Movement Entropy in a Gardening Design Task as a Diagnostic Marker for Mental Disorders: Results of a Pilot Study

Sebastian Unger[1], Sebastian Appelbaum[2], Thomas Ostermann[2] and Christina Niedermann[2,3]
[1]*Didactics and Educational Research in Health Science, Witten/Herdecke University, Germany*
[2]*Methods and Statistics in Psychology, Faculty of Health, Witten/Herdecke University, Germany*
[3]*Fine Arts, University of Applied Sciences and Arts Ottersberg, Germany*

Keywords: Mental Health, Garden Design, Movement Analysis, Heatmap Analysis, Entropy, Homography.

Abstract: Movement, actions, and intentions are important psychological skills in human behavior. Studies have shown correlations between movement activity and a variety of mental disorders. In this context, planning and designing of gardens and outdoor spaces as an intentional activity might play an important role as a marker for mental health. Thus, in this study, 16 subjects (8 female) aged between 19 and 60 were asked to do a gardening task in an experimentally constructed environment while their movement activity was recorded with a camera from a fixed viewpoint. Movement heatmaps and entropy then was calculated and correlated with mental state measured via the Global Severity Index (GSI) of the Brief Symptom Inventory (BSI-18) questionnaire. After finding an optimal grid size of the heatmaps, we were able to find a moderate negative correlation of $r = -0.463$ between these quantities in an overall of both genders, explaining 21.4 % of variance. After considering the gender of the test group, a noticeable gender effect could be revealed. We found a significant interaction effect of entropy with gender meaning that a lower movement entropy in a gardening task correlates with a higher mental distress for men, but lower for women. Multivariate regression found that this model explained 77.44 % of variance (R = 0.88). Despite of these promising results, further investigations in this area should overcome some limitations in this pilot study in the field of position tracking and movement feature extraction.

1 INTRODUCTION

Movement, actions, and intentions are important psychological skills in human behavior. A recent systematic review of the relationships between motor proficiency physical abilities and academic performance in mathematics and reading tasks showed that motor proficiency was able to predict the academic performances of children and adolescents, in particular in the early years of school (Macdonald et al., 2018). Other reviews from the field of clinical psychology showed correlations between pathological movement features and a variety of mental disorders. A recent review of Rohani et al. (2018) found significant correlations between behavioral features and depressive mood symptoms in adults, while the review of Zhu et al. (2019) found that physical activity of children and adolescents is associated with a reduced risk of experiencing anxiety. Other studies in patients suffering from dementia reported in (Collier et al., 2018) suggest that human movement analysis can be used as a diagnostic marker for early dementia. In this respect, the intentional meaning of movement seems to play an important role. According to (Clark et al., 2015; p.1) mindful movement "may improve the functional quality of rehearsed procedures, cultivating a transferrable skill of attention".

Hence and in agreement with the findings of (O'Brien et al., 2017), continuous and everyday monitoring of activity and motion could be a promising real-world biomarker for early detection of mental disorders.

With respect to the definition of "real world", studies in elderly populations found that the planning and designing of gardens and outdoor spaces was attributed as an intentional activity with importance for active daily living (Kim and Ohara, 2010; Milke et al., 2009; Wang and Glicksman, 2013; Yen et al., 2014). Moreover, gardening seems to have a low threshold with respect to participation and a high degree of prior experience or interest for a broad range of participants (Bleasdale et al., 2011).

Unger, S., Appelbaum, S., Ostermann, T. and Niedermann, C.
Movement Entropy in a Gardening Design Task as a Diagnostic Marker for Mental Disorders: Results of a Pilot Study.
DOI: 10.5220/0010227203370343
In *Proceedings of the 14th International Joint Conference on Biomedical Engineering Systems and Technologies (BIOSTEC 2021) - Volume 5: HEALTHINF*, pages 337-343
ISBN: 978-989-758-490-9

Our pilot study thus aimed at investigating, how gardening activity could be assessed and used as a diagnostic marker in an experimental setting. We therefore used human movement entropy. As described in (O'Brien et al., 2017), entropy is interpreted as a measure that describes how "vital" a movement is. Low entropy thus represents stationary and slow movement, while a high entropy is associated with expansive and faster movement behavior.

