Interdisciplinary Journal of Virtual Learning in Medical Sciences

Original Article

Azimuth-Based Assessment of Spatial Orientation Performance: A Diagnostic Tool for Cognitive Impairments

Zainab Gorzinmataee[1], PhD Candidate; Ebrahim Talaee[1]*, PhD; Omid Noroozi[2], PhD; Javad Hatami[1], PhD

[1]*Department of Educational Science, Faculty of Humanities, Tarbiat Modares University, Tehran, Iran*
[2]*Education and Learning Sciences, Wageningen University and Research, Wageningen, Netherlands*

ABSTRACT

Background: Geographical/geometric indicators like azimuth provide a real-time and low-cost method of measuring spatial performance during navigation, especially in view of their accessibility on mobile phones in the form of a compass or GPS. This study aimed to investigate azimuth-based assessment of spatial orientation performance and its potential in diagnosing cognitive problems.

Methods: This was a descriptive survey, and included multivariate logistic regression and multi-layer neural network analysis. We measured the spatial orientation performance of participants using an azimuth-based compass. Their demographic data, including age, gender, years of driving experience, field of study, and cognitive health status were collected. The statistical population consisted of 52 females and 48 males, 18 of whom had experienced cognitive problems in their lives. The participants were from different ethnic backgrounds living in the US, and in the age range of 20-85. The census method was then applied. Multivariate data analysis was conducted to illustrate the effectiveness of each feature variable on spatial orientation performance. Logistic regression was run by fitting a logit function, and multi-layer neural network analysis was developed and evaluated to predict the risk of cognitive problems based on spatial orientation performance and four other features under study.

Results: Multivariate analysis showed that participants' age ($P=0.005$), years of driving experience ($P<0.001$), and cognitive problems ($P<0.001$) contributed to predicting spatial orientation performance. Those who had experienced cognitive problems deviated 13.50 degrees from the destination with increasing age. The accuracy of the fitted logit model by NN analysis over training process was 0.8, indicating that the model can predict 8 out of 10 cases accurately.

Conclusion: According to the findings, azimuth-based assessment of performance and other demographic data could be an appropriate means of determining individuals' spatial orientation ability, especially when performed on larger and more homogeneous groups.

Keywords: Cognitive problems, Impairments, Spatial ability, Spatial orientation, Navigation

**Corresponding author:*
Ebrahim Talaee, PhD;
Department of Educational Science, Faculty of Humanities, Tarbiat Modares university, Tehran, Iran
Tel: +98-9359705036
Email: e.talaee@modares.ac.ir

Please cite this paper as:
Gorzinmataee Z, Talaee E, Noroozi O, Hatami J. Azimuth-Based Assessment of Spatial Orientation Performance: A Diagnostic Tool for Cognitive Impairments. Interdiscip J Virtual Learn Med Sci. 2021;12(1):38-48.doi:10.30476/ijvlms.2021.88545.1064.

Received: 02-11-2020
Revised: 24-01-2021
Accepted: 25-01-2021

Introduction

Many of our daily activities, especially those related to spatial navigation skills, can be easily assessed using authentic, real-time, and inexpensive geographical/geometric indicators (1-3), whereas situation-controlled, simulated, and expensive tests are generally conducted in clinical settings (4, 5). Most common advanced clinical tests are also performed on patients struggling with cognitive deficits or impairments (6, 7). Given the experimental manipulation of virtual environments, the nature of individual performance in these settings is different from that of the real world (8).

Since the spatial ability deficits like disorientation or defective spatial navigation can be considered as an early symptom of mild cognitive impairments, including Alzheimer's disease, aging brain and dementia, a more accurate assessment of individual performance in these areas allows for a better diagnosis of the conditions in question (9-11).

Like a compass or global positioning system (GPS), most spatial monitoring devices use specific geographical/geometric indicators like azimuth and elevation during a navigation task (12). They can measure the accuracy of spatial performances such as spatial orientation and route finding via these indicators, which are now available on mobile phones for free and are accessible to all users (13).

Since measuring spatial ability is a major diagnostic test for detecting imminent cognitive impairments, spatial orientation performance was considered as the main component of the navigation task in this study. A survey of literature on real-time spatial navigation indicators reveals that a direct observation of the azimuth of orientation produces more authentic assessment results (14), compared to the traditional paper-pencil tests or virtual reality-based navigation tasks (15, 16).

