Novices Make More Noise!
The D&K Effect 2.0?

Schneider, Jan; Mat Sanusi, Khaleel Asyraaf; Limbu, B.H.; Schmitz, Marcel; Schiffner, Daniel

Publication date
2023

Document Version
Final published version

Published in
CrossMMLA 2023

Citation (APA)
Schneider, J., Mat Sanusi, K. A., Limbu, B. H., Schmitz, M., & Schiffner, D. (2023). Novices Make More Noise! The D&K Effect 2.0? In D. Di Mitri , N. Srivastava , R. Martinez-Maldonado, & M. Cukurova (Eds.), *CrossMMLA 2023: Leveraging Multimodal Data for Generating Meaningful Feedback* (Vol. 3439, pp. 43-48). (CEUR Workshop procedings; Vol. 3439). CEUR-WS. https://ceur-ws.org/Vol-3439/paper6.pdf

Novices Make More Noise! The D&K Effect 2.0?

Jan Schneider [1], Khaleel Asyraaf Mat Sanusi [2], Bibeg Limbu[3], Marcel Schmitz[4], and Daniel Schiffner[1]

[1] *DIPF | Leibniz Institute for Research and Information in Education, Frankfurt, Germany*
[2] *Cologne Game Lab, TH Köln, Cologne, Germany*
[3] *Center for Education and Learning, TU Delft, The Netherlands*
[4] *Zuyd University of Applied Sciences, Heerlen, The Netherlands*

Abstract

This paper presents an approach that helps distinguish expert and novice performance easily by observing the sensor data without having to understand nor apply models to the sensor signal. The method consists of plotting the sensor data and identifying irregularities. We corroborate, with the help of sensors, that expert performances are smoother, contain fewer irregularities, and have consistently uniform patterns than novice performances. In this paper, we present six different cases pointing out this assertion, namely bachata and salsa dances, tennis swings, football penalty kicks, badminton, and running.

Keywords

Multimodal Learning Analytics, Sensors, Signal Interpretation, Equity, Diversity and Inclusion

1. Introduction

In recent years, a multiplicity of smart devices with sensing capabilities have been introduced to the market, hence, nowadays it is common for ordinary people to own and use these devices regularly. In the particular area of Human Learning, sensing technologies support the cognitive, affective, and psychomotor domains of learning especially by aiding the collection of important data and the provision of feedback to learners [1]. Sensing technologies can also be used to record/model expert performance and use it to train novices [2].

Sensor data is usually noisy, and difficult to interpret. Moreover, in many learning scenarios, the stream of data captured by one sensor might not be sufficient to make sense of the learning task. For example, while training public speaking skills, the voice, words, gestures, and posture of the presenter should be congruent. Therefore, to train it effectively, multiple modalities and thus sensors need to be used to capture the learning performance. If one modality is already difficult to analyze, using multiple modalities just complicates everything. The study of Di Mitri et al., [3] proposes a model to make sense of the multimodal data through machine learning and use the machine learning predictions to provide feedback to learners. This model has already been used to develop learning applications to train cardiopulmonary resuscitation [4], predict different Table Tennis strokes [5], identify task-switching performance based on physiological markers [6], etc.

The model, however, does not provide an out-of-the-box solution that is easy to implement, there are recurrent challenges that appear whenever someone wants to develop a multimodal learning solution [7]. Moreover, even by following pragmatic approaches [8] and using customizable tools to collect [9] and annotate multimodal data [10], it is time-consuming, tedious, and difficult to get

[1]CROSSMMLA @ LAK 2023. Workshop: Leveraging Multimodal Data for Generating Meaningful Feedback LAK'23 – March 14, 2023 Arlington Texas, USA
EMAIL: j.schneider@dipf.de (A. 1); ks@colognegamelab.de (A. 2); b.h.limbu@tudelft.nl (A. 3)
ORCID: 0000-0001-8578-6409 (A. 1); 0000-0001-6766-4416 (A. 2); 0000-0002-1269-6864 (A. 3)

enough accurate annotated recordings to train machine learning models capable of making useful predictions using multimodal data.