According to a study of Rohani et al. (2018) movement entropy was found to have a negative correlation with mental burden. Thus, a high entropy would indicate a better mood of the participants, which is the underlying hypothesis of this pilot study.

2 METHODS

2.1 Setting and Participants

The study was announced in the Witten/Herdecke University and University staff members, their relatives and friends and students were invited to participate in the study on a voluntary basis.

Prior to the gardening task, all participants had to sign an informed consent form and were asked to complete a questionnaire, including demographic items such as age, gender, self reported gardening experience, creativity as well as the Brief Symptom Inventory (BSI-18) to assess the mental state expressed by the global severity index (GSI) of the BSI-18 (Spitzer et al., 2011).

The main task for the participants consisted in creating a landscape in a 2.5 x 2.5 m squared sandpit area (Figure 1) in a maximum of 30 min (minutes).

Material to be used included plants, flowers, branches and stones. They were allowed to use the full space of the gardening area and were not limited in their spatial movement or in times of resting. Participants started from an identical point and were videotaped with a user-independent camera installed on a tripod at a height of 1.50 m and a 30-degree angle.

Ethical approval for this study was obtained from the ethical committee of Arts Therapies of the University of Applied Science, Nürtingen. The complete study description is provided in (Niedermann and Ostermann, 2019).

2.2 Data Acquisition

To analyze movement behavior, all videos of the test group were played by a self-developed windows application to manually track the positions of the participants. For this task, five psychology students (3females and 2 males between the ages 21 and 24) from the Department of Psychology and Psychotherapy of the Witten/Herdecke University volunteered. They were asked to always follow the movements of the subjects by holding the mouse pointer as near as possible to the subjects' ankle. Since some of the videos were quite long and the student's ability to concentrate should not be overstrained, they could pause the movement tracking process at any time. During this period, the tracking automatically stopped.

A

B

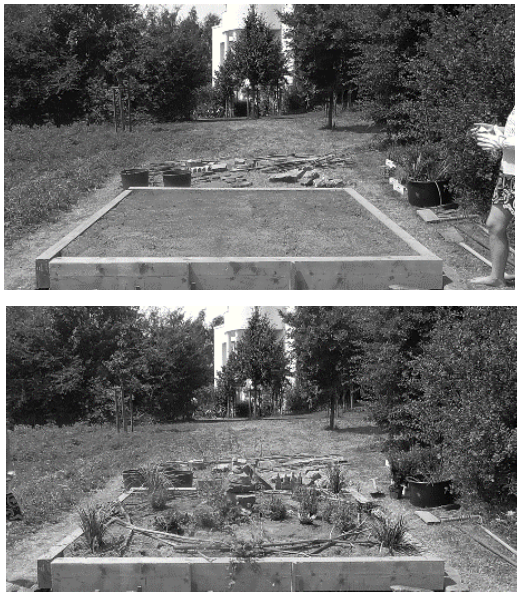

Figure 1: Setting of the sandpit from the camera perspective (a) before and (b) after the gardening task.