Research shows that an individual's performance in spatial tasks depends on various factors directly or indirectly related to their cognitive function. There is ample empirical evidence suggesting that aging has a significant effect on spatial abilities and often leads to declined levels (17-19). Studies have also demonstrated a difference in spatial navigation strategies and subsequent performances between men and women (20-22). Moreover, performance in such tasks is associated with some routine daily activities like driving skills. Prior studies indicate that performance in multifactorial tasks involving visually mediated executive functions and visual-spatial skills is related to driving performance (23-26). The other factor affecting spatial performance can be an individual's mathematical knowledge and background, especially in geometry and spatial disciplines. Evidence suggests that the more familiar a person is with spatial knowledge and geometry, the better performance they display in spatial tasks. Studies also show that engineering students have a higher performance than others in spatial tasks, especially those related to the visualization of rotation. These skills have gradually become a standard tool for assessing an engineering student's academic and career achievements (27-31).

This study was thus conducted to assess individuals' performance in a real-world spatial orientation navigation task, taking into account their age, gender, years of driving experience, fields of study, and a history cognitive impairments (if any) in their lives. Therefore, the main objectives of the study can be summarized in two research questions:

1- What demographic factors (age, gender, driving experience, field of study, and cognitive problem) affect individuals' spatial orientation performance?

2- To what extent can we rely on individuals' performance in a spatial orientation navigation task, along with the abovementioned demographic characteristics, to predict the risk of cognitive problems?

Methods

Research Design

This was a descriptive survey and included multivariate, logistic regression, and multi-layer neural network analysis. We measured the spatial orientation performance of participants using an open-access azimuth-based iOS compass. The participant's demographic information, including age, gender, years of driving experience, field of study, and cognitive problems (if they had experienced in their life), was collected, and a dataset consisting of information on 100 participants and their spatial orientation performance was obtained. The collected data were analyzed using Rstudio 3.6.1 and Python 3.8.

Participants and Sampling Method

The study sample encompassed students and staff from different universities such as Boston, Harvard Medical School, Northeastern, Texas, and Michigan (n=100). A particular set of criteria were considered in selecting the participants, and then the census method was applied (32). Given the emphasis in the literature on the effects of aging, gender, and educational fields on spatial skills, individuals of different ages (ranging from 20 to 85 years) were included in the study, who were mostly homogenous in terms of gender. To include participants from various academic disciplines (related to engineering, geometry, mathematics or other fields), they were selected from different institutions. Based on the study's main goal, it was required to have participants with cognitive problems or impairments; therefore, about 35% of the population were selected from CVS Pharmacies, Boston Medical Center, and the Neuroscience Department of Ascension Park Providence Hospital in Michigan.

Time of the Study, Inclusion and Exclusion Criteria

The study was carried out in the United States of America from October 2019 to February 2020. There was no limitation in selecting the participants; however, the basic familiarity with navigational activities such as angles, directions, and rotation ability was necessary to perform the spatial orientation task. The only exclusion criterion was the participant's unwillingness to participate in the research or test. First, the experimental setup was orally explained to the research population, all of whom could do the tasks well. They were included in the study, and their willingness to participate in the test were considered.

Data Collection Tools

The participants' basic information was asked from them and collected by the researcher. Data were coded, summarized, and recorded in an excel file (.xls), then imported as a dataset in Rstudio. To assess the participants' spatial orientation ability, a free open access iOS application developed by Savvas Petrou in 2012 (Compass-PRO) was used. It is a gyroscope-enhanced compass that tracks the participants' orientation by following magnetic azimuth. Its interface and function are shown in Figure 1.

To use this application, the participants had to remain at a point; the initial direction of their face showed their magnetic azimuth at

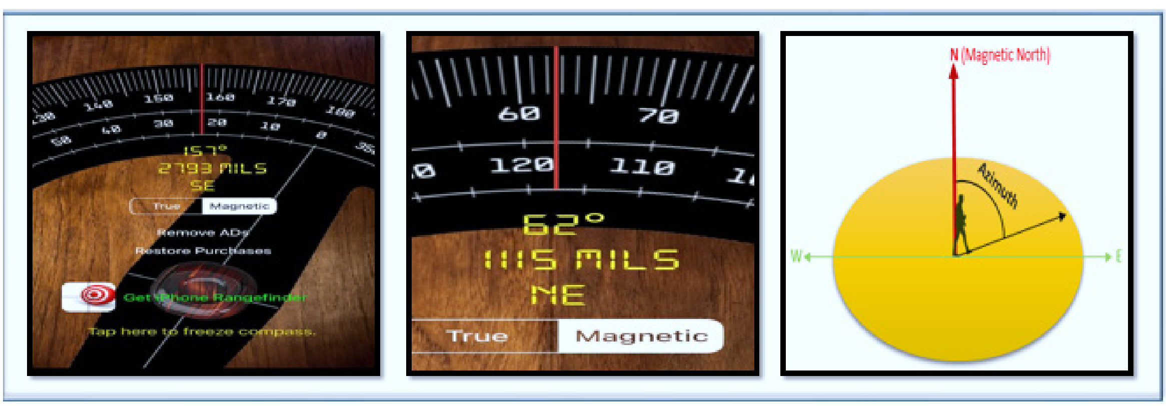

Figure 1. Compass-PRO's interface and function while tracking Magnetic Azimuth of a direction with distance.

that point via Compass-PRO; then, they were asked to rotate clockwise by 80 degrees and traverse a distance of 5 feet. Finally, when the participants completed the task at the final position, their overall orientation was tracked via the app by following the magnetic azimuth.

