Received March 2, 2019, accepted May 4, 2019, date of publication May 27, 2019, date of current version June 13, 2019.

Digital Object Identifier 10.1109/ACCESS.2019.2919162

Applicability of Immersive Analytics in Mixed Reality: Usability Study

BURKHARD HOPPENSTEDT[1], THOMAS PROBST[2], MANFRED REICHERT[1], WINFRIED SCHLEE[3], KLAUS KAMMERER[1], MYRA SPILIOPOULOU[4], JOHANNES SCHOBEL[1], MICHAEL WINTER[1], ANNA FELNHOFER[5], OSWALD D. KOTHGASSNER[6], AND RÜDIGER PRYSS[1]

[1]Institute of Databases and Information Systems, University of Ulm, 89081 Ulm, Germany
[2]Department for Psychotherapy and Biopsychosocial Health, Danube University Krems, 3500 Krems an der Donau, Austria
[3]Department of Psychiatry and Psychotherapy, University of Regensburg, 93053 Regensburg, Germany
[4]Faculty of Computer Science, Otto von Guericke University Magdeburg, 39106 Magdeburg, Germany
[5]Department of Pediatrics and Adolescent Medicine, Medical University of Vienna, 1090 Vienna, Austria
[6]Department of Child and Adolescent Psychiatry, Medical University of Vienna, 1090 Vienna, Austria

Corresponding author: Burkhard Hoppenstedt (burkhard.hoppenstedt@uni-ulm.de).

ABSTRACT Nowadays, visual analytics is mainly performed by programming approaches and viewing the results on a desktop monitor. However, due to the capabilities of smart glasses, new user interactions and representation possibilities become possible. This refers especially to 3D visualizations in the medical field, as well as, the industry domain, as valuable depth information can be related to the complex real-world structures and related data, which is also denoted as immersive analytics. However, the applicability of immersive analytics and its drawbacks, especially in the context of mixed reality, are quite unexplored. In order to validate the feasibility of immersive analytics for the aforementioned purposes, we designed and conducted a usability study with 60 participants. More specifically, we evaluated the effects of spatial sounds, performance changes from one analytics task to another, expert status, and compared an immersive analytics approach (i.e., a mixed-reality application) with a desktop-based solution. Participants had to solve several data analytics tasks (outlier's detection and cluster recognition) with the developed mixed-reality application. Thereby, the performance measures regarding time, errors, and movement patterns were evaluated. The separation into groups (low performer vs. high performer) was performed using a mental rotation pretest. When solving analytic tasks in mixed reality, participants changed their movement patterns in the mixed reality setting significantly, while the use of spatial sounds reduced the handling time significantly, but did not affect the movement patterns. Furthermore, the usage of mixed reality for cluster recognition is significantly faster than the desktop-based solution (i.e., a 2D approach). Moreover, the results obtained with self-developed questionnaires indicate 1) that wearing smart glasses are perceived as a potential stressor and 2) that the utilization of sounds is perceived very differently by the participants. Altogether, industry and researchers should consider immersive analytics as a suitable alternative compared to the traditional approaches.

INDEX TERMS Immersive analytics, mixed reality, spatial sounds, visual analytics, hololens.

I. INTRODUCTION

Augmented reality glasses, so-called *smart glasses*, are used in various contexts and their interaction patterns and visualizations help to simplify many procedures and processes. However, their main advantage is that users can continue their work by using their hands, while interacting with the smart glasses via voice or gaze commands for other work tasks. This is, for example, beneficial for maintenance tasks that have to be accomplished in industry [1] or medicine [2]. Moreover, cognitive processes may benefit from bodily experiences [3] and, hence, required learning processes to accomplish these tasks can be improved. Furthermore, when dealing with dangerous working environments [4], the use of augmented-reality glasses allows for a realistic interaction with a machine without being on-site. Additionally, augmented-reality glasses allow for a flexible and exchangeable visualization of expensive and complex objects, such