In this paper, we present a preliminary study where we tested a completely different approach that might help to quickly and simply assess human performance/expertise levels based on sensor data. We hypothesize that experts display consistent and uniform differences from novices in their performance as a consequence of their repeated practice and extended experience [11]. Therefore, regardless of the task, when contrasting the sensor recordings of expert performances against novice performances, the recording of expert performance should present a clearer pattern and less noise than the one of the novice.

2. Method

To test our hypothesis we recorded expert and novice performances of different tasks using the accelerometers from an android smartphone. The tasks that we recorded were the basic Bachata steps, basic Salsa steps, tennis swings, football penalty kicks, running, and badminton drills.

For the Basic Bachata Steps, the expert performance was recorded from a bachata teacher dancing. The novice was a person who had never danced bachata before and memorized the basic steps before the recording. For the recording, both participants wore the smartphone in the back left pocket of their trousers and danced to the same slow bachata song. The procedure was repeated with the Salsa basic steps with the difference that the novice was not able to follow the steps to the song, therefore the novice and the expert steps were recorded without following the music.

For running, the expert performance was recorded from a competitive amateur runner that has been running regularly for over two decades. The novice performance was recorded from a participant who runs once in a while and has joined a few races in his life. Both participants held the smartphone in their left hand and ran for one minute on a treadmill at 12km/h.

For the badminton drills, the chosen expert, now in his late 50s, has played and trained for years since his childhood. He also participated in competitions during his early years. On the other hand, the novice also in his late 50s only started playing badminton once or twice a week for a year. A simple task in which the shuttle was fed from a middle court position at a high angle towards the back, and required the receiver to return the shuttle to the feeder which is more or less stationary, was chosen as the novice were incapable of executing complicated techniques such as jump smash. The receivers held the smartphone in their left hands during the whole process.

In the case of the tennis swings, for the recording of the expert performance the smartphone was attached to the upper arm of the dominant hand of an amateur tennis player who has been practicing the sport for over two decades. The player then performed ten forehand swings, ten backhand swings and ten tennis serves. For the novice performance, the recordings came from the same player using the non-dominant hand with the smartphone attached to the non-dominant hand's upper arm.

In the case of the football penalty kicks, for the recording of the expert performance, the smartphone was attached to the dominant lower leg of an amateur football player who has been practicing the sport for over two decades. For the novice performance, the recordings came from the same player using the non-dominant lower leg. Four penalty kicks were performed. For effective recordings, a visual representation of a goal post was marked on a wall as a target, ensuring that the techniques are performed correctly.

The recorded data was saved on .csv files storing the X, Y, and Z accelerometer values obtained from the smartphone. To analyze the level of noise in the recordings we used the following procedure. First, we trimmed the .csv files. The procedure for trimming included a plot of the data to identify when the activity started and ended, and extract only the data points of the actual activity. In the case of dancing steps, running, and badminton drills we further trimmed the files to 1000 frames to have an objective comparison of the plots. For the tennis swings and penalty kicks, we trimmed the recordings to 1500 frames.

Once the .csv files were trimmed, we plotted the values for each of the accelerometer axes using the x-axis as time and the y-axis as the accelerometer value. We argue that just by looking at the plotted values for a human it is easy to detect which recordings belong to a novice or an expert just by looking at the irregularities (noise) of the plotted data points (see Figures 1, 2, 3,4,5,6,7,8).

However, formalizing the level of noise of a signal without knowing the expected function is a hard problem. Thus, we explored whether the compressed size of a plotted image would provide us with an indicator of the amount of noise. For that, we saved the plots as .png files.

3. Results

In the following section, we present the plots of the sensor recordings contrasting the novice performance against the expert performance. Figure 1 displays the plots of the Bachata Basic Steps performances. We can observe that in the x-axes the novice performance has nine peaks going down and four going up in contrast to the expert performance that has seven up and 0 down. In the case of the Y and Z axes, there are 0 down-peaks for the expert. On the other hand, for the novice, there are 13 for the Y and six for the Z axis. Moreover, the amplitude of the values is lower in the case of expert performance.