Validity and Reliability of the Measurements

In this study, two different measurement tools(Compass-PRO application and Electronic Gyroscope) are adopted, which are usually known as valid and equivalent tools for tracking azimuth. To determine Compass-PRO measurements' reliability, the spatial performance of 40 participants was re-measured by a gyroscope. Regarding the nature of the variable (numerical/quantitative), Pearson's correlation coefficient analysis was run (33), and two measurements were positively correlated ($r(38)=0.98$, $P<0.001$).

Statistical Methods

A generalized linear model was run to the dataset to detect which features of the participants can be used to predict the output response variable based on the linear order of several explanatory input variables. A Logistic regression analysis was run by setting the cognitive problem as a binomial output and all five other variables as inputs. Logistic binomial regression, often known as Logistic regression, is also used to predict the probability of observation. It falls into one of two categories of a dichotomous dependent variable based on one or more independent variables, which can be either continuous or categorical. Logit link function with the binomial family was used in this analysis, and the fitness of the model was assessed using Mcfadden's pseudo-R-squared (34-36). Finally, following the implementation of an artificial neural network system via Logistic Regression analysis of inputs and output stream, we were to capture the relationship between the input features of age, gender, years of driving experience, field of study, and participant's performance in the spatial orientation test with the output feature of cognitive problem. A multi-layer neural network analysis was also run. The NN model was extracted with inputs/output weighted connection map and Logit activation function via allocating three hidden layers that each hidden layer included 32 number of neurons as hidden units and associated weights and biases. For each hidden layer, a Rectified Linear Unit (ReLU) activation function was applied. The activation function applied to the output layer was a Sigmoid or Logistic function selected based on the binary attribute of the dataset output. After allocating the model to the dataset, the final step was training it. The ANN model's training process was run to optimize parameters, empower prediction, obtain the best set of weights in a stimulant combination of all parameters, and pick up the most accuracy (37, 38), for the training process dataset was divided into training and test sets. The training set is used to optimize the prediction procedure, and the test set is a criterion to calculate the model's accuracy in a different training cycle (39). The ANN model ran for 20 epoch cycles. The parameters were initialized with random weights and biases, and data were shuffled to ensure data point samples, 90% of the samples were used to train the ANN model, and the other 10% were left for the validation with three hidden layers (40).

Results

Demographic Data Analysis

The participants were from different racial categories (Asian, White, Black American, Latino) with the age range of 20-85 years and the mean age of 42.52 and standard deviation of 15.01; of whom 52% were women, and 48% were men. The field of study of 60 participants was related to mathematics (including engineering, geometry, and mathematics), and 40 other participants were studying other fields (including medicine, natural science, law, and education). They also had 14.08 years of driving experience on average with a standard deviation of 12.13. Eighteen participants reported that they had experienced mild cognitive problems (any kind of cognitive deficit, impairment, or declining) in their life and 82 others acknowledged that they were perfectly healthy.

Multiple Linear Regression Analysis

To answer the first research question, multiple linear regression was used to predict participants' performance in the spatial orientation test based on their age, gender, field of study, years of driving experience, and cognitive problem. A significant equation was found ($F(5, 94)=18.72$, $P=7.166e-13$) at $P=0.01$ with R-squared of 0.49 and adjusted R-squared of 0.40. When R-squared is approximately equal to adjusted R-squared, the independent variables added to the model are selected correctly.

The multivariate data analysis results determine the relative contribution of each of the predictors to the total performance. Analysis indicated the importance of all inputs except gender ($P=0.40$) and field of study ($P=0.48$) with the participant's performance. Participant's spatial performance is equal to 82.294 – 0.516(age)+0.766 (years of driving experience) – 13.505 (cognitive problem).

In this case, age ($P=0.005$) and years of driving experience ($P=0.0004$) are measured in numbers, and cognitive problem ($P=0.0001$) is coded as 1 (No) and 2 (Yes). The participants who had experienced cognitive problems in their life were 13.50 more deviated from the destination by increasing ages than others.