The associate editor coordinating the review of this manuscript and approving it for publication was Tai-hoon Kim.

as houses or construction machines [5]. In this context, augmented reality is categorized through the virtual-reality continuum [6]. Hereby, mixed reality [7] is known to have the highest overlap of reality and virtuality, trying to maximize the *mixing* of reality and virtuality compared to augmented reality. Mixed reality, in turn, relies on the concept of spatial mapping, also denoted as 3D reconstruction [8]. In a previous work, we showed the applicability of mixed reality in the medical context for the purposes of visual analytics [9] as well as for augmented data analytics [10], which is also denoted as *immersive analytics* [11]. However, the work at hand addresses the following research questions when performing immersive analytic tasks by using mixed-reality applications in challenging contexts like medicine or Industry 4.0:

RQ1: *Does the task performance differ significantly for participants with different spatial imagination abilities?* We denote *high performers* as participants with a high spatial imagination ability. Note that we measure spatial imagination abilities using a mental rotation test and declare those participants with a higher score than the median as high performers, while the remaining participants are denoted as low performers. For these two groups, we analyze whether high performers have a greater benefit from an augmented reality solution than low performers [12].

RQ2: *Does the task performance differ significantly over time?* With the help of a smart glass, we measure the time and movement patterns (e.g., walking paths and gaze) in several tasks to investigate whether these variables change significantly from task to task over time.

RQ3: *Do spatial sounds significantly improve the task performance in a mixed-reality application*? The used device, a Microsoft HoloLens [13], includes the possibility to provide spatial sounds coming from a set of speakers around the user's head. This concept offers the possibility to draw the participants attention to a spot in the room [14]. Notably, we do not visualize these sounds as suggested by other related works (e.g., [15]). The goal of this approach was to evaluate the pure perception of these sounds.

RQ4: *How stressful is the use of a mixed-reality application in general?* In general, stress is an important factor in the context of augmented representations [16]. Next to the *motion-induced sickness*, there exists a *simulator sickness* due to the unknown visual stimulation [17]. Furthermore, the weight of a smart glass might be a disturbing factor. For example, the Microsoft HoloLens weights 579 g (1.28 lb), which causes a noticeable different feeling when worn. Therefore, the psychosocial stress-level is measured via self-developed questionnaires. Additionally, a skin conductance measurement was carried out, which is not included in this paper, but will be evaluated in further studies.

RQ5: *Do users pose a better task performance when using an 3D approach compared to an 2D approach?* The general question whether immersive analytics are superior to 2D representations is intensively discussed in the scientific community. Gracia *et al.* [18], for example, stated that 3D representations are more suitable than 2D plots. To be more precise, [18] carried out a study based on loss of quality quantification, using the tasks point classification, distance perception, and outlier's identification as use cases. However, the visualizations were shown without any augmented-reality glasses. The theory that a high degree of physical immersion results in lower interaction times is proposed by [19]. Another study favored the 3D space [20], by comparing 2D and 3D visualizations on interaction times and errors. Study participants were asked to identify clusters, determine the dimension of a dataset, and classify the sparseness of data. Immersive analytics can be combined with advanced analytics, such as dimensionality reduction for an improved visualization of scatter plots. However, another study [21] reveals advantages of 2D scatter plots when reducing the dimensionality of a data set, as it leads to lower interaction costs. Therefore, this study compares an 3D approach with a desktop-based solution.

The remainder part of this work is structured as follows. In Section II, the used materials and methods are presented, while Section II discusses the results of the conducted study. The latter section includes the limitations of this work as well as a summary and an outlook, while the first-mentioned section includes the discussion of related works.

