Puzzling Patterns: Assessing Neck Range of Motion Using a Mobile Puzzle Exergame

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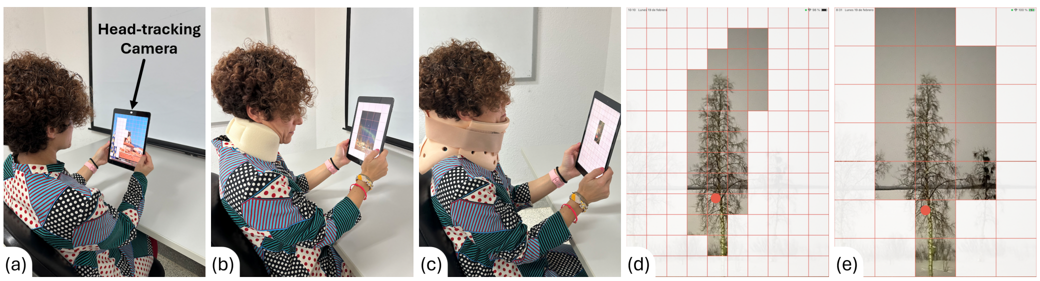

Figure 1: Picture-reveal puzzle game – an exergame to explore cervical range of motion (ROM). (a) No mobility restriction. (b) Soft collar mobility restriction. (c) Rigid collar mobility restriction. Puzzle difficulty varied through two levels of gain (high, low) and two configurations of tiles. (d) 13×10 tiles. (e) 7×5 tiles.

ABSTRACT

Cervical range of motion (ROM) is a crucial aspect of assessment following a neck injury and prior to cervical rehabilitation. We explored using an exergame with a head-tracker to predict the degree of cervical ROM. Using head movement, users moved a cursor over a picture-reveal puzzle to remove tiles and reveal an underlying picture. In a within-subjects user study, we controlled mobility restriction by fitting participants with either a rigid cervical collar (severe restriction), a soft cervical collar (moderate restriction), or no collar (no restriction). We also controlled task difficulty through two levels each of number of tiles (13×10, 7×5) and gain (high, low). Selection rate by mobility restriction ranged from ≈30% for severe to ≈95% with none, and ≈50% for moderate. Results suggest the following ascending ranks for difficulty based on number of tiles and gain: (1) 7×5, high gain, (2) 7×5, low gain, (3) 13×10, high gain, and (4) 13×10, low gain. This ascending difficulty order is recommended for presenting the puzzles to people with cervical conditions to avoid overexertion. The collected data were also used in machine learning with a Random Forest model. Mobility restriction category (severe, moderate, none) was correctly predicted in 80.6% of 36 samples. The results are a first step in using an exergame and machine learning to automatically categorize patients according to their cervical ROM.

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CCS CONCEPTS

• **Human-centered computing → Empirical studies in HCI**; • **Applied computing → Health care information systems**.

KEYWORDS

Cervical rehabilitation, mobile devices, eHealth, head-tracker, physiotherapy, exergame, range of motion

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1 INTRODUCTION

Neck pain is a common and significant health issue in our society [7, 18], and one of the most important musculoskeletal conditions in terms of prevalence and years lived with a disability. It is chronic in 30–50% of cases [6, 12]. Despite that, neck pain has received little attention from eHealth applications. We have developed a system called RehbeCa in the field of digital health. The system addresses therapeutic exercise for cervical rehabilitation and consists of a mobile application (used by patients) and a web application (used by physiotherapists), allowing the remote monitoring of patient performance, compliance, and progress.

The mobile application integrates a serious game designed to encourage patients to perform therapeutic neck exercises, adapting to their capability and evolution during recovery (guided by a physiotherapist). It is designed with clinical criteria and includes a variety of exercises in a home physiotherapy regime. In this way, a physiotherapist individualizes the treatment and adjusts the exercise program according to the needs and evolution of the patient.

The traditional way of assessing cervicalgia involves several steps, including the measurement of the neck range of motion (ROM). See Figure 2. ROM is the totality of movement that a joint of a body part is capable of. ROM measurements are an integral to assessment, as they allow monitoring a patient's status and progress. Therefore, the physiotherapist combines the measures of the neck with the patient's performance in the serious game to adapt the treatment over time. The goal of the current research is to determine if we can use an exergame to categorize a patient into a level of neck injury (i.e., degree of cervical ROM).

Figure 2: ROM measurements done by a physiotherapist with a goniometer.