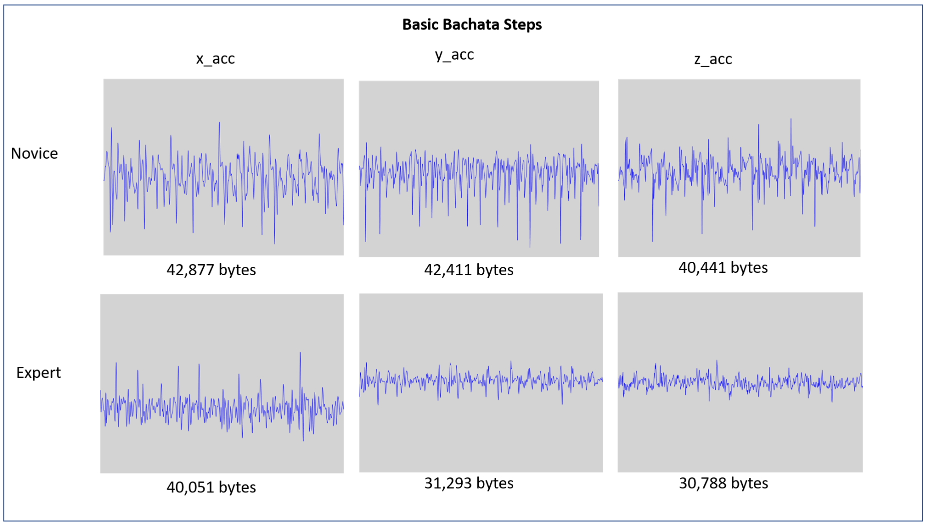

Figure 1. Plots of accelerometer data for Basic Bachata Steps. The Y-Axis represents the sensor values and the X-Axis represents the time.

Figure 2 shows the plots for the novice and expert performances for Salsa Basic Steps without the assistance of music. Once more we can see that for all axes the amplitude displayed in the novice plots is larger and shows more peaks. We can also observe that besides the Z axes, the size of the plotted images for the novice performance is larger.

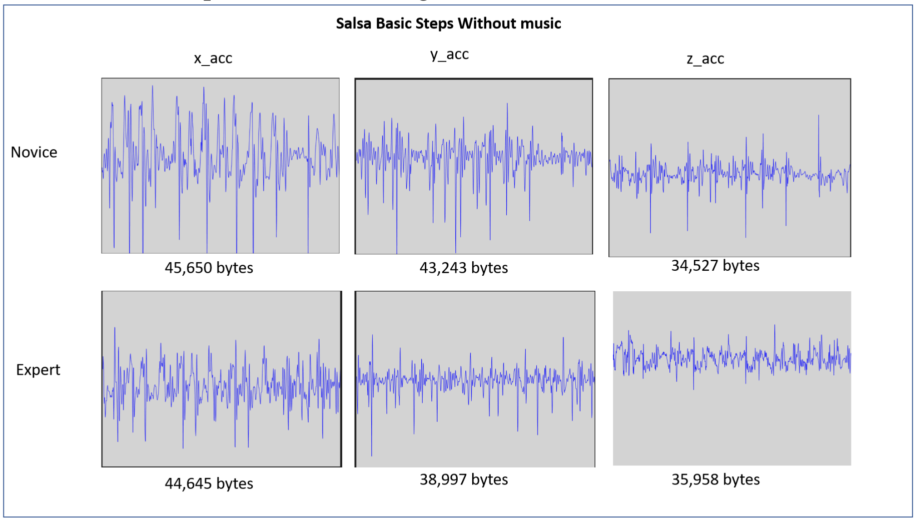

Figure 2. Plots of accelerometer data for Salsa Basic Steps. The Y-Axis represents the sensor values and the X-Axis represents the time.

Figure 3 displays the plots of the novice and expert performance of ten tennis forehand swings. In contrast to the dancing plots, these plots show a clearer pattern in the data. The expert plots show more uniformity and a clearer distinction where the swing happened.

