunamoid to Go). The training was delivered by hUGO, a social robot platform based on NAO, programmed through Choregraphe with Python and equipped with automatic speech recognition (ASR) and text-to-speech (TTS) capabilities [4]. The training spanned three sessions, progressively increasing in difficulty and cognitive demand: Session 1 (≈ 60 minutes): introduction to dual-task recall (e.g., word and category retrieval); Session 2 (≈ 30 minutes): intermediate-level recall and task-switching. Session 3 (≈ 25 minutes): advanced tasks with interference control and increased memory load. The robot guided the participants through verbal prompts and exercises, providing feedback and transitions between training blocks. The sessions were designed to progressively increase in difficulty by manipulating cognitive load and task-switching requirements (e.g., recalling animal names, recognizing acoustic cues, serial recall tasks).

Figure 1: hUGO in a training session with an older adult

2.3. Measures

2.3.1. Technology Acceptance Model 3

To assess participants' attitudes toward the robot and its interaction, we administered a reduced set of TAM3 items. This was done to minimize cognitive load, especially for older participants, and preserve the core psychological constructs relevant to Human-Robot Interaction (HRI). The selected dimensions were: 1) Enjoyment (e.g., "Using the robot is enjoyable"); 2) Self-Efficacy (e.g., "I feel confident in interacting with the robot"); 3) Anxiety (e.g., "I feel anxious when using robots"); 4) External Control (e.g., "The system is under the control of an external entity"). This selection was guided by the TAM3 model's focus on user perception and affective responses in technology mediated environments and aligned with prior literature on technology acceptance in aging populations. Additionally, in line with the approach described in [8], we computed a composite Perceived Ease of Use (PEOU) score by averaging the four selected dimensions (Enjoyment, Self-Efficacy, Anxiety, and External Control). This composite measure was calculated for both pre- and post-intervention conditions to evaluate changes in overall perceived usability of the robotic system. The use of composite PEOU reflects the integrated cognitive affective appraisal of the system's accessibility and aligns with the theoretical underpinnings of TAM3.

2.3.2. Technophobia Scale

In this study, we adopted an extended version of the Technophobia Scale originally developed by Sinkovics et al. [10], which was originally designed to assess anxiety and resistance toward automated technologies such as ATMs. Given the significant contextual shift from financial technologies to socially assistive robots (SAR), we opted to include a broader set of items adapted to our specific experimental setting involving human-robot interaction during cognitive training. All items were grouped post hoc into three conceptual dimensions aligned with contemporary research in HRI and technophobia: 1) Perceived Personal Failure; 2) Convenience Perception; 3) Human–Robot Comparison/Preference. Rather than adhering strictly to the original subscales (discomfort, cognitive anxiety, attitudinal resistance), we aggregated items thematically to form constructs that better reflect contemporary challenges in socially assistive robotics and user self-perception, especially among vulnerable populations. This decision followed the exploratory and adaptive use of Sinkovics' scale as suggested in related literature, such as its use in SAR and HRI research. This item grouping approach was informed by recent studies on the acceptance of social robots among older adults, which emphasize hybrid constructs involving emotional, cognitive, and comparative perceptions [7] [6]. These adapted dimensions reflect user attitudes more holistically in HRI scenarios.