In this paper, we used a picture-reveal puzzle game to detect a user's mobility status – i.e., cervical mobility in terms of range of motion – based on his/her performance on a task. The first step is to determine if different cervical mobility conditions correlate with task performance. To do this, we designed an experiment controlling neck mobility and examined the effect on user performance in the picture-reveal puzzle game. The neck mobility conditions were combined with additional conditions – number of tiles and gain of the head-tracking system – to vary the game difficulty.

In addition, the collected data from our experiment were used as a dataset to train and test a Random Forest model. Preliminary results give promise to the possibility of predicting the level of cervical ROM using the measures of performance extracted from the exergame. This constitutes a first step to using the exergame to automatically categorize patients according to their cervical ROM.

1.1 Related Work

Research has consistently demonstrated that incorporating games into therapeutic exercise enhances its efficacy and promotes adherence [1, 24]. Consequently, serious exergames exist for rehabilitation, utilizing both off-the-shelf commercial games and devices within a rehabilitation context [1, 9]. Shahmoradi et al. [22] provide a detailed review.

Serious exergames are effective in addressing a range of neurological and musculoskeletal conditions [2, 8]. Notably, the development of virtual reality (VR) serious games for rehabilitation, both immersive and non-immersive, has surged in recent years [2, 17]. When targeting specific body parts, such as the neck, developers often resort to wearable sensors attached to a body part or utilize full-body camera detection [16].

Baranyi et al. [2, 3] pioneered the development of a serious game system for post-stroke rehabilitation that integrates with smartphones or mobile devices, leveraging their built-in sensors. Although Mihajlovic et al. [15] created a virtual reality serious game for the neck region, immersion necessitates the use of a headset by the patient. Additionally, some researchers explored neck exercise systems using integrated sensors in mobile devices, such as camera-based head trackers [13]. Although capable of calculating neck flexion and monitoring head posture during smartphone use, these systems do not detect or monitor other directions of movement.

Quah et al. [19] proposed a portable computer vision-based marker-less head tracking exergame for neck rehabilitation which also incorporates movement modulation during posture overcompensation. They report promising results, but provide no rigorous user testing or validation of the system's precision. Also, their work does not report methods to assess the neck range of motion of the users.

As far as we know, the challenge of predicting the neck ROM using an exergame in a mobile device remains to be addressed.

2 NECK MOBILITY RESTRICTIONS

As an exploratory study, we did not work with people with cervical conditions, but with healthy subjects. However, we needed users to performed the task with different degrees of mobility restriction. For this purpose, we created three levels of mobility restriction:

(1) Severe – applying a rigid cervical collar (Fig. 3a).
(2) Moderate – applying a soft collar (Fig. 3b).
(3) None – healthy subject without an external restriction (Fig. 3c).

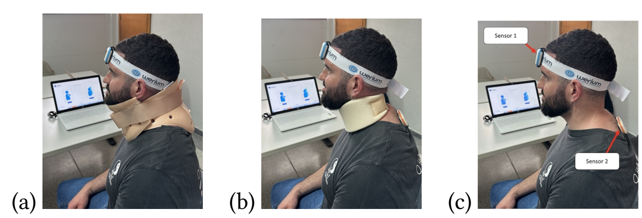

Figure 3: Three mobility restrictions: (a) severe restraint – a rigid cervical collar, (b) moderate restraint – a soft cervical collar, and (c) no mobility restraint. Setup includes wearing a ENLAZA inertial sensor to measure neck range of motion.

Then, we studied the mobility limitation caused by the collars to determine if they aptly serve as experimental conditions by mimicking the ROM for patients with a neck injury. To do this, we performed ROM measurements in flexion, extension, lateral flexion, and rotation of the neck. See Fig. 4. Flexion is bending the head forward towards the chest from an upright position, with a normal

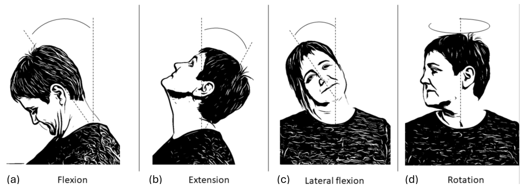

Figure 4: Cervical area movements. See text for discussion.

ROM up to 45º (Fig. 4a). Extension is the opposite movement, bending the head backwards from an upright position, with a normal ROM up to 45º (Fig. 4b). Lateral flexion is tilting the head to the side, trying to reach the shoulder with the ear (without moving the chin tip), with a ROM of 45º each side (Fig. 4c). Rotation is turning the head to the side, with the chin parallel to the floor, with a normal ROM of 70º each side (Fig. 4d).