II. METHODS

A. PRETEST APPLICATIONS

1) MENTAL ROTATION TEST

A mental rotation test assesses the ability of spatial vision and imagination. Since the 3D point clouds contain an enormous amount of information regarding spatial distance, we assume that a good spatial vision is essential to solve the analytics tasks (see RQ1). We classify the spatial imagination based on a digitalized version of the mental rotation test presented by [22]. In general, a study participant has to solve problems by rotating 3D objects in his mind. In previous studies using mental rotation tests, males scored significantly higher than females. However, more recent studies reported a smaller gap [23]. For our study, we implemented a graphical user interface for a desktop computer (see Fig. 1), where the user gets the task to select two identical objects using buttons. The time limit of two minutes for this test is displayed by a red progress bar and an arbitrary number of tasks can be solved

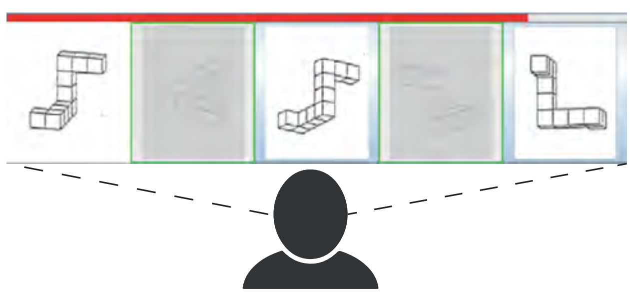


FIGURE 1. Screenshot of the digital mental rotation test.

within these two minutes. Then, when the user clicks a button, the current timestamp is recorded. Hereby, the median value of correctly solved tasks was four.

2) SPATIAL SOUND TEST

The HoloLens offers a concept named *spatial sound* [24]. Hereby, the sound is emitted from a set of microphones around the user's head and the latter is enabled to indicate the direction and location of a hologram in the room. We conduct this test using a headset that emulates a Dolby 5.1 system with the channels *left(l)*, *central(c)*, *right(r)*, *left surround(ls)*, and *right surround (rs)* (see Fig. 2A). Without any time limit, users have to choose the direction using four buttons, schematically indicated in Fig. 2B. Six times, an audio sample of 13 seconds with the sound of footsteps is played and presented to the participants, without any repetition. After each playback, the participant has to guess the right direction. The aim of this test was to identify participants with low scores (less than two solved tasks) as potential outliers for the spatial sound part of this study. However, all participants passed this test and solved more than two tasks.

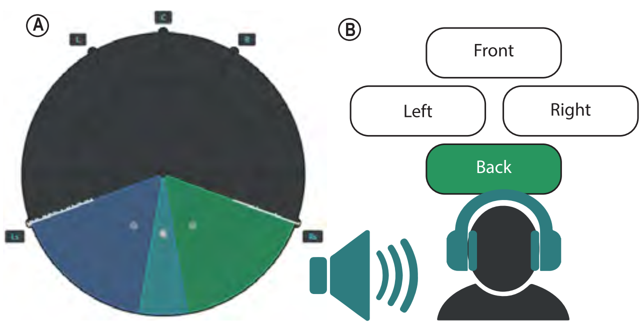


FIGURE 2. (A) Audio configuration for the task *Back*, (B) schematic user interface.

B. MEASURES

The following performance measures were assessed in the use case of outlier's detection (see below): time, path, and angle. The following performance measures were collected in the use case of cluster recognition (see below): time and errors. Note that the processed questionnaires and performed stress measurements are related to both use cases.

1) TIME

Timestamps were added to a *CSV* file during the study. Those timestamps were collected when pressing a button in a 2D interface, sending a voice command in the HoloLens application, or after completing a task. This allowed us to evaluate the required time to complete respective tasks.

2) ERRORS

This performance measure is only applicable to the use case *cluster recognition* [25], as the answer for recognized clusters can be compared to the real value. Furthermore, it is possible to measure the degree of error, as the answer of recognized clusters can be either seen binary (true/false) or of numeric character (distance to real value). Note that we solely focused on the binary scale.