Binomial Logistic Regression Analysis

To answer the second research question, the risk of cognitive problems were examined based on the individuals' spatial orientation performance and four demographic features of age, gender, years of driving experience, and field of study. Logistic regression was run by fitting a Logit function model on the dataset. Binomial Logistic regression estimates the probability of cognitive problems occurring as an odds ratio of 1 (risk of suffering from any kind of cognitive problem, deficit, or impairment) and 0 (no evidence of any cognitive problem, deficit, or impairment). The estimated probability of cognitive problems based on predictor variables is set to be greater than or equal to 0.5. In that case, the Logit model returns 1 (as a positive risk of having a cognitive problem). In contrast, the estimated probability of $P<0.5$ returns 0 (as an adverse risk of having a cognitive problem).

The coefficient for every input is shown in Table 1. For the Z-statistic of each input

Table 1. Different coefficients of all inputs in logistic regression analysis

Coefficients **Estimate Std. Error z value Pr(>|z|)**					
(Intercept)	**Age**	**Gender**	**Math**	**Driving**	**Performance**
0.83	0.00	-0.03	-0.03	0.00	-0.01
glm variable importance results(Overall)					
Performance	Driving	Age	Gender	Math	
100	58.49	40.50	11.63	0.00	
Likelihood ratio test 1 **Model 1: COGNITIVE.PROBLEM ~ AGE + SEX + DRIVING + MATH + Performance** **Model 2: COGNITIVE.PROBLEM ~ DRIVING + Performance**					
Model	**Df**	**LogLik**	**Df**	**Chisq**	**Pr(>Chisq)**
1	6	-13.66			
2	3	-19.75	3	12.18	0.007
Likelihood ratio test 2 **Model 1: COGNITIVE.PROBLEM ~ AGE + SEX + DRIVING + MATH + Performance** **Model 2: COGNITIVE.PROBLEM ~ AGE + Performance**					
Model	**Df**	**LogLik**	**Df**	**Chisq**	**Pr(>Chisq)**
1	6	-13.66			
2	3	-18.58	3	9.842	0.019
Fitting null model for pseudo-r2					
llh	**llhNull**	**G2**	**McFadden**	**r2ML**	**r2CU**
-13.66	-27.03	26.74	0.49	0.36	0.60

variable, we have P≤0.05, providing evidence for the likely relevance of all five variables to predict the output of the model. Finally, an overall review of the significance of all inputs and their effects in predicting the output results is presented in the second part of Table 1. According to this result, we set two different definitions of the Logit model; model-1 (COGNITIVE.PROBLEM ~AGE+SEX+DRIVING+MATH+Performance) with all five inputs and model-2 (COGNITIVE.PROBLEM ~DRIVING+Performance) with the two more important inputs of performance and driving. The maximum likelihood function run in logistic regression gave us P=0.007, while X^2 (3, N=100) = 12.18 with this order. At the next step, to detect whether this definition of the fitted model makes sense or not, McFadden's pseudo R^2 was used, the result was 0.49.

Artificial Neural Network System Analysis

Figure 2 presents the extracted ANN model, which consists of five inputs and one output connected by three hidden layers.

Training Process, Loss Function, and Accuracy of Multi-Layer Neural Network

To examine the extracted NN model's accuracy and answer the final research question, a multi-layer NN model was run in 20 epoch cycles. The first quantity observed in training was the loss function in each epoch cycle, as shown in Figure 3 (left graph). Figure 3 (right graph) tracks the accuracy of training procedure when fitting the logistic model to the dataset.

The total accuracy score of the model was 0.8 in the Confusion Matrix of:
[8 0]
[2 0].

The confusion matrix shows that the model can accurately predict eight cases per 10 samples, which is associated no risk of cognitive problems.

Discussion

In this study, we first analyzed the impact of five different variables (namely age, gender, driving year experiences, field of study, and cognitive problems) on the participants' spatial orientation performance in a navigation task. Multiple linear regression analysis indicated that participants, especially the elders with cognitive problems deviated more from the destination. This is in line with the research background on aging and