These measurements were repeated under the three mobility restriction conditions: rigid collar (severe), soft collar (moderate), and no restraint (none). See Fig. 5.

Figure 5: Movements performed under the three mobility restriction conditions. From left to right, the movements are extension, flexion, right lateral flexion, and left lateral flexion, right rotation, left rotation. The first row corresponds to severe mobility restriction (rigid collar), the second row to moderate mobility restriction (soft collar), and third row to no mobility restriction.

Ten healthy participants (five female) were recruited among staff and students from a local university. To be included, participants had to be aged 18 to 70. The average age was 41.2 years (SD = 11.8). They were excluded if they reported or complained of neck, shoulder, and/or head impairments or if they had experienced pain in the preceding month. Participants were measured in an experiment room, seated in a chair in an upright position. They were asked to follow the instructions provided by the physiotherapist to perform three movements in each direction of the anatomical plane (flexion, extension, left lateral flexion, right lateral flexion, left rotation, right rotation). Fig. 4 illustrates the movements.

Neck movements were measured using two inertial sensors, ENLAZA [23], which recorded real-time movements performed by participants. The ranges captured by the sensors facilitated kinematic analyses. Following the manufacturer's protocol, one sensor was placed on the subject's forehead and another on the T1-T2 thoracic vertebrae (see *Sensor 1* and *Sensor 2* in Fig. 3c). Sensor 1 acted as the movable arm of a goniometer, while Sensor 2 served as the stationary part of the goniometer over the fulcrum of movement, enabling real-time angle measurements in the coronal, sagittal, and transverse anatomical planes.

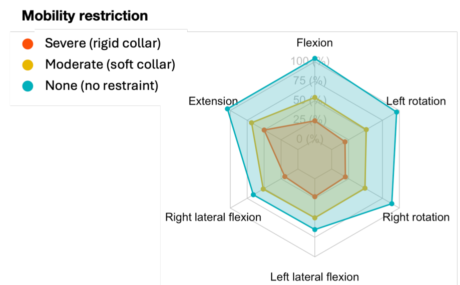

Figure 6: Range of motion (ROM) obtained from the measurements with the three mobility restriction conditions compared to normal mobility data of the population.

Fig. 6 and Table 1 depict the ROMs measured with the mobility restriction conditions. The measurements obtained without mobility restriction agree with the normal mobility data of the population where cervical area mobility is 45° flexion, 45° extension, up to 45° lateral flexion (each side), and 70° rotation (each side) [4, 11, 18]. Our measurements with no restraint yielded means of 46.9° flexion (SD = 9.5), 47.0° extension (SD = 12.3), 29.7° right lateral flexion (SD = 7.3), 29.3° left lateral flexion (SD = 4.9), 62.2° right rotation (SD = 9.4), and 67.2° left rotation (SD = 11.1).

The ROMs obtained from the measurements with the soft cervical collar showed moderate limited mobility, with means of 24.4° flexion (52% of the non-restraint ROM), 30.9° extension (66% of the non-restraint ROM), 23.1° right lateral flexion (78% of the non-restraint ROM), 22.5° left lateral flexion (77% of the non-restraint ROM), 34.4° right rotation (55% of the non-restraint ROM), and 35.8° left rotation (54% of the non-restraint ROM).

The ROMs obtained from the measurements with the rigid cervical collar showed severe limited mobility, with means of 11.0° flexion (23% of the non-restraint ROM), 22.5° extension (48% of the non-restraint ROM), 8.7° right lateral flexion (29% of the non-restraint ROM), 10.3° left lateral flexion (35% of the non-restraint ROM), 14.1° right rotation (23% of the non-restraint ROM), and 13.8° left rotation (21% of the non-restraint ROM).

These results indicate that the three mobility restriction conditions were valid as experimental conditions to limit cervical mobility. This serves as a prelude to a user study to determine how the mobility restrictions impact user performance in a mobile puzzle exergame.

3 METHOD

This experiment explores whether the cervical range of motion (ROM) allowed by the neck mobility restrictions affects user performance in a picture-reveal exergame puzzle. User performance refers to the percentage of tiles selected (i.e., removed) and the time interacting with each puzzle. Difficulty was varied further by the number of tiles in a puzzle and the gain of the head tracker.

Table 1: Mean over all participants of the maximum range of motion (ROM) by mobility restriction. Results of the F-tests showing F-statistic and significance. Results of a Scheffé post hoc analysis for significance between pairs.