In order to compensate distortions and other sources of error that could arise from the tracking, the whole set of the videos was fed through the analysis software of each individual volunteer as shown in Figure 2. While the students followed the movements,

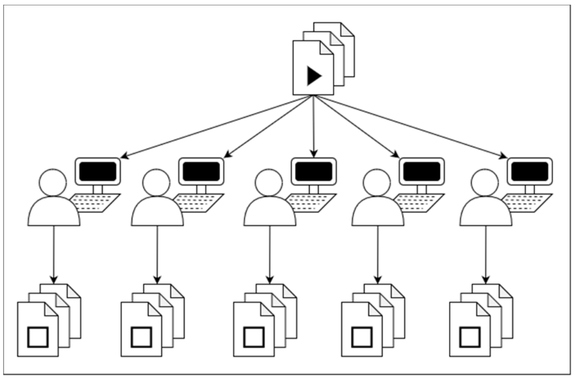

Figure 2: Experimental setup.

a background process tracked the position of the mouse pointer. The interval between two time points was set at 100 ms (milliseconds). Due to the 30-degree angle between camera and ground, the collected coordinates (x_i, y_i) were transformed by a homography approach.

This approach is based on the Direct Linear Transform (DLT), which uses a 2D (two-dimensional) transformation matrix H (Hartley and Zissermann, 2003). For the calculation of this 3 x 3 normalized matrix, a special case was considered, i.e. there were 8 degrees of freedom and the position h_{33} was set to one. The remaining eight 2D points (P_1 ... P_4 and P'_1 ... P'_4) were obtained by measuring the corners of the projected sandpit using the following formula:

$$(A^T \times A)^{-1} \times (A^T \times B) = \begin{pmatrix} h_1 \\ \vdots \\ h_8 \end{pmatrix} \tag{1}$$

For each point pair P_j and P'_j (j = 1…4) two rows of the matrix A were calculated as follows:

$$\begin{pmatrix} P_{j_x} & 0 \\ P_{j_y} & 0 \\ 1 & 0 \\ 0 & P_{j_x} \\ 0 & P_{j_y} \\ 0 & 1 \\ -P_{j_x} \times P'_{j_x} & -P_{j_x} \times P'_{j_y} \\ -P_{j_y} \times P'_{j_x} & -P_{j_y} \times P'_{j_y} \end{pmatrix}^T = \begin{pmatrix} a_{1+(j-1)\times 2} \\ a_{2+(j-1)\times 2} \end{pmatrix} \tag{2}$$

The same algorithm was applied to matrix B, except that only the projection points were needed:

$$\begin{pmatrix} P'_{j_x} & P'_{j_y} \end{pmatrix}^T = \begin{pmatrix} b_{1+(j-1)\times 2} \\ b_{2+(j-1)\times 2} \end{pmatrix} \tag{3}$$

Figure 3 visualizes the viewpoints, one (O) that is related to the location of the camera and is the state before the transformation and one (O') that represents the state after the homography was applied. Both point in the direction of the sandpit. The two 2D planes that are located in between show the resulting sandpit from each view. Whereas it is formed as an isosceles trapezoid near the bottom, looking from viewpoint O, from viewpoint O' it is drawn as square, which is in the middle of its plane.

The whole data, including the calculated coordinates, video length, video identifier and date, was exported as a comma-separated values file (CSV-file) for further statistical analysis.

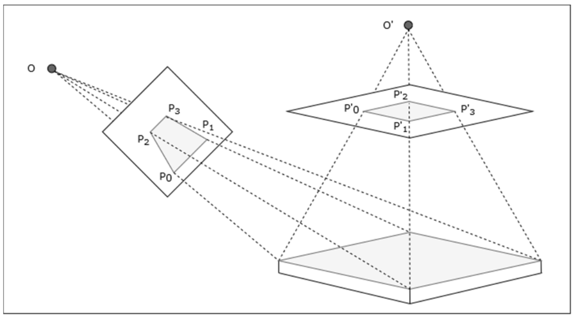

Figure 3: Viewpoints toward the sandpit.

2.3 Data Processing

For data processing, the images from the total of five data sets were combined into a single one for each of the 16 videos, using a special algorithm implemented in *R*, which summarized the pixel coordinates of the related images in disjoint intervals with a span of 0.5 s (seconds). Every interval contained around 20 measurement points, from which the median was taken to set the pixel of the final image. Compared to averaging with the mean, the advantage of this method is that the original trace of the subjects could be retained.