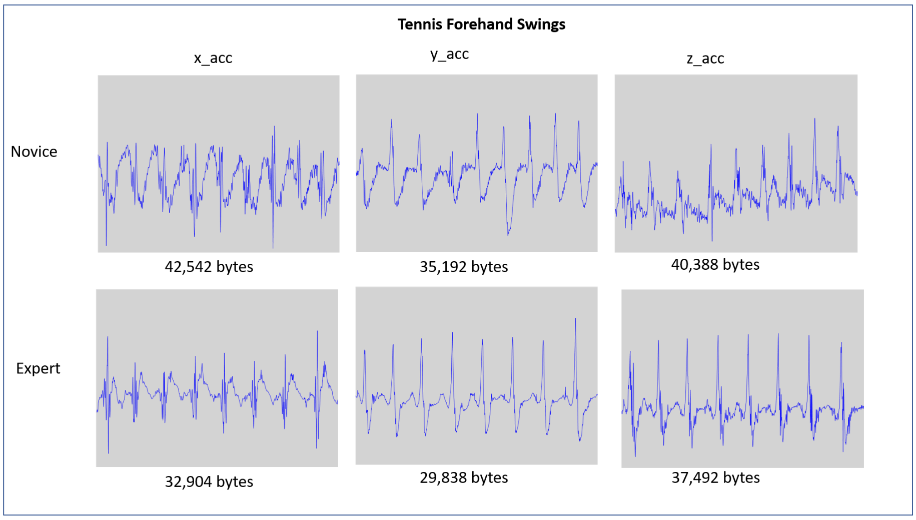

Figure 3: Plots of accelerometer data for Tennis Forehand Swing. The Y-Axis represents the sensor values and the X-Axis represents the time.

Figure 4 displays the plots for the novice and expert performance for the badminton drill. In this particular case, the expert's performance looks more random and full of noise, and that was actually the case, as the expert rally during the drill forced him to move more around the court.

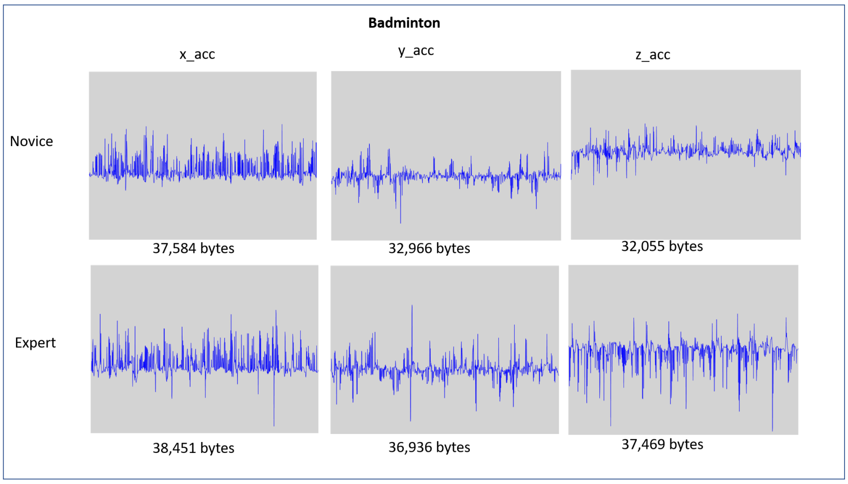

Figure 4. Plots of accelerometer data for badminton. The Y-Axis represents the sensor values and the X-Axis represents the time

Figure 5 displays the plots of the novice and expert performance of ten tennis backhand swings. The plots from the expert performance seem more regular than the ones from the novice. In the case of the z-Axis recording for the novice, it is possible to notice four irregular peaks in the last swings. The size of the plotted images for all of the axes is larger for the swings performed by the novice.