	Mobility Restriction			F-Test		Scheffé post hoc (sig.)		
Movement	Severe	Moderate	None	$F_{2,18}$	sig.	rigid vs. soft	rigid vs. none	soft vs. none
Flexion	11.0°	24.4°	46.9°	92.1	***	**	***	***
Extension	22.5°	30.9°	47.0°	125.6	***	***	**	***
Right lateral flexion	8.7°	23.1°	29.7°	62.6	***	***	***	.
Left lateral flexion	10.3°	22.5°	29.3°	37.4	***	**	***	-
Right rotation	14.1°	34.4°	62.2°	74.4	***	**	***	***
Left rotation	13.8°	35.8°	67.2°	73.5	***	**	***	***

Note: '-' = $p < 1$, '.' = $p < .1$, '*' = $p < .05$, '**' = $p < .01$, '***' = $p < .001$.

3.1 Participants

A gender-balanced set of twelve healthy participants (six females) were recruited from staff and students at a university campus in Spain. To be included, participants had to be aged 18 to 70 years. The mean age was 42.8 years (SD = 10.5). They were excluded if they reported or complained of neck, shoulder, or head impairments or if they had experienced pain in the preceding month.

3.2 Apparatus

The experiment was conducted on an Apple *iPad* (9th generation) with a resolution of 2160 × 1620 px and a pixel density of 264 ppi.

The software implemented a picture-reveal puzzle game. A picture was covered with an $n \times m$ grid of tiles in two configurations. See Fig. 7. Using head movement, participants moved a cursor over tiles to remove them and to uncover the picture. A tile was selected and removed immediately when the cursor (red circle in Fig. 7) passed through the tile. This selection mode is equivalent to a 0-ms dwell-time criterion.

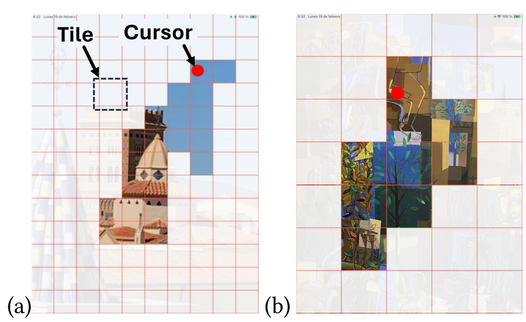

Figure 7: Screenshots with annotations of the picture-reveal puzzle game with the two configurations of tiles: (a) 13×10, and (b) 7×5. The cursor appears as a red circle.

The game uses a camera-based head-tracker. Input uses movement of the head which in turn moves the cursor. This transforms the game into a cervical exergame. The head-tracker was previously validated with users with and without disabilities [14, 20]. Head movement is monitored by detecting the nose position in the images provided by the front camera of the mobile device. It works without additional sensors or elements on the user.

The head-tracker includes a gain factor – the amount of cursor movement in response an amount of movement of the user's head in the camera images. The gain affects the velocity of the cursor in pixels/frame. For a cervical rehabilitation application, the head-tracker gain is crucial for clinical criteria and rehabilitation goals. A high gain allows users to perform despite having less mobility, while a low gain requires increased movement, as well as more motor control for holding the cursor steady. See Roig-Maimó et al. [21] for details of the integrated head-tracker interface.

3.3 Procedure

The experiment was conducted by three members of the research team, including a physiotherapist. All received training on the procedure. Before testing, participants were given a study overview and with clarification on the informed consent process. Informed consent was obtained from all participants.

Participants were instructed how to play the picture-reveal puzzle game using the provided iPad. In the game, they uncovered a hidden picture by moving the cursor over the tiles of a puzzle using head movements. Participants sat upright on a fixed chair in front of a table, so they could comfortably rest their arms and hold the mobile device naturally. See Fig. 1. This seating arrangement was designed to minimize compensatory movements. Participants were instructed to move the cursor by holding the device still and moving their head only; they were asked not to move the device while interacting with the application. The only requirement was that their entire face was visible by the front camera of the device.

Then, participants proceeded to conduct the experiment for each mobility restriction condition.

It was anticipated that participants might not be able to remove all the tiles in some experimental conditions. In such cases, they were instructed to terminate the trial by performing a three-finger touch anywhere on the display surface. They did this when they felt unable to remove more tiles. Participants rested as needed between sequences. Testing lasted ≈30 minutes per participant.