Based on the approach of (Riungu et al., 2018) who analyzed park visitors' spatial behavior, heatmaps were created as a graphical aid to analyze place and frequency of the participants' movement in the work environment. In this heatmaps, any point that was ever visited from the participant were highlighted in color. The range of the colors starts with dark red, meaning that the pixel coordinate was tracked once. If there is more than one visit, a lighter color is indicated, up to a pure white, which denotes the highest visiting frequency. All other pixels of the output image, i.e. coordinates that never occurred at least once, remained in a dark black.

Based on the distribution of the movement, Shannon's entropy E was calculated. It is based on a system of mutually exclusive and exhaustive spatial clusters A_1, A_2, …, A_n and a set of probabilities $p_1 := p(A_1)$, $p_2 := p(A_2)$, …, $p_n := p(A_n)$, describing the probability of having visited a respective cluster (Ostermann and Schuster., 2015), and has been applied in a variety of settings in health services research. Then, the entropy is given by

$$E(p_1, \ldots, p_n) = -\sum_{k=1}^{n} p_k \log p_k \tag{4}$$

where $0 \times \log 0 = 0$ is assumed.

Because of an unknown optimal grid size for producing the maps, several densities were used in order to find the optimal resolution, regarding to the cluster dimension. For that reason, Pearson's correlation coefficient of the global severity index GSI and the movement entropy was calculated and plotted against the grid size g of the clusters. In a final step, a curve was fitted through the points using an ordinary least square (OLS) approach. We assumed a convergence of the correlation from a certain grid size and thus used the exponential approach

$$r = ae^{-bg} + c \tag{5}$$

to fit the curve. After the parameters a, b, and c were found, the optimal grid was determined for the grid size g where the tangent had a slope $m = -1$. This specific point divides the e-function into two symmetrically equal parts and was determined using the first derivation:

$$r' = -ba \times e^{-bg} = -1 \tag{6}$$

To detect for further associations, we finally fitted a multivariate regression model with the GSI as dependent variable and entropy, gender and two self-assessed items (gardening experience and creativity) as independent variables.

3 RESULTS

Sixteen individuals (8 female) aged between 19 and 60 years ($\bar{x}_{age} = 28.67$ years) participated in this pilot study. Scores of the GSI showed a range of 2 to 27 points indicating a low to moderate mental burden. The length of the videos ranged between 4.00 min to 30.00 min ($\bar{x}_{length} = 23.00$ min).

An example of the trajectory lines is given in Figure 4. This example shows two dissimilar movement styles. The tracing lines on the left belongs to a participant with an extraordinarily high GSI value. Other than the trajectories on the right, which visualizes the active movement style of a participant with a very low GSI value, these lines visually seem less condensed and thin while the trajectories on the right are bold indicating a higher pixel density and thus a more active movement in the same area.

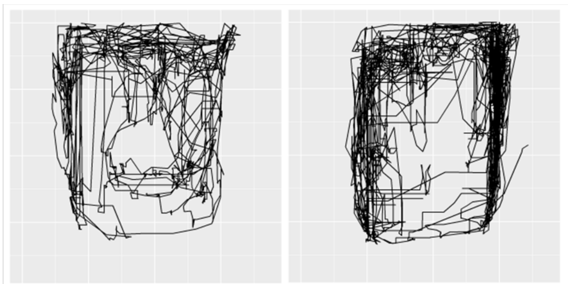

Figure 4: Trajectory lines of a participant with a high BSI on the left and a participant with a low BSI on the right. The white lines exemplify a given grid.

Figure 5 displays four heatmaps, corresponding to the right participant of Figure 4. The maps were created by using different grid sizes. From left to right and from top to bottom, the raster increases in width and height. A closer look reveals that this increases the image resolution, too. If these heatmaps were compared to those from the left participant of Figure 4, the latter would show a much lower distribution of track points, resulting in an inferior entropy.