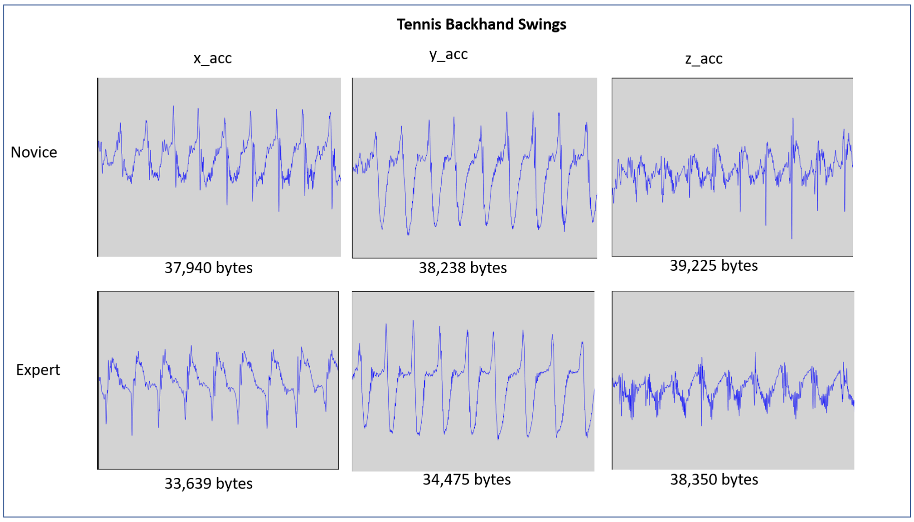

Figure 5. Plots of accelerometer data for Tennis Backhand Swing. The Y-Axis represents the sensor values and the X-Axis represents the time.

Figure 6 displays the plots of the novice and expert performance of ten tennis serves. Once more, for all axes, the expert plots show a more uniform and clear pattern. Except for the X_axis, the size of the plotted images for the novice performance is larger.

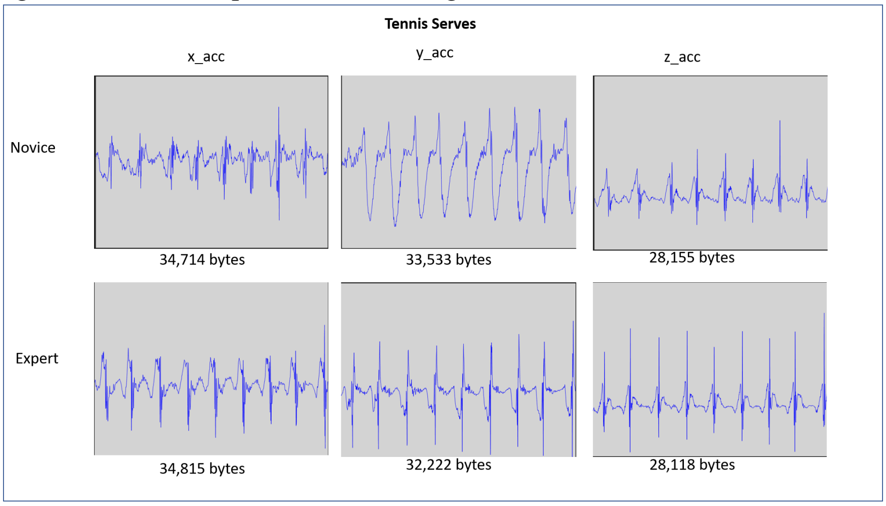

Figure 6. Plots of accelerometer data for Tennis Serve. The Y-Axis represents the sensor values and the X-Axis represents the time.

Figure 7 displays the plots of the novice and expert performing nine football penalty kicks. One thing worth mentioning that is not observed in the plots is that the expert kicks were more powerful than the novice kicks, hence making the comparison a bit more tricky. However, based on the plots, we observed that both novice and expert have similar patterns but with the latter showing a slightly more uniform and consistent pattern.