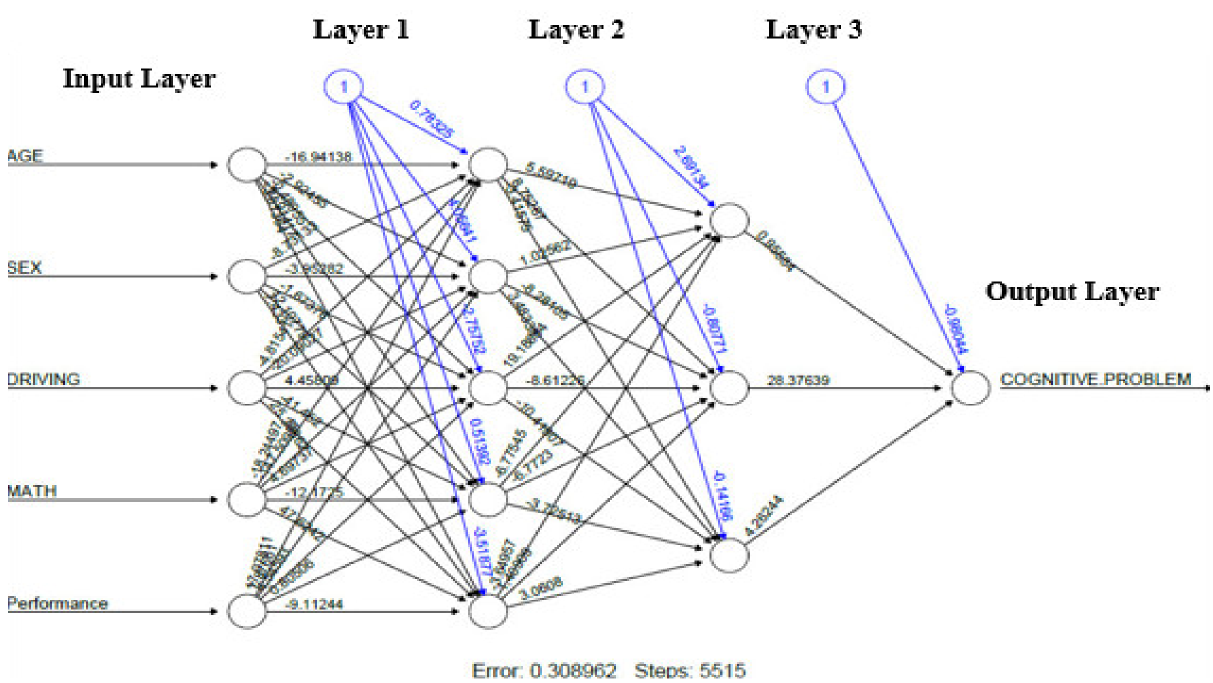

Figure 2. Probability Density Plot of Input variables (age, gender, years of driving experience, field of study & spatial orientation performance) and Output variable (risk of having a cognitive problem, deficit or impairments) with three hidden layers

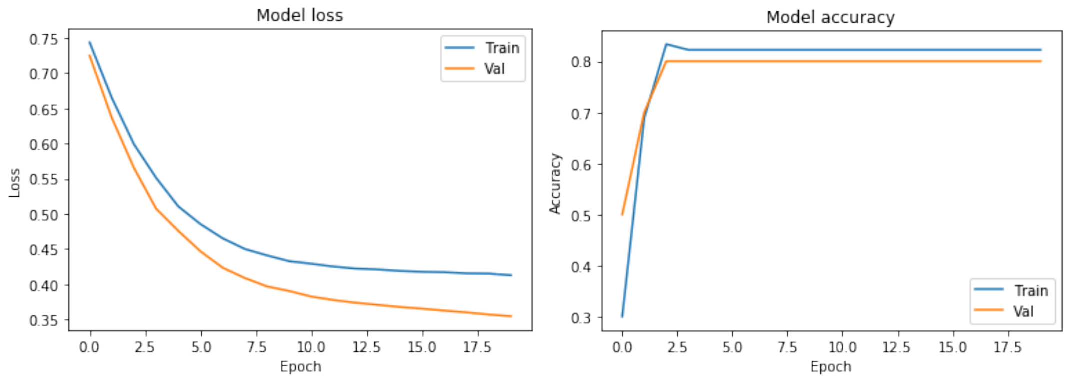

Figure 3. Left graph: A loss function in each of the 20 epoch cycles. Right graph: Training set vs. validation set (Loss and Accuracy graph).

spatial ability relevance in adults (17, 19). No significant relationship was found between gender and spatial performance of the participants, in contrast to the relevant studies (20-22) claiming that men had a higher spatial performance than women. According to Bairaktarova, Reyes, and Pe (27), Gunderson et al. (28), Hawes and Ansari (29), participants studying engineering or having more mathematical knowledge show significantly higher spatial performance in comparison to other participants; however, the findings of the present study were not in line with their finding.

Based on logistic regression analysis results, McFadden's pseudo R^2 was 0.49, indicating that the fitted model with five inputs (four demographic data; age, gender, years of driving experiences, and field of study in line with participants' spatial performance) can predict cognitive problems better than the null model with only intercept as the input variable. It can thus be concluded that the spatial orientation test and its observation by a mobile compass app or gyroscope can be an appropriate technique to determine individuals' spatial orientation ability, especially those with cognitive problems. This finding is in line with Flanagin, Fisher, Olcay, Kohlbecher, & Brandt's (2019) research, who criticized pencil-and-paper tests and recommended the method of measuring Azimuth and Elevation of rotation in a real spatial task as a complementary application of cognitive status.