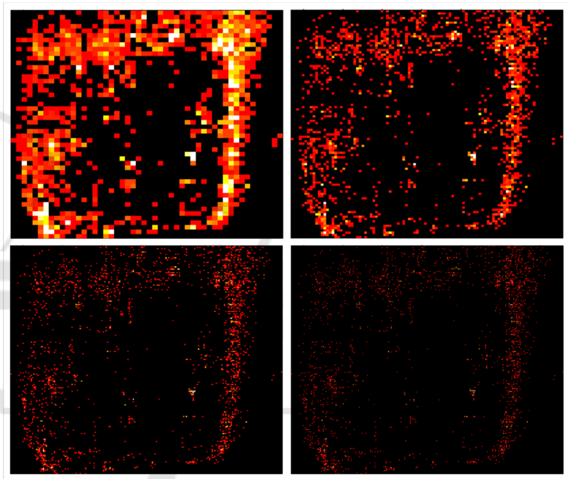

Figure 5: Heatmaps using different raster sizes. Top left ≙ *50 x 50*. Top right ≙ *100 x 100*. Bottom left ≙ *200 x 200*. Bottom right ≙ *300 x 300*.

Pearson's correlation coefficient of the global severity index GSI and the movement entropy plotted against the grid size g of the clusters is displayed in Figure 6. The red line denotes the curve found by OLS-regression and is given by the following exponential function:

$$r = 0.44\, e^{-0.023g} - 0.476 \tag{7}$$

Using equation (6), an optimal grid was found at $g = 198.8$, which resulted in a rounded grid size of *200 x 200* considered as optimum.

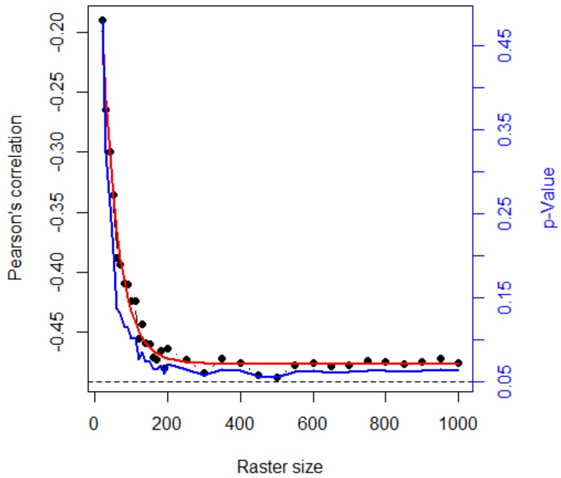

Figure 6: Correlation between the size of the raster and Pearsons's r (approximated as red curve) as well as the corresponding p values (blue curve).

Looking at the optimum point, the Pearson's correlation value of $r_0 = -0.463$ nearly reached the maximum of all the values, which ranged between $r_{min} = -0.19$ and $r_{max} = -0.487$. Statistical significance with a value of $p_0 = 0.071$ was slightly missed and ranged between $p_{min} = 0.48$ and $p_{max} = 0.056$ for all grid sizes (see the blue line in Figure 6).

Thus as a first result, it could be assumed that a more vital and spacious movement can be associated with lower mental burden which is displayed in the bottom graph of Figure 7, in which the GSI is plotted against the movement entropy for all participants for the optimal grid size.

However, a closer examination of the dataset by dividing it into two gender-based subgroups revealed a clear gender specific effect, similar as found by Van Tuyckom et al. (2012). The assumption made above only applies to males (top graph of Figure 7), while females participants behaved in the complete opposite way (middle graph of Figure 7), presumably to compensate their depressive mood with an increased activity in order to achieve a feeling of satisfaction by looking at their work of art afterwards on the gardening task (Milligan et. al., 2004).