3.4 Design

The experiment design was 3 × 2 × 2 within-subjects with the following independent variables and levels:

- Mobility restriction: severe, moderate, none.
- Number of tiles: 13×10, 7×5.

- Gain: high (2.0), low (1.5).

For each condition, two trials were performed. The primary independent variable was mobility restriction with three levels (rigid collar, soft collar, no collar). Number of tiles and gain were varied to ensure the trials covered a reasonable range of task difficulties. The gain independent variable corresponds to the gain factor of the head-tracker, i.e., the velocity of the cursor (see Section 3.2).

For each puzzle difficulty (number of tiles × gain), participants performed a sequence of $n \times m$ sub-tasks, where $n \times m$ is the number of tiles to remove in solving the puzzle.

The three mobility restrictions were counterbalanced using six groups covering all combinations. The number of tiles and gain conditions were randomized within sequences.

The dependent variables were selection rate (%) and time (s). Selection rate was the number of selected tiles divided by the number of tiles in a puzzle. Time corresponded to the time to complete a puzzle or the time until a participant decided they had reached their limit in selecting tiles.

The total number of trials (i.e., puzzles) was 12 participants × 3 mobility restrictions × 2 number of tiles × 2 gains × 2 trials/condition = 288.

Following the sex and gender equity in research (SAGER) guidelines [10], we also investigated whether there was a difference by sex over the dependent variables. And so, we gathered a balanced set of participants and included sex as a factor in the analysis. For the effect of sex, we used a between-subjects design where the primary independent variable was sex with levels female and male.

4 RESULTS AND DISCUSSION

This section gives results for selection rate and time. First, we note that the group effect was not statistically significant on selection rate ($F_{5,6} = 0.76$, ns) nor on time ($F_{5,6} = 1.99$, $p > .05$). Thus, counterbalancing had the desired effect of offsetting order effects.

Then, we examined the learning effect over the two trials for each condition. The learning effect (i.e., trial effect) on selection rate was not statistically significant ($F_{1,11} = 0.83$, ns), while on time the effect of trial was statistically significant ($F_{1,11} = 5.21$, $p < .05$). Participants were about 6% faster in completing the puzzle in the second trial, suggesting some degree of adaptation with the task. However, as we are particularly interested in analyzing the tiles that participants were able to remove, no matter the time needed, subsequent analyses used the data for both trials per puzzle.

4.1 Selection Rate

The grand mean for selection rate was 59.7%. Recall that selection rate is the percentage of tiles removed in solving a puzzle. The results for selection rate by mobility restriction, number of tiles, and gain are shown in Fig. 8.

The mean selection rate for severe mobility restriction was 31.1%. This was about 59% lower than the mean 53.1% for moderate mobility restriction. This suggests that the severe restriction seriously hampered participants' ability to navigate and interact with the puzzle. As expected, participants with no mobility restriction achieved a higher mean selection rate of 94.8%, indicating a marked improvement in performance when mobility was not restrained. The statistical analysis further confirmed the significance of these findings ($F_{2,22} = 84.93$, $p < .001$) indicating that the effect of mobility restriction on selection rate was not due to chance.

Additionally, a Scheffé post hoc analysis revealed that the differences between all pairs (severe vs. moderate, severe vs. none, moderate vs. none) were statistically significant, further reinforcing the impact of mobility restriction on task performance.

The mean selection rate for puzzles with more tiles (13×10) was 56.8%, while with fewer tiles (7×5), the selection rate was about 10% higher at 62.5%. An ANOVA revealed a significant effect of the number of tiles on selection rate ($F_{1,11} = 42.24$, $p < .0001$).

The effect of gain on selection rate was also statistically significant ($F_{1,11} = 12.54$, $p < .01$). The mean selection rate with high gain was 61.0%, while with low gain the selection rate was ≈4% lower at 58.3%. This is inline with the expected effect for gain of the head-tracker described in Section 3.2: A higher gain allows users to perform despite less mobility (increasing their range of movement on the device screen), while a lower gain requires greater cervical movement.

Fig. 9 shows the results for selection rate by mobility restriction and puzzle difficulty (number of tiles × gain). For each mobility restriction, selection rate increased from left to right: light blue, dark blue, light orange, dark orange (from hardest to easiest). With reference to the legend in Fig. 9 and the means of selection rate by puzzle difficulty (number of tiles × gain), we note the following levels in order for decreasing difficulty:

(1) 13×10, low gain: 56.0% selection rate.
(2) 13×10, high gain: 57.7% selection rate.
(3) 7×5, low gain: 60.7% selection rate.
(4) 7×5, high gain: 64.3% selection rate.