In the neural network analysis, we tried to examine model accuracy by setting a multi-layer NN model by the logistic regression to the dataset and train and test it to predict the risk of cognitive problems from five inputs (four demographic variables, including age, gender, years of driving experience, and field of study in line with the participants' spatial performance). In the present study, the dataset was divided into training and test sets. The training set was used to optimize the prediction procedure, and the test set was a benchmark to calculate the model's accuracy in different training cycles. The NN model ran during 20 epoch cycles. The parameters initialized with random weights and biases and data shuffled to ensure data point samples induce an independent effect on the model. Moreover, 90% of the samples were used to train the NN model, and the other ten percent was used for validation by the three hidden layers. When performing a training dataset, it is important to track model accuracy from the validation sample. The first quantity we monitored during training was the loss function in any epoch cycle. With increasing epoch cycle, the model loss decreased, and the training set showed a decline at the end of the loss function compared to the validation set. This means the training set did a better job when fitting a logistic model than the validation set. We tracked training procedure accuracy when fitting the model to the dataset, and it was noticed that the training set's accuracy surpasses the validation set after the first epoch; however, the little gap indicates that the model is not capable enough and needs more parameters to perform better. This is while the model was well-fitted. The model's overall accuracy score was 0.8, a decent score for a human behavior model. The confusion matrix shows that the model can accurately predict eight among every ten samples with no cognitive problems.

Despite all these positive observations and promising results, our study had some limitations, including the use of Azimuth-based assessment of spatial orientation as a diagnostic tool for cognitive problems. Regarding the small sample size of the cognitive problems, the extracted NN model could not accurately identify positive (cognitive impaired) cases. The study sample was heterogeneous in terms of age, gender, and divergent cognitive impairments. This might affect the predicted findings as potent positive cases. Accordingly, it is recommended to include large sample size of individuals with a homologous spectrum of cognitive impairments to reach more reliable results.

Availability of Data and Materials

The data supporting the findings of this study are available upon the request from the corresponding author.

Ethical Considerations

In this study, the following ethical issues were considered: After obtaining the approval from the Education Department of Tarbiat Modares University, the research program began in October 2019 and ended in February 2020. At the beginning of the study, the researcher introduced herself, explained the objectives of the study, clarified the experimental setup and procedures, examined the participant's preliminary skills to perform the related task, and finally informed them that the extracted findings would be used in her Ph.D. thesis. Their willingness and satisfaction to participate in the test were considered, and they had the right to leave in any stage of the research. A voluntary written consent was also obtained from the study participants, and they were ensured of the confidentiality of their personal information.

Authors' Contributions

Z.G. designed the study concept and performed the analyses, coordinated the data collection procedure, and performed data collection. E.T. supervised the intervention, data collection, and analysis. O.N. critically revised the manuscript, and J.H. revised the manuscript.

Conflict of Interest

The authors declare that they have no conflict of interests.

Acknowledgments

We would like to express our gratitude to the participants, who were university students and the elderly from medical centers and pharmacies.

We thank three "anonymous" reviewers for their in-depth insights; however, any error is our fault and they are not to blame.

Funding/Support

No outside funding or support was provided for this study.

References

1 Diersch N, Wolbers T. The potential of virtual reality for spatial navigation research across the adult lifespan. Journal of Experimental Biology. 2019 Feb 6;222(Suppl 1). doi: 10.1242/jeb.187252
2 Robillard M, Roy-Charland A, Cazabon S. The role of cognition on navigational skills of children and adolescents with autism spectrum disorders. Journal of Speech, Language, and Hearing Research. 2018 Jul 13;61(7):1579-90. doi: 10.1044/2018_JSLHR-S-17-0206. PMid:29933432
3 Schaat S, Koldrack P, Yordanova K, Kirste T, Teipel S. Real-Time Detection of Spatial Disorientation in Persons with Mild Cognitive Impairment and Dementia. Gerontology. 2020;66(1):85-94. doi: 10.1159/000500971
4 Descloux V, Maurer R. Perspective taking to assess topographical disorientation:

Group study and preliminary normative data. Applied Neuropsychology: Adult. 2020 May 3;27(3):199-218. doi: 10.1080/23279095.2018.1528262
5 Bodien YG, Martens G, Ostrow J, Sheau K, Giacino JT. Cognitive impairment, clinical symptoms and functional disability in patients emerging from the minimally conscious state. NeuroRehabilitation. 2020 Jan 1(Preprint):1-0. doi: 10.3233/NRE-192860
6 Howett D, Castegnaro A, Krzywicka K, Hagman J, Marchment D, Henson R, Rio M, King JA, Burgess N, Chan D. Differentiation of mild cognitive impairment using an entorhinal cortex-based test of virtual reality navigation. Brain. 2019 Jun 1;142(6):1751-66. doi: 10.1093/brain/awz116
7 Vannier-Nitenberg C, Dauphinot V, Bongue B, Sass C, Bathsavanis A, Rouch I, Deville N, Beauchet O, Krolak-Salmon P, Fantino B. Performance of cognitive tests, individually and combined, for the detection of cognitive disorders amongst community-dwelling elderly people with memory complaints: the EVATEM study. European Journal of Neurology. 2016 Mar;23(3):554-61. doi: 10.1111/ene.12888
8 Cogné M, Taillade M, N'Kaoua B, Tarruella A, Klinger E, Larrue F, Sauzeon H, Joseph PA, Sorita E. The contribution of virtual reality to the diagnosis of spatial navigation disorders and to the study of the role of navigational aids: A systematic literature review. Annals of physical and rehabilitation medicine. 2017 Jun 1;60(3):164-76. doi: 10.1016/j.rehab.2015.12.004. PMid:27017533
9 Coughlan G, Laczó J, Hort J, Minihane AM, Hornberger M. Spatial navigation deficits—overlooked cognitive marker for preclinical Alzheimer disease?. Nature Reviews Neurology. 2018 Aug;14(8):496-506. doi: 10.1038/s41582-018-0031-x. PMid:29980763
10 Verghese J, Lipton R, Ayers E. Spatial navigation and risk of cognitive impairment: A prospective cohort study. Alzheimer's & Dementia. 2017 Sep 1;13(9):985-92. doi: 10.1016/j.jalz.2017.01.023. PMid:28264767 PMCid:PMC5582021
11 Vlček K, Laczó J. Neural correlates of spatial navigation changes in mild cognitive impairment and Alzheimer's disease. Frontiers in behavioral neuroscience. 2014 Mar 17;8:89. doi: 10.3389/fnbeh.2014.00089. PMid:24672452 PMCid:PMC3955968
12 Ventola CL. Mobile devices and apps for health care professionals: uses and benefits. Pharmacy and Therapeutics. 2014 May;39(5):356. PMID: 24883008
13 Flanagin VL, Fisher P, Olcay B, Kohlbecher S, Brandt T. A bedside application-based assessment of spatial orientation and memory: approaches and lessons learned. Journal of neurology. 2019 Sep 1;266(1):126-38. doi: 10.1007/s00415-019-09409-7. PMid:31240446 PMCid:PMC6722154
14 Sholl MJ, Acacio JC, Makar RO, Leon C. The relation of sex and sense of direction to spatial orientation in an unfamiliar environment. Journal of Environmental Psychology. 2000 Mar 1;20(1):17-28. doi: 10.1006/jevp.1999.0146
15 Allahyar M, Hunt E. The assessment of spatial orientation using virtual reality techniques. International Journal of Testing. 2003 Sep 1;3(3):263-75. doi: 10.1207/S15327574IJT0303_5
16 Wolbers T, Hegarty M. What determines our navigational abilities?. Trends in cognitive sciences. 2010 Mar 1;14(3):138-46. doi: 10.1016/j.tics.2010.01.001. PMid:20138795
17 Lester AW, Moffat SD, Wiener JM, Barnes CA, Wolbers T. The aging navigational system. Neuron. 2017 Aug 30;95(5):1019-35. doi: 10.1016/j.neuron.2017.06.037. PMid:28858613 PMCid:PMC5659315
18 Rusconi ML, Suardi A, Zanetti M, Rozzini L. Spatial navigation in elderly healthy subjects, amnestic and non amnestic MCI patients. Journal of the neurological sciences. 2015 Dec 15;359(1-2):430-7. doi:

10.1016/j.jns.2015.10.010. PMid:26478129
19 Rodgers MK, Sindone III JA, Moffat SD. Effects of age on navigation strategy. Neurobiology of aging. 2012 Jan 1;33(1):202-e15. doi: 10.1016/j.neurobiolaging.2010.07.021. PMid:20832911 PMCid:PMC4283776
20 Boone AP, Gong X, Hegarty M. Sex differences in navigation strategy and efficiency. Memory & cognition. 2018 Aug 1;46(6):909-22. doi: 10.3758/s13421-018-0811-y. PMid:29790097
21 Scali RM, Brownlow S, Hicks JL. Gender differences in spatial task performance as a function of speed or accuracy orientation. Sex roles. 2000 Sep 1;43(5-6):359-76. doi: 10.1023/A:1026699310308
22 Tzuriel D, Egozi G. Gender differences in spatial ability of young children: The effects of training and processing strategies. Child development. 2010 Sep;81(5):1417-30. doi: 10.1111/j.1467-8624.2010.01482.x. PMid:20840231
23 Amick MM, Grace J, Ott BR. Visual and cognitive predictors of driving safety in Parkinson's disease patients. Archives of Clinical Neuropsychology. 2007 Nov 1;22(8):957-67
24 Bernardi G, Cecchetti L, Handjaras G, Sani L, Gaglianese A, Ceccarelli R, Franzoni F, Galetta F, Santoro G, Goebel R, Ricciardi E. It's not all in your car: functional and structural correlates of exceptional driving skills in professional racers. Frontiers in human neuroscience. 2014 Nov 11;8:888. doi: 10.3389/fnhum.2014.00888
25 Schultheis MT, Weisser V, Ang J, Elovic E, Nead R, Sestito N, Fleksher C, Millis SR. Examining the relationship between cognition and driving performance in multiple sclerosis. Archives of physical medicine and rehabilitation. 2010 Mar 1;91(3):465-73. doi: 10.1016/j.apmr.2009.09.026. PMid:20298841
26 Weisberg SM, Schinazi VR, Newcombe NS, Shipley TF, Epstein RA. Variations in cognitive maps: Understanding individual differences in navigation. Journal of Experimental Psychology: Learning, Memory, and Cognition. 2014 May;40(3):669. doi: 10.1037/a0035261. PMid:24364725
27 Bairaktarova D, Reyes M, PE MN. Spatial skills development of engineering students: Identifying instructional tools to incorporate into existing curricula. age. 2015 Jun 14;26:1. doi: 10.18260/p.24726
28 Gunderson EA, Ramirez G, Beilock SL, Levine SC. The relation between spatial skill and early number knowledge: the role of the linear number line. Developmental psychology. 2012 Sep;48(5):1229. doi: 10.1037/a0027433. PMid:22390659
29 Hawes Z, Ansari D. What explains the relationship between spatial and mathematical skills? A review of evidence from brain and behavior. Psychonomic Bulletin & Review. 2020 Jan 21:1-8. doi: 10.3758/s13423-019-01694-7. PMid:31965485
30 Hawes Z, Moss J, Caswell B, Seo J, Ansari D. Relations between numerical, spatial, and executive function skills and mathematics achievement: A latent-variable approach. Cognitive Psychology. 2019 Mar 1;109:68-90. doi: 10.3389/fpsyg.2018.00755. PMid:29915547 PMCid:PMC5994429
31 Young CJ, Levine SC, Mix KS. The connection between spatial and mathematical ability across development. Frontiers in psychology. 2018 Jun 4;9:755. doi: 10.3389/fpsyg.2018.00755. PMCid:PMC5994429
32 Lavrakas PJ. Encyclopedia of survey research methods. Sage publications; 2008 Sep 12. doi: 10.4135/9781412963947.n61
33 de Winter JC, Gosling SD, Potter J. Comparing the Pearson and Spearman correlation coefficients across distributions and sample sizes: A tutorial using simulations and empirical data. Psychological methods. 2016 Sep;21(3):273. doi: 10.1037/met0000079. PMid:27213982
34 Dreiseitl S, Ohno-Machado L. Logistic regression and artificial neural network classification models: a methodology

review. Journal of biomedical informatics. 2002 Oct 1;35(5-6):352-9. doi: 10.1016/S1532-0464(03)00034-0

35 Liu J, Shang S, Zheng K, Wen JR. Multi-view ensemble learning for dementia diagnosis from neuroimaging: An artificial neural network approach. Neurocomputing. 2016 Jun 26;195:112-6. doi: 10.1016/j.neucom.2015.09.119

36 Pradhan B, Lee S. Delineation of landslide hazard areas on Penang Island, Malaysia, by using frequency ratio, logistic regression, and artificial neural network models. Environmental Earth Sciences. 2010 May 1;60(5):1037-54. doi: 10.1007/s12665-009-0245-8

37 Elshorbagy A, Simonovic SP, Panu US. Performance evaluation of artificial neural networks for runoff prediction. Journal of Hydrologic Engineering. 2000 Oct;5(4):424-7. doi: 10.1061/(ASCE)1084-0699(2000)5:4(424

38 Lino A, Rocha Á, Sizo A. Virtual teaching and learning environments: automatic evaluation with artificial neural networks. Cluster Computing. 2019 May 1;22(3):7217-27. doi: 10.1007/s10586-017-1122-y

39 YAKUT E, GUNDUZ M, DEMİRCİ A. Comparison of classification success of human development index by using ordered logistic regression analysis and artificial neural network methods. J Appl Quant Methods. 2015 Sep 1;10(3):15-34. doi: 10.20491/isader.2015415532

40 Sikder MF, Uddin MJ, Halder S. Predicting students yearly performance using neural network: A case study of BSMRSTU. In2016 5th International Conference on Informatics, Electronics and Vision (ICIEV) 2016 May 13 (pp. 524-529). IEEE. doi: 10.1109/ICIEV.2016.7760058