3) PATH

The HoloLens collects the current position as a 3D vector relative to the starting position [26] at a frame rate of 60 frames per second [27]. The distance between two points is denoted as *section*. The y coordinate (height of person) is ignored and the points are mapped to the xz-plane (floor). Based on this data, several *features* can be extracted. First, the length of the path (*path*) can be calculated. This value indicates whether the participant walked a lot during the accomplishment of the respective task. Second, the mean of all sections (*pathAvg*) can be calculated. This expression represents the average speed of the participant, represented by the unit *meter per frame*. Third, the variance of all sections (*pathVar*) represents the erraticness of a movement. Finally, the Bounding Box (*BBox*) of the movement is calculated as the area limited by the maximum and minimum positions in x- and z-directions. Consequently, participants, who often change their perspective to different positions, lead to high BBox values.

4) ANGLE

The angle measures the rotation between the aforementioned 3D vectors. Analogous to the path, we calculate the average (*angleAvg*) to represent the rotation speed in degrees per frame. In addition, we measure the erraticness of the rotation using the variance (*angleVar*).

5) STRESS-LEVEL

The state version of the *State-Trait Anxiety Inventory* (STAI) questionnaire [28] was utilized and handed out in the beginning and in the end of this study. This questionnaire consists of 20 items and measures state anxiety, a construct similar to state stress. Hereby, positive attributes (e.g., calm) and negative attributes (e.g., worried) are answered, using the scale [1,2,3,4]. For the evaluation of this questionnaire, all positive attributes are flipped (e.g., an answer '4' becomes a '1'), and all answers are summed up to reveal a final STAI score. Moreover, skin conductance was measured with 30 randomly selected users with the tool movisens [29], but this physiological measure of stress will be analyzed in future studies.

6) SELF-DEVELOPED QUESTIONNAIRE

A self-developed questionnaire (see Appendix A) asks for the participant's feedback. The scale was set from one to ten, for which ten represents a high value of agreement to the question. This questionnaire was handed out in the end of this study.

7) DEMOGRAPHIC QUESTIONNAIRE

Using a demographic questionnaire, we assessed gender, age, and education of all participants.

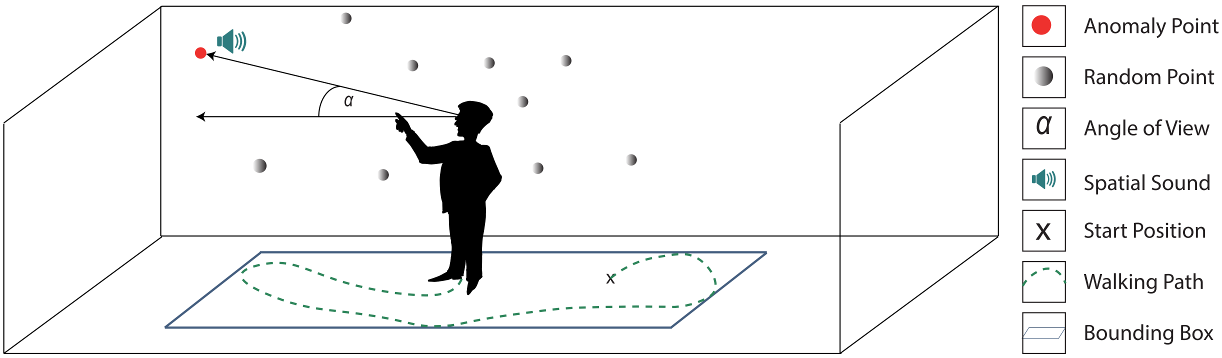


FIGURE 3. Sketch of use case: Outlier's detection.

C. MIXED-REALITY APPLICATION AND 2D ALTERNATIVE

New possibilities in spatial sounds, gaze, and voice commands offer interesting perspectives for simplifying data analytics. Therefore, we implemented a prototype to tackle *outlier's detection* as well as *cluster recognition* as use cases for data analytics. Our used device is a Microsoft HoloLens. This smart glass is able to generate a virtual representation of the room and projects holograms into the room. These holograms stay in place, while the user is able to walk around the room and inspect them from different angles.