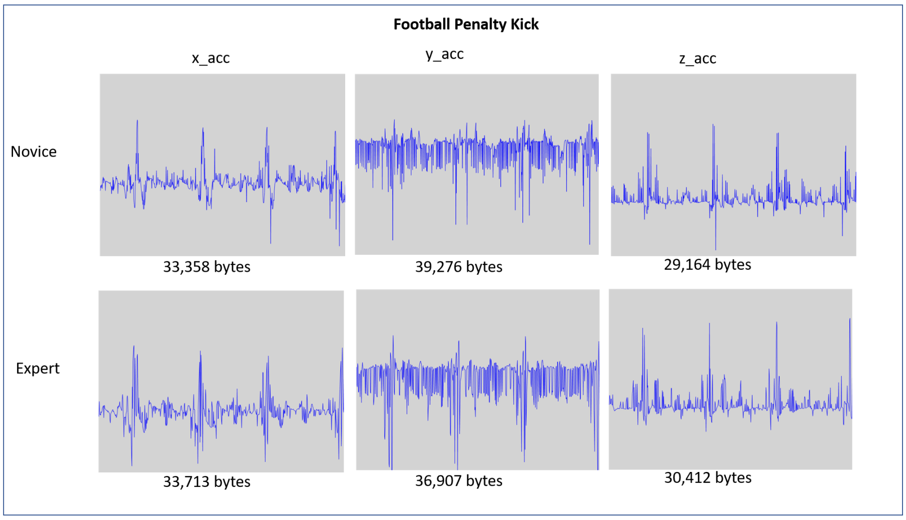

Figure 7. Plots of accelerometer data for Football Penalty Kicks. The Y-Axis represents the sensor values and the X-Axis represents the time.

Figure 8 displays the plots of the novice and expert performance for the running case. Similar to the tennis forehand swing plots, we observed that the plots of the expert performance have more uniform and consistent patterns. In contrast, there are irregularities in the plots of the novice performance for all axes.

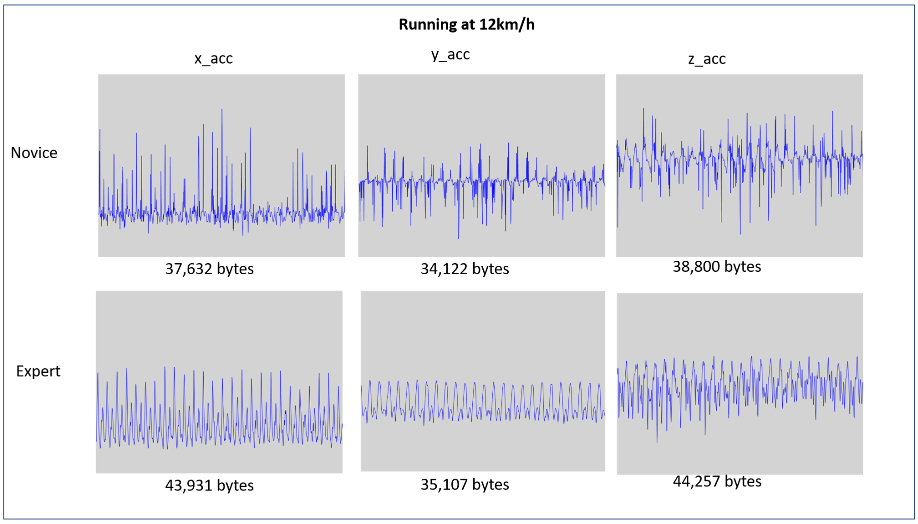

Figure 8. Plots of accelerometer data for running at 12km/h. The Y-Axis represents the sensor values and the X-Axis represents the time.

4. Discussion

In this paper, we collected accelerometer data of a domain expert and a novice performing tasks in semi-constrained settings. The sensors were used to capture the behavioral process instead of the outcomes that directly represent performance differences. Our results showed that independently from the domain, for very controlled tasks such as running at exactly 12 km/hr, performing a swing, executing a basic step, etc. the recordings of expert performances are more uniform and present less noise. This distinction gets fussier when there is more variation in the control of the task, for example, in the case of the penalty kicks when the expert kicks harder than the novice, it becomes more difficult to identify a clear difference in uniformity between the expert and the novice performance. Finally, we can observe in the badminton case, where the recordings are no longer comparable due to the differences in the task.