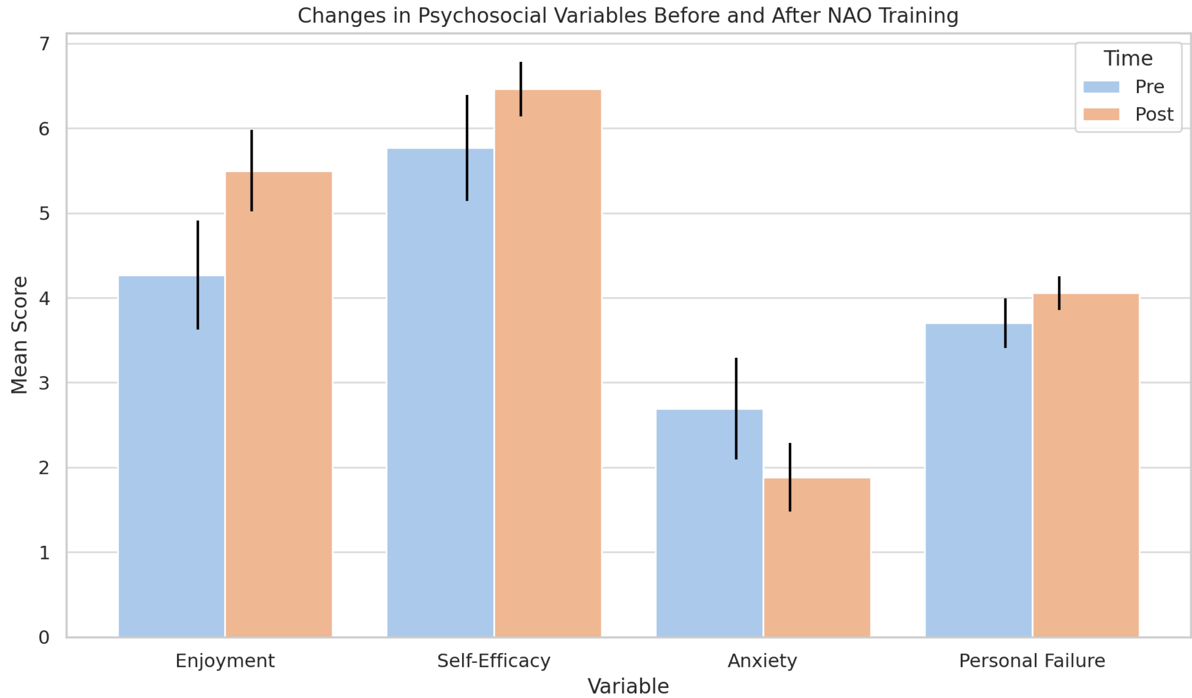

Figure 2: Mean scores of psychosocial variables (Enjoyment, Self-Efficacy, Anxiety, and Personal Failure) before and after the NAO-based training. Error bars represent 95% confidence intervals. Significant increases were found in Enjoyment and Self-Efficacy, along with a significant reduction in Anxiety. A marginal improvement was observed in Personal Failure

2.3.3. Usability

Perceived usability of the hUGO system was assessed using the System Usability Scale [9]. The SUS was only included in the post-test phase, after participants had completed all training sessions.

3. Results

The sample consisted of 26 participants, equally distributed between an experimental group ($n = 13$), who could choose the robot's interaction style, and a control group ($n = 13$), who interacted with a neutral version of the robot.

3.1. Within-Subjects Analyses (Pre–Post Differences)

Table 1
Summary of paired-sample *t*-test results for psychological variables before and after the NAO-based intervention.

Variable	*t*(df)	*p*	Cohen's *d*	Effect Size	Result
Enjoyment	−3.261 (25)	.003	0.639	Large	Significant increase
Self-efficacy	−2.214 (25)	.036	0.434	Medium	Significant increase
Anxiety	2.195 (25)	.038	0.430	Medium	Significant decrease
Personal failure	−1.909 (25)	.068	–	Trend-level	Marginal reduction
External control	ns	ns	–	–	No significant difference
Convenience	ns	ns	–	–	No significant difference
Human–machine comparison	ns	ns	–	–	No significant difference

To assess the effects of cognitive training with NAO, paired-sample *t*-tests were conducted. The results are presented in Fig. 2 and Table 1.:

- Enjoyment significantly increased after the training, $t(25) =$ ˘3.261, $p = .003$, $d = 0.639$, indicating enhanced engagement during human–robot interaction.
- Self-efficacy also improved, $t(25) =$ ˘2.214, $p = .036$, $d = 0.434$, reflecting greater perceived ability in managing the robot.
- Anxiety levels significantly decreased, $t(25) = 2.195$, $p = .038$, $d = 0.430$, suggesting reduced emotional discomfort in interacting with the system.
- Personal failure showed a marginal reduction, $t(25) =$ ˘1.909, $p = .068$, indicating a trend toward reduced frustration or self-blame following the training.

No significant pre-post differences were found for perceived external control, convenience, or human vs. machine comparison. Additionally, a composite score for Perceived Ease of Use (PEOU) was calculated as the mean of the four TAM3 dimensions: Enjoyment, Self-Efficacy, Anxiety, and External Control. This score showed a marginal improvement post-intervention, $t(25) =$ ˘1.997, $p = .0568$, with a medium effect size ($d = 0.392$), suggesting a possible increase in overall usability perception.

3.2. Between-Subjects Analyses (Experimental vs Control Group)

Table 2
Summary of between-group comparisons on change scores (post–pre) using ANCOVA and MANCOVA.