Fig. 10 shows patterns for success by mobility restriction and puzzle difficulty (number of tiles × gain). As with previous results, we observed similar patterns for puzzles with 13×10 tiles (high and low gain). See Fig. 10a-b. Increased difficulty (Fig. 10c-d) coincides with more opacity, implying more tiles left in place and obscuring the underlying picture. The reverse pattern is seen as mobility restriction decreases (from severe to none). Accordingly, tiles at the center of the screen are the most transparent as they are the easiest to remove. For each condition, success decreases for tiles closer to the corners; i.e., tiles near the corners are the hardest to remove.

Fig. 11 gives examples of participant path traces. Although no specific order was required, participants tended to use a strategy under no mobility restriction: removing tiles row by row or column by column. See Fig. 11c. When participants performed with moderate mobility restriction, they tried to act the same but left tiles in place in inaccessible areas: around the corners of the display. See Fig. 11b. However, when performing with severe mobility restriction, movements became erratic: They just wandered around trying to remove as many tiles as their mobility allowed. See Fig. 11a. This path behavior is observed in people with multiple sclerosis with different degrees of mobility and head control and with people with no mobility restriction when using a head-tracking interface [14].

4.2 Time

The grand mean for time was 21.9 s. This is the time participants took to solve a puzzle or the time until they felt they could not

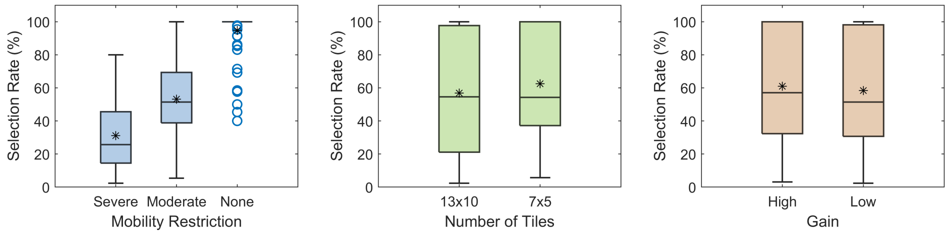

Figure 8: Results for selection rate (%) by mobility restriction, number of tiles, and gain. Asterisks show the means.

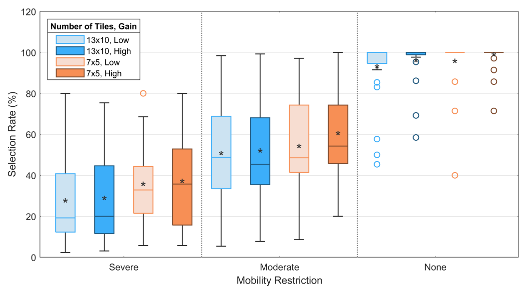

Figure 9: Results for selection rate (%) by mobility restriction and puzzle difficulty (number of tiles × gain). Within each mobility restriction, difficulty decreases from left to right. Asterisks show the means.

continue beyond their current effort. The results for time (s) by mobility restriction, number of tiles, and gain are shown in Fig. 12.

The mean completion times for mobility restriction were 18.2 s for severe, 23.0 s for moderate, and 24.7 s for none. However, the effect of mobility restriction on time was not statistically significant ($F_{2,22} = 2.63$, $p > .05$). The maximum times to complete a puzzle by mobility restriction were 61 s (severe), 60 s (moderate), and 67 s (none). Therefore, future user studies could set a maximum time of one minute to measure the selection rate in solving a puzzle without overexertion, independent of the mobility restriction of the patient. The mean completion time for 13×10 tiles was 29.5 s while the mean for 7×5 tiles was ≈50% less at 14.4 s. The effect of number of tiles on time was statistically significant ($F_{1,11} = 68.97$, $p < .001$). However, the effect of gain on time was not statistically significant ($F_{1,11} = 3.37$, $p > .05$).

4.3 Sex and Age

The results for sex are shown in Table 2. Statistical significance was not obtained for the effect of sex on selection rate ($F_{1,286} = 1.05$, $p > .05$) or on time ($F_{1,286} = 3.48$, $p > .05$).

Table 2: Selection rate (%) and time (s) by sex.