1) OUTLIER'S DETECTION

For the use case outlier's detection, we create a 3D point cloud with normal distribution. These points are displayed all over the room, in which the study takes place. All of them appear white to the user, except one, which is red. The user's task is to find the red-marked point. Hereby, eight tasks for outlier's detection have to be solved, without any time limit, whereby four tasks are supported by spatial sounds. A constant sound of 44100 Hz is coming from the direction of the red point. If the user approaches the red point, the volume increases. In contrast, if the participant walks away, the sound volume decreases. The current gaze is indicated by a green point. The participant confirms the finding of an outlier's point by focusing his/her gaze to the point. When an outlier is found, the color changes to white and a next outlier has to be found. Sound-supported and sound-unsupported tasks alternate in their order. Furthermore, one test group starts with sound support, while the other one without it. Participants were assigned randomly to these two conditions, so that high performers and low performers are in both conditions. The outlier's points are chosen in different distances and angles, relatively to the start position. The order of the tasks is the same for every participant and it is not sorted by distances to outlier's points, but randomly. Moreover, in order to be able to automatically collect the data needed for the evaluation, a *log mode* was implemented. The application tracks the *time* during the tasks, as well as the *current position* and the *angle* relative to the starting pose. Therefore, every participant starts at the same spot and with the same gaze focus. Based on the position and angle, more performance measures, such as *bounding box* or *length of path*, can be calculated (see Fig. 3).

2) CLUSTER RECOGNITION

For the second use case (cluster recognition), we compare a 2D and a 3D approach. All participants had to solve 12 cluster recognition tasks without time limit, whereby six had to be analyzed using the HoloLens and six with the 2D approach. Half of the participants, chosen randomly, started with the six tasks using the HoloLens, followed by the six tasks using the 2D approach, whereas the other half started with the six tasks using the 2D approach, followed by the six tasks using the HoloLens. Therefore, high performers and low performers were in each of the two conditions. Then, after every six tasks of one approach are finished, the other six tasks had to be accomplished. The six tasks are the same for both approaches and must be solved without any time limit. For the tasks in general, we used several normally distributed point clouds, denoted as *clusters*. The tasks are generated by combining these clusters into one plot, for which the number of clusters in one plot differs. Hereby, the number of clusters and the degree of overlap are changed between each task, whereby a high number of clusters and overlaps might be considered as more difficult. Again, the six tasks within each approach (2D and 3D) are sorted randomly, but in the same order for each participant. The resulting plots have to be inspected from different angles to eventually recognize the clusters (see Fig. 4). For the 2D approach, a Matlab GUI on a Desktop PC was introduced. When using the HoloLens, the participants have the possibility to walk around the cluster to visually separate the clusters. In contrast, the Matlab plot can be rotated using the mouse wheel. The confirmation of the number of clusters is done using voice command when using the HoloLens, and with the help of a TextBox + Button when accomplishing tasks in Matlab.

D. STUDY PROCEDURE

A controlled environment was chosen for this study in order to be able to quickly react to upcoming problems. For the study, one laptop and the HoloLens were provided. Before each session, the study was carefully prepared.

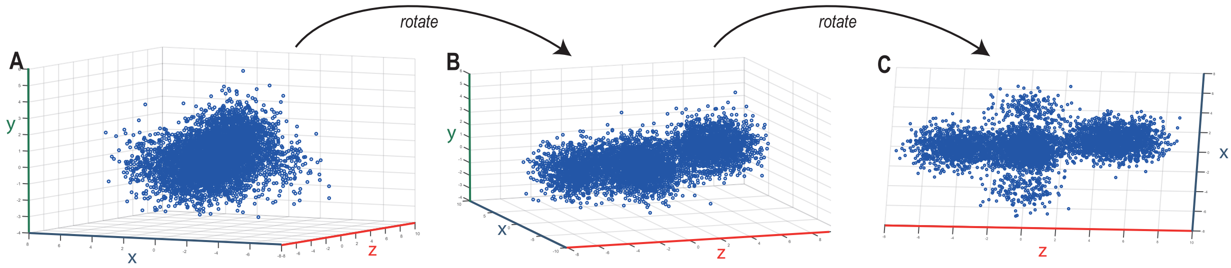


FIGURE 4. **A gaze at the same point cloud from different angles (A-C) reveals clusters.**