Variable	Test	F(df)	*p*	η^2	Effect	Interpretation
External Control	ANCOVA	F(1,23) = 5.18	.032	.184	Exp > Ctrl	Significant group difference
Group effect (DVs)	MANCOVA	F(7,14) = 3.86	.011	.660	–	Significant multivariate effect
Convenience	ANCOVA	F(1,20) = 3.95	.061	–	Ctrl > Exp	Trend-level difference
SUS Usability Score	t-test	–	ns	d = −0.679	Exp > Ctrl	Moderate effect, not significant
Enjoyment	t-test	–	ns	–	–	No significant difference
Self-efficacy	t-test	–	ns	–	–	No significant difference
Anxiety	t-test	–	ns	–	–	No significant difference

Independent sample *t*-tests and ANCOVA were used to examine group differences in the change scores (post–pre), controlling for baseline values where appropriate. A significant group effect emerged for perceived external control, $F(1, 23) = 5.18$, $p = .032$, $\eta^2 = .184$, with the experimental group reporting more external control than the control group. This suggests that being allowed to choose the robot's style paradoxically increased the feeling that external factors influenced the interaction. The MANCOVA showed a significant multivariate effect of group on the dependent variables, Wilks' $\Lambda = .34$, $F(7, 14) = 3.86$, $p = .011$, $\eta^2 = .66$. Post hoc tests confirmed the difference in external control and suggested a trend toward higher perceived convenience in the control group, $F(1, 20) = 3.95, p = .061$. No statistically significant between-group differences emerged for enjoyment, self-efficacy, anxiety, or SUS usability scores, although descriptively the experimental group showed higher usability (SUS) scores ($M = 38.65$ vs. 30.58), with a moderate effect size ($d =$ ˘0.679), pointing to a possible impact of interactive agency on perceived usability (see Table 2)

Table 3
Regression models predicting usability and psychological variables.

Outcome	Predictor	β	*p*	Model F(df)	R²	Interpretation
SUS Score	Enjoyment	.509	.006	F(3,21) = 4.98	.416	Positive predictor of usability
	External Control	−.454	.012			Negative predictor of usability
Enjoyment (Post)	External Control	.572	.003	–	–	External control increases enjoyment
Self-efficacy	External Control	.471	.014	–	–	Positive effect on confidence
	Anxiety	−.402	.041	–	–	Negative effect on confidence

Regression analyses explored the predictors of key subjective outcomes, as shown in Fig. 3 and Table 3.

Figure 3: Linear regression plots illustrating the predictive relationship between changes in Enjoyment and External Control (independent variables) and the SUS usability score (dependent variable). The blue line represents the positive association between Enjoyment and usability, while the green line shows the negative association between External Control and usability.

- Usability (SUS score) was significantly predicted by both enjoyment ($\beta = .509$, $p = .006$) and external control ($\beta =$ ˘.454, $p = .012$), $F(3, 21) = 4.98$, $p = .009$, $R^2 = .416$. This supports the hypothesis that a positive and autonomous interaction experience enhances usability perceptions.
- Enjoyment post-intervention was positively predicted by external control, $\beta = .572$, $p = .003$, suggesting that perceiving more control (even if externally driven) can enhance engagement.
- Self-efficacy was positively influenced by external control ($\beta = .471$, $p = .014$) and negatively by anxiety ($\beta =$ ˘.402, $p = .041$), confirming the role of emotional and cognitive factors in shaping confidence in human–robot interaction.

Being able to choose the robot's interaction style may increase the subjective perception of external control, suggesting that too much agency in HRI may not always result in increased autonomy. The control group, which had no choice, reported less external control and possibly more convenience. Future studies may explore whether less customization results in a smoother, more seamless interaction. Enjoyment and external control are strong predictors of usability. This suggests that interventions should balance autonomy with simplicity to optimize perceived effectiveness and user satisfaction.