In addition to the visual illustration of the gender effect, it was also statistically verified: whereas the correlation between the GSI and the entropy strongly increased in the females' group ($r_{females} = 0.661$), there was an extremely sharp decrease in the correlation line for the males ($r_{males} = -0.922$).

Finally, using a multiple regression model with the independent variables entropy, gender and the product of both, a high significance could be obtained ($p < 0.001$ for all predictors; $r = 0.88$). Other

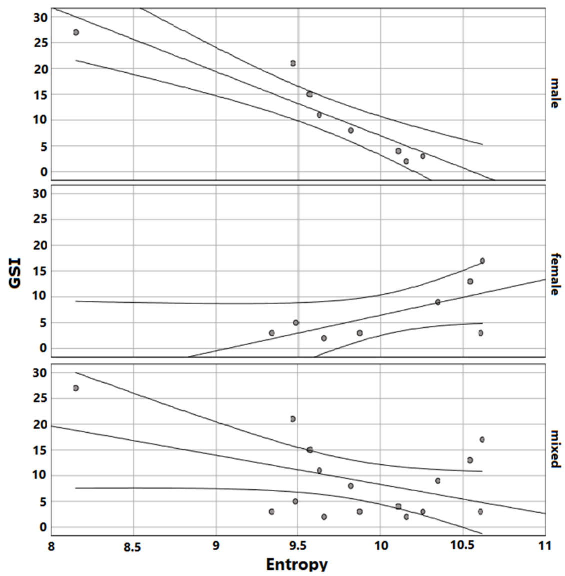

Figure 7: GSI plotted against the movement entropy for all participants for the optimal grid size of $g = 200 \times 200$ separated into three gender groups.

variables such as self reported gardening experience or creativity did not have any influence on the outcome as it is shown in Table 1 below.

Table 1: Results of the multivariate regression model.

Variable	Standardized β	Significance
Entropy	-2.544	0.001
Gender	-13.086	0.001
Entropy × Gender	13.841	0.001
Experience	0.001	0.995
Creativity	0.117	0.518

4 CONCLUSIONS

In the field of garden and landscape design, therapeutic studies have already shown effectiveness (Clatworthy et al., 2013). In the field of diagnostics, however, there were so far only rudimentary approaches to record corresponding movement and behavior patterns.

In this pilot study we thus aimed at investigating, whether a reduced spatial movement in a gardening task was related to higher value of mental distress. By using a movement entropy approach and after finding an optimal grid size, we finally were able to find a highly significant association between these quantities, which however were moderated by gender and explained 77.4 % of variance. We thus can assume that depending on the gender, movement entropy in a gardening task is significantly associated with mental distress.

This result is in accordance with other findings in the field of human movement analysis. In the Systematic Review of Rohani et al. (2018), entropy amongst other features was the most promising candidate to predict mental distress in 6 of 46 included studies. Moreover, the amount of explained variance was also comparable with the results of an exploratory study (Saeb et al, 2015) on depressive symptom severity in daily-life behavior and normalized entropy as an indicator of mobility between favorite locations ($r^2 = 33.64$ %, $p = 0.012$).

Other approaches which examined the movement patterns in drawing tests also found associations of cognitive impairment and drawing entropy (Robens et al., 2019). And in contrast to potentially similar measures like pixel density (Unger et al., 2020), the association between entropy and the GSI was more pronounced.

From a methodological point of view, a further important effect could be discovered. Changing the size of the raster that ran over the input images had a clear impact on the correlation of entropy and GSI: The larger the dimensions was adjusted, the higher was the amount of correlation. This went down until a raster size of around *300 x 300* pixels after which the amount of coefficient seemed to stagnate.

An explanation for this effect could be that a raster with a lower resolution only generates heatmaps, in which the clusters for the calculation are too close together. However, the constant course of the curve, after reaching the optimal value at a grid size of 200, could be an indicator that the true value of r is located within this area.