Measure	Female	Male	Mean
Selection rate (%)	57.7%	61.7%	59.7%
Time (s)	20.5 s	23.4 s	22.0 s

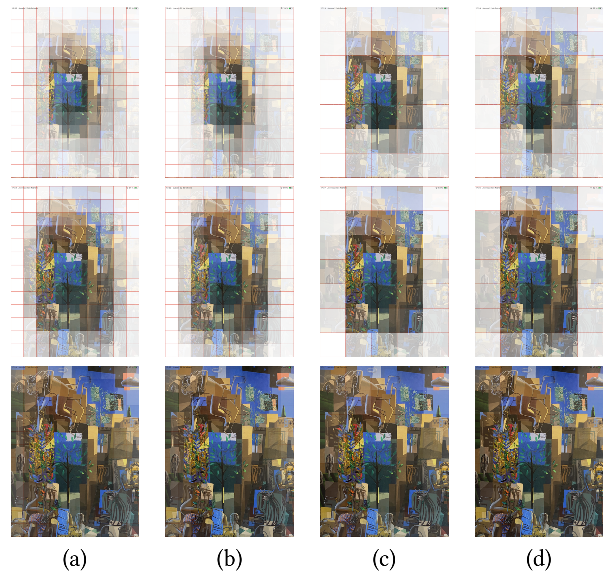

Figure 10: Level of success over all trials and participants for each mobility restriction (rows) and difficulty (columns). Opacity of a tile shows the level of success: an opaque tile means it has never been removed, a transparent tile means it was removed in all trials. Rows from top to bottom correspond to mobility restriction: severe, moderate, none. Columns left to right correspond to increasing difficulty: (a) 13×10, low; (b) 13×10, high; (c) 7×5, low; and (d) 7×5, high.

As there was a wide spread in age among the participants (from 25 to 58 years), we looked for a relationship between age and performance (i.e., selection rate). The correlation between selection rate and age was very low ($r = 0.128$). Therefore, we report no effect of age on selection rate (with this limited sample of participants).

5 USING MACHINE LEARNING TO PREDICT CERVICAL MOBILITY

One motivation for the present study was to explore the potential to predict a user's cervical mobility using machine learning models. To this end, data from the present experiment served as a preliminary dataset. Even with this limited data, choosing an appropriate machine learning model is paramount to ensure reliable results. Decision trees were used due to their simplicity, interpretability, and ability to efficiently handle small datasets. By employing decision

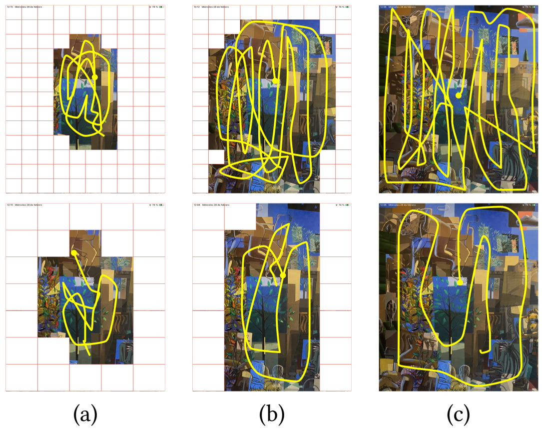

Figure 11: Example path traces from one participant to solve different puzzle conditions. First row: 13×10 tiles, second row: 7×5 tiles. Columns are for mobility restriction: (a) severe, (b) moderate, and (c) none.

trees, we will determine which models offer viable solutions to use in the future with additional data. As well, selected features from the present experiment will be analyzed without designer intervention to study their importance for cervical mobility categorization.

For this study, the features are selection rate and time for each puzzle difficulty (number of tiles × gain) and sex. This leads to nine features. See Fig. 13. The goal was to correctly label the mobility restriction in the test data as severe, moderate, or none. For this, we used first-trial data for learning and second-trial data as test data. This results in 36 samples each for learning and testing, where each sample is the trial data for four difficulty conditions. Using only a decision tree, as expected, the model overfits. Therefore, a Random Forest model [5] was selected. After setting the hyperparameters, the best accuracy was with 100 trees and a maximum depth of three levels. For the 36 test samples, 29 (80.6%) were correctly labeled. The seven incorrectly labeled correspond to false positives or false negatives involving the moderate mobility restriction; that is, an extreme mobility restriction sample (severe or none) incorrectly labelled as moderate, or a moderate sample incorrectly labelled as one of the extremes. Samples of moderate mobility restriction blur the thresholds with the extreme mobility restrictions (severe or none). Taking into account the small dataset, this result is promising. Concerning the moderate mobility restriction condition, users in this condition had more variance in ROM. We attribute this to the soft collar restraint: Wearing a soft collar, movements of the neck are easily forced, depending on the motivation of the participant (even if they were instructed not to force the movements), because they were healthy participants and, therefore, had no pain; actual patients will be restrained by pain.