4. Discussion

The results of this study suggest that even a brief cognitive training protocol mediated by the NAO robot can promote significant psychological improvements, particularly in terms of enjoyment, self-efficacy, and reduced anxiety. These findings align with previous research highlighting the potential of Socially Assistive Robotics (SAR) to support active aging and psychosocial well-being among older adults [11] [4]. The HUGO congnitive trainig platform, based on NAO, likely served as a motivational facilitator, fostering engagement through its embodied presence, social cues, and structured interaction [22]. Beyond the general pre–post improvements, a significant difference was observed between the experimental and control groups in terms of perceived external control. Specifically, participants who had the opportunity to choose the robot's interaction style (e.g., "friendly" or "authoritative") reported higher levels of external control. This counterintuitive result may be explained by the phenomenon of illusory choice, as discussed by Sullivan-Holt and collaborators [23]. When personalization options are presented in a superficial or abstract manner without clear consequences or observable differences, they may undermine the sense of user agency by highlighting the system's pre-programmed nature. In our study, participants made their choice prior to any actual interaction with the robot, which likely prevented them from meaningfully associating the chosen label with specific behaviors. Without a concrete referent, the choice may have felt vague or irrelevant, failing to create a genuine sense of personalization. Instead of enhancing autonomy, this superficial customization may have inadvertently increased participants' awareness that the system was externally controlled and scripted, thus increasing their perceived external control rather than reducing it. Regression analyses further support this interpretation. Enjoyment was a positive predictor of perceived usability (SUS), whereas external control negatively predicted usability. These results are consistent with previous HRI findings, where positive affect enhances user evaluations, while a lack of perceived autonomy undermines trust and engagement [7] [23]. Taken together, these findings highlight the delicate balance between personalization and user empowerment in Human–Robot Interaction. Overall, while personalization is widely considered a means of increasing user engagement and autonomy, the current study shows that poorly timed or insufficiently grounded choices may backfire, especially when users are asked to make decisions before understanding their implications. These results contribute to the ongoing development of adaptive and embodied cognitive assessment tools emphasizing the value of integrating interaction style, user preferences, and neuropsychological modelling within SAR based interventions [24]. Future research should investigate how the timing, framing, and concreteness of customization influence user perceptions, especially in vulnerable populations such as older adults. In this regard, adaptive neurorobotic platforms such as those proposed in cognitive modelling studies [24], could be designed to replicate diagnostic tasks in real world settings, building on recent efforts to enhance ecological validity through intelligent systems and tangible interfaces [14].Introducing progressive or experience based personalization, where choices are offered after the user has interacted with the system, may represent a more effective strategy to support both perceived agency and usability in SAR applications.

Declaration on Generative AI

The authors declare that parts of this paper were assisted by generative AI technologies (e.g., language refinement, formatting support), and have been thoroughly reviewed and edited by the authors. The authors take full responsibility for the content of the publication.

References

[1] A. Robaczewski, J. Bouchard, K. Bouchard, S. Gaboury, Socially assistive robots: The specific case of the nao, International Journal of Social Robotics 13 (2021) 795–831.

[2] T. Vandemeulebroucke, K. Dzi, C. Gastmans, Older adults' experiences with and perceptions of the use of socially assistive robots in aged care: A systematic review of quantitative evidence, Archives of Gerontology and Geriatrics 95 (2021) 104399.

[3] S. Costa, H. Lehmann, K. Dautenhahn, B. Robins, F. Soares, Using a humanoid robot to elicit body awareness and appropriate physical interaction in children with autism, International journal of social robotics 7 (2015) 265–278.

[4] O. Gigliotta, C. Padulo, E. Chinzer, B. Fairfield, hugo, a humanoid robot for training memory: A pilot study on healthy younger and older adults, in: 2024 IEEE International Conference on Metrology for eXtended Reality, Artificial Intelligence and Neural Engineering (MetroXRAINE), IEEE, 2024, pp. 1055–1058.

[5] O. Pino, G. Palestra, R. Trevino, B. De Carolis, The humanoid robot nao as trainer in a memory