Despite of these promising results, there are also some limitations. First of all, the number of participants is too low to draw any statistically robust conclusions out of our analyses. As this study was a pilot study, we did not primarily focus on a sufficient sample size to detect significant correlations, but rather tried to investigate the feasibility of the approach. Thus, our conclusions have to be interpreted with care.

In addition, other specific factors would be expected to influence movement entropy such as creativity or previous gardening experience. Although this was only a pilot study we were able to show, that these variables did not influence our results, indicating that no prior gardening experience or a special amount of creativity is needed. However, further studies should try to replicate our results with a higher sample size to determine whether the results remain stable.

Moreover, our result could be improved by looking at the intersection lines that would result from connecting two geographic tracing points. On the other hand, this method is much more complex and would rather appreciate the precise position of the subjects.

From a technical point, the automatic object detection and electronic tracking methods as summarized in (Hatwar et al., 2018) might be used to get a more precise picture of movement patterns. In addition, the markerless measurement and evaluation of kinetic features as proposed in (Trujillo et al., 2019) might also contribute to a more differentiated movement analysis without deterioration of the original setup and might produce more reliable data.

REFERENCES

Bleasdale, T., Crouch, C., & Harlan, S. L. (2011). Community gardening in disadvantaged neighborhoods in Phoenix, Arizona: Aligning programs with perceptions. *Journal of Agriculture, Food Systems, and Community Development, 1(3)*, 99-114.

Clark, D., Schumann, F. & Mostofsky, S.H. (2015). Mindful movement and skilled attention. *Frontiers in Human Neuroscience*, *9*, 297.

Clatworthy, J., Hinds, J. & Camic, M.P. (2013). Gardening as a mental health intervention: a review. *Mental Health Review Journal*, *18*(4), 214–225.

Collier, S., Monette, P., Hobbs, K., Tabasky, E., Forester, B. P. & Vahia, I. V. (2018). Mapping Movement: Applying Motion Measurement Technologies to the Psychiatric Care of Older Adults. *Current Psychiatry Reports*, *20*(8), 64.

Ghosh, S. & Ghosh, S.K. (2018). Exploring the association between mobility behaviours and academic performances of students: a context-aware traj-graph (CTG) analysis. *Progress in Artificial Intelligence*, *7*(4), 307–326.

Hartley, R. & Zisserman, A. (2003). *Multiple view geometry in computer vision* (2nd ed.). Cambridge University Press.

Hatwar, R.B., Kamble, S.D., Thakur, N.V. & Kakde, S. (2018). A Review on Moving Object Detectionand Tracking Methods in Video. *International Journal of Pure and Applied Mathematics*, *118*(16), 511–526.

Kim, D. & Ohara, K. (2010). A Study on the Role of Gardening and Planning of Green Environments for Daily Use by Residents in Senior Housing. *Journal of Asian Architecture and Building Engineering*, *9*(1), 55–61.

Macdonald, K., Milne, N., Orr, R., & Pope, R. (2018). Relationships between motor proficiency and academic performance in mathematics and reading in school-aged children and adolescents: a systematic review. *International journal of environmental research and public health*, 15(8), 1603.

Milke, D.L., Beck, C.H.M., Danes, S. & Leask, J. (2009). Behavioral Mapping of Residents' Activity in Five Residential Style Care Centers for Elderly Persons Diagnosed with Dementia: Small Differences in Sites Can Affect Behaviors. *Journal of Housing for the Elderly*, *23*(4), 335–367.

Milligan, C., Gatrell, A. & Bingley, A. (2004). Cultivating health: therapeutic landscapes and older people in northern England. *Social Science & Medicine*, *58*, 1781–1793.

Niedermann, C. & Ostermann, T. (2019). Zur Bedeutung von Gartengestaltung für die Erfassung mentaler Gesundheit: Konzeptentwurf eines Pilotprojekts. In C. Schulze-Stampa & K. Schoch (Eds.), *In/ter/ven/tion: in mit durch Kunst* (5th ed., pp. 58–63). Hochschule für Künste im Sozialen Ottersberg.