We demonstrated that through the plots of sensor recordings for controlled comparable tasks it is possible to successfully (at least anecdotally) distinguish between experts and novices. In general, novices' recordings had more randomness or anomalies in contrast to experts who, through years of deliberate practice, have fine-tuned their movements to be precise and efficient.

However, to spice things up, the observations are purely anecdotal and we do not make any empirical conclusions. Furthermore, data were collected only from six domains with an expert and a novice each, which limits the generalisability of the conclusions (Is salt a spice? Take it with a pinch of salt). In addition, since the X,Y,Z values from the accelerometer are dependent on each other, in principle, they cannot be individually compared. The purpose of this study is to propose a potential simplistic approach based on observation of a repeated pattern which we believe is sufficiently highlighted by the method we have chosen.

This work ushers a new era of technology-mediated study of experts and expertise. Beyond understanding expertise, future works can focus on identifying and capturing the true essence of expertise in any domain which can then be used to document expertise and expedite the process of expertise development in novices across various domains.

The preliminary results from our study display how novices with their performances produce more noise than experts analogous to the Dunning and Kruger effect, which states that people with very limited knowledge tend to think they are experts and often make irrelevant statements in subject matter discourse, or as we call it noise. Similarly in our context, learners with limited experience tend to make more unrefined movements that do not contribute to the goal of the action resulting in randomness or noise in their sensor data.

[1] Schneider, J., Börner, D., Van Rosmalen, P., & Specht, M. (2015). Augmenting the senses: a review on sensor-based learning support. Sensors, 15(2), 4097-4133.

[2] Limbu, B. H., Jarodzka, H., Klemke, R., & Specht, M. (2018). Using sensors and augmented reality to train apprentices using recorded expert performance: A systematic literature review. Educational Research Review, 25, 1-22.

[3] Di Mitri, D., Schneider, J., Specht, M., & Drachsler, H. (2018). From signals to knowledge: A conceptual model for multimodal learning analytics. Journal of Computer Assisted Learning, 34(4), 338-349.

[4] Di Mitri, D., Schneider, J., & Drachsler, H. (2022). Keep me in the loop: Real-time feedback with multimodal data. International Journal of Artificial Intelligence in Education, 32(4), 1093-1118.

[5] Mat Sanusi, K. A., Mitri, D. D., Limbu, B., & Klemke, R. (2021). Table tennis tutor: Forehand strokes classification based on multimodal data and neural networks. Sensors, 21(9), 3121.

[6] Buraha, T., Schneider, J., Mitri, D. D., & Schiffner, D. (2021, September). Analysis of the "D'oh!" Moments. Physiological Markers of Performance in Cognitive Switching Tasks. In European Conference on Technology Enhanced Learning (pp. 137-148). Springer, Cham.

[7] Di Mitri, D., Schneider, J., Specht, M., & Drachsler, H. (2018, March). The Big Five: Addressing Recurrent Multimodal Learning Data Challenges. In CrossMMLA@ LAK.

[8] Di Mitri, D., Schneider, J., Specht, M. M., & Drachsler, H. J. (2019, August). Multimodal Pipeline: A generic approach for handling multimodal data for supporting learning. In First workshop on AI-based Multimodal Analytics for Understanding Human Learning in Real-world Educational Contexts.

[9] Schneider, J., Mitri, D. D., Limbu, B., & Drachsler, H. (2018, September). Multimodal learning hub: A tool for capturing customizable multimodal learning experiences. In European conference on technology enhanced learning (pp. 45-58). Springer, Cham.

[10] Di Mitri, D., Schneider, J., Klemke, R., Specht, M., & Drachsler, H. (2019, March). Read between the lines: An annotation tool for multimodal data for learning. In Proceedings of the 9th international conference on learning analytics & knowledge (pp. 51-60).

[11] Ericsson, K. A., Hoffman, R. R., Kozbelt, A., & Williams, A. M. (2018b). The Cambridge Handbook of Expertise and Expert Performance. Cambridge University Press.