program for elderly people with mild cognitive impairment, International Journal of Social Robotics 12 (2020) 21–33.
[6] M. Fridin, Storytelling by a kindergarten social assistive robot: A tool for constructive learning in preschool education, Computers & education 70 (2014) 53–64.
[7] C. Bröhl, J. Nelles, C. Brandl, A. Mertens, V. Nitsch, Human–robot collaboration acceptance model: development and comparison for germany, japan, china and the usa, International Journal of Social Robotics 11 (2019) 709–726.
[8] V. Venkatesh, H. Bala, Technology acceptance model 3 and a research agenda on interventions, Decision sciences 39 (2008) 273–315.
[9] J. Brooke, et al., Sus-a quick and dirty usability scale, Usability evaluation in industry 189 (1996) 4–7.
[10] R. R. Sinkovics, B. Stöttinger, B. B. Schlegelmilch, S. Ram, Reluctance to use technology-related products: Development of a technophobia scale, Thunderbird International Business Review 44 (2002) 477–494.
[11] F. Cavallo, R. Esposito, R. Limosani, A. Manzi, R. Bevilacqua, E. Felici, A. Di Nuovo, A. Cangelosi, F. Lattanzio, P. Dario, et al., Robotic services acceptance in smart environments with older adults: user satisfaction and acceptability study, Journal of medical Internet research 20 (2018) e9460.
[12] J. Broekens, M. Heerink, H. Rosendal, et al., Assistive social robots in elderly care: a review, Gerontechnology 8 (2009) 94–103.
[13] D. Feil-Seifer, M. J. Mataric, Defining socially assistive robotics, in: 9th International Conference on Rehabilitation Robotics, 2005. ICORR 2005., IEEE, 2005, pp. 465–468.
[14] A. Cerrato, M. Ponticorvo, O. Gigliotta, P. Bartolomeo, O. Miglino, The assessment of visuospatial abilities with tangible interfaces and machine learning, in: J. M. Ferrández Vicente, J. R. Álvarez-Sánchez, F. de la Paz López, J. Toledo Moreo, H. Adeli (Eds.), Understanding the Brain Function and Emotions, Springer International Publishing, Cham, 2019, pp. 78–87.
[15] A. Cerrato, M. Ponticorvo, O. Gigliotta, P. Bartolomeo, O. Miglino, Btt-scan: uno strumento per la valutazione della negligenza spaziale unilaterale, Sistemi intelligenti, Rivista quadrimestrale di scienze cognitive e di intelligenza artificiale (2019) 253–270. URL: https://www.rivisteweb.it/doi/10.1422/93573. doi:10.1422/93573.
[16] F. Somma, A. Argiuolo, A. Cerrato, M. Ponticorvo, L. Mandolesi, O. Miglino, P. Bartolomeo, O. Gigliotta, Valutazione dello pseudoneglect mediante strumenti tangibili e digitali, Sistemi intelligenti, Rivista quadrimestrale di scienze cognitive e di intelligenza artificiale (2020) 533–549. URL: https://www.rivisteweb.it/doi/10.1422/99075. doi:10.1422/99075.
[17] A. Argiuolo, F. Somma, P. Bartolomeo, O. Gigliotta, M. Ponticorvo, Indexes for the e-baking tray task: A look on laterality, verticality and quality of exploration, Brain Sciences 12 (2022). URL: https://www.mdpi.com/2076-3425/12/3/401. doi:10.3390/brainsci12030401.
[18] S. Shamsuddin, H. Yussof, L. Ismail, F. A. Hanapiah, S. Mohamed, H. A. Piah, N. I. Zahari, Initial response of autistic children in human-robot interaction therapy with humanoid robot nao, in: 2012 IEEE 8th International Colloquium on Signal Processing and its Applications, IEEE, 2012, pp. 188–193.
[19] M. Assad-Uz-Zaman, M. Rasedul Islam, S. Miah, M. H. Rahman, Nao robot for cooperative rehabilitation training, Journal of rehabilitation and assistive technologies engineering 6 (2019) 2055668319862151.
[20] E. Borella, B. Carretti, F. Riboldi, R. De Beni, Working memory training in older adults: evidence of transfer and maintenance effects., Psychology and aging 25 (2010) 767.
[21] E. Borella, E. Carbone, M. Pastore, R. De Beni, B. Carretti, Working memory training for healthy older adults: the role of individual characteristics in explaining short-and long-term gains, Frontiers in human neuroscience 11 (2017) 99.
[22] T. Belpaeme, J. Kennedy, A. Ramachandran, B. Scassellati, F. Tanaka, Social robots for education: A review, Science robotics 3 (2018) eaat5954.
[23] H. Sullivan-Toole, J. A. Richey, E. Tricomi, Control and effort costs influence the motivational consequences of choice, Frontiers in Psychology 8 (2017) 675.

[24] O. Gigliotta, P. Bartolomeo, O. M. and, Approaching neuropsychological tasks through adaptive neurorobots, Connection Science 27 (2015) 153–163. URL: https://doi.org/10.1080/09540091.2014.968094. doi:10.1080/09540091.2014.968094. arXiv:https://doi.org/10.1080/09540091.2014.968094.