O'Brien, J. T., Gallagher, P., Stow, D., Hammerla, N., Ploetz, T., Firbank, M., Ladha, C., Ladha, K., Jackson, D., McNaney, R., & Ferrier, I. N. (2017). A study of wrist-worn activity measurement as a potential real-world biomarker for late-life depression. *Psychological medicine*, 47(1), 93-102.

Ostermann, T., & Schuster, R. (2015). An Information-theoretical Approach to Classify Hospitals with Respect to Their Diagnostic Diversity using Shannon's Entropy. *Proceedings of the International Conference on Health Informatics* 2015: 325-329.

Riungu, G. K., Peterson, B. A., Beeco, J. A. & Brown, G. (2018). Understanding visitors' spatial behavior: a review of spatial applications in parks. *Tourism Geographies*, *20*(5), 833–857.

Robens, S., Heymann, P., Gienger, R., Hett, A., Müller, S., Laske, C., Loy, R., Ostermann, T. & Elbing, U. (2019). The Digital Tree Drawing Test for Screening of Early Dementia: An Explorative Study Comparing Healthy Controls, Patients with Mild Cognitive Impairment, and Patients with Early Dementia of the Alzheimer Type. *Journal of Alzheimer's Disease: JAD*, *68*(4), 1561–1574.

Rohani, D. A., Faurholt-Jepsen, M., Kessing, L. V., & Bardram, J. E. (2018). Correlations between objective behavioral features collected from mobile and wearable devices and depressive mood symptoms in patients with affective disorders: systematic review. *Journal of medical Internet research, mHealth and uHealth*, 6(8), e165.

Spitzer, C., Hammer, S., Löwe, B., Grabe, H. J., Barnow, S., Rose, M., Wingenfeld, K., Freyberger, H. J. & Franke, G. H. (2011). The short version of the Brief Symptom Inventory (BSI -18): preliminary psychometric properties of the German translation. *Fortschritte der Neurologie-Psychiatrie*, *79*(9), 517–523.

Saeb, S., Zhang, M., Karr, C. J., Schueller, S. M., Corden, M. E., Kording, K. P., & Mohr, D. C. (2015). Mobile phone sensor correlates of depressive symptom severity in daily-life behavior: an exploratory study. *Journal of medical Internet research*, 17(7), e175.

Trujillo, J.P., Vaitonyte, J., Simanova, I. & Özyürek, A. (2019). Toward the markerless and automatic analysis of kinematic features: A toolkit for gesture and movement research. *Behavior Research Methods*, *51*(2), 769–777.

Unger, S., Ostermann, T., Appelbaum, S. & Niedermann, C. (2021). Tracking Human Spatial Motion in the Design of Gardens as a Potential Method to detect Mental Disorders – A Pilot Study. *Acta Horticulture*, Accepted for publication.

Van Tuyckom, C., Van de Velde, S., & Bracke, P. (2012). Does country-context matter? A cross-national analysis of gender and leisure time physical inactivity in Europe. *European Journal of Public Health*, *23*(3), 452–457.

Wang, D. & Glicksman, A. (2013). "Being Grounded": Benefits of Gardening for Older Adults in Low-Income Housing. *Journal of Housing for the Elderly*, *27*(1-2), 89–104.

Yen, I. H., Flood, F. J., Thompson, H., Anderson, L. A. & Wong, G. (2014). How design of places promotes or inhibits mobility of older adults: Realist synthesis of 20 years of research. *Journal of Aging and Health*, *26*(8), 1340–1372.

Zhu, X., Haegele, J. A., & Healy, S. (2019). Movement and mental health: Behavioral correlates of anxiety and depression among children of 6–17 years old in the US. *Mental Health and Physical Activity*, 16, 60-65.