Upon completion of training, the Random Forest model possesses inherent mechanisms for elucidating the importance of features in classification tasks. Fig. 13 shows the importance of each feature for predicting the mobility categorization. While the sex feature has marginal importance, the most informative features are the four selection rates for each puzzle difficulty condition. This leads us to the conclusion that all of the puzzle difficulty conditions must be considered (jointly with selection rate).

6 CONCLUSION AND FUTURE WORK

In this paper we presented an experiment to explore the feasibility of using a mobile exergame (a picture-reveal puzzle) to categorize a patient's cervical mobility. The exergame required participants to control a cursor moving their head to remove tiles covering an underlying picture. Puzzle difficulty varied through two configurations of tiles (13×10, 7×5) and two levels of gain (high, low). We collected user performance in terms of selection rate and time.

To analyze if the collected data could be used to infer different degrees of mobility restriction, we simulated three levels of mobility restriction by applying mechanical restraints: severe (wearing a rigid collar), moderate (wearing a soft collar), and none (without mechanical restriction). Then, participants tried to solve the puzzle with each mobility condition. A gender-balanced set of twelve healthy participants was recruited for a within-subjects user study.

As expected, there was a significant difference on selection rate by mobility restriction, from ≈30% for severe to almost 95% with none, and ≈50% for moderate. This result encourages us to use selection rate as a measure to classify degrees of mobility restriction.

Furthermore, a common pattern of success emerged: The easiest tiles to remove were those at the center of the screen, with difficulty increasing for tiles near the corners. Therefore, the present research provides empirical evidence of an anticipated behavior: A decrease in the radius of the circular pattern of the tiles removed is coincident with increased mobility restriction.

Regarding solving strategies, participants acted rationally in removing tiles under no mobility restriction. Their strategy became more chaotic with increased mobility restriction. Based also on selection rate, we ranked the four puzzle difficulties (number of tiles × gain) in ascending difficulty: (1) 7×5, high gain, (2) 7×5, low gain, (3) 13×10, high gain, and (4) 13×10, low gain. This ascending difficulty order is recommended for presenting the puzzles to people with cervical conditions (to avoid overexertion). Results obtained for time were not promising to be used for degrees of mobility restriction classification. We found no difference by sex nor by age.

In addition, the collected data were used to train and test a Random Forest model. Despite the small dataset, preliminary results were promising and lead to the possibility of predicting the degree of mobility restriction using the measures of selection rate of the four difficulty conditions. This opens the door to using the developed exergame with people with cervical conditions to generate a dataset to train an AI classifier to predict the user's cervical mobility status.

These findings are a step forward in utilizing an exergame for automated patient categorization according to cervical range of motion (ROM), offering potential benefits for personalized treatment, remote monitoring, and assisting as a diagnostic tool for physiotherapists. However, further research is warranted to validate and refine our findings and to explore scalability and generalizability across diverse patient populations and clinical settings.

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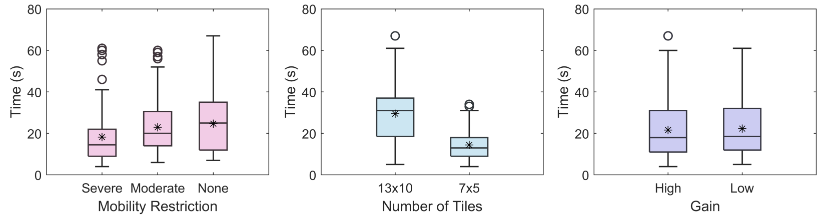

Figure 12: Results for time (s) by mobility restriction, number of tiles, and gain. Asterisks show the means.

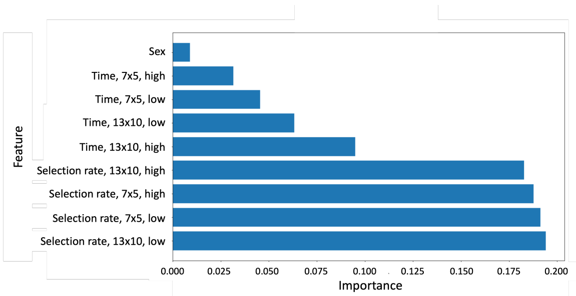

Figure 13: Feature importance after learning with Random Forest model.

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