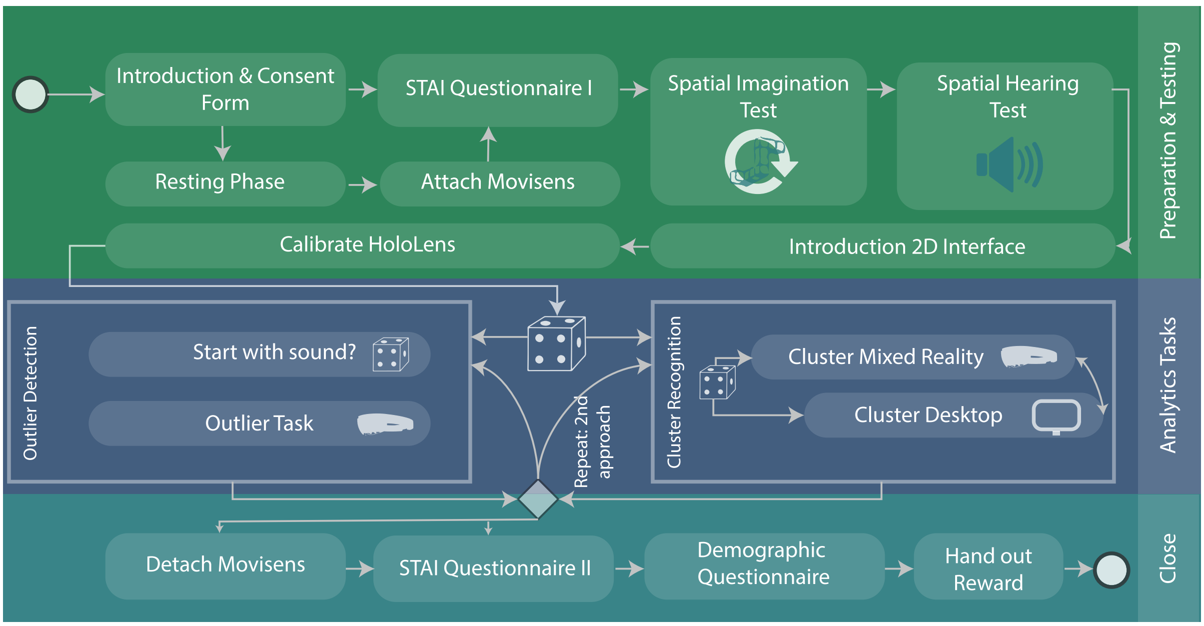


FIGURE 5. **Study design.**

This includes, for example, setting up the log mode and setting all applications into a default state as well as preparing the questionnaires.

Participants solved tasks from the use cases outlier detection and cluster recognition in one session (i.e., avg 43 min). Half of the participants started with the outlier detection, while the other half started with cluster recognition tasks. The initial use case was chosen randomly. If the participants started with the eight tasks of outlier detection, afterwards, the same participants performed the 12 tasks of cluster recognition and vice versa (see Fig. 5, blue box). The procedure of the study is outlined in Fig. 5. The study started with welcoming the participants and introducing the goal of the study as well as the overall procedure. Participants using the movisens (skin conductance measurement) had to stick to a short resting phase, to receive a baseline measure. All participants filled out the state version of the STAI questionnaire before the start of the experiment. Next, the participants performed the mental rotation test (see Fig. 1) to be able to divide them into high and low performers, followed by the spatial sound test (see Fig. 2) to measure their spatial hearing ability. We used a median split (median = 4) of the test scores in the mental rotation test, which resulted in 29 high performers (48.33%) and 31 low performers (51.67%). Next, the participants are separated randomly into two groups to start either with outlier detection or cluster recognition and continue with the missing use case afterwards. Concluding the session, participants had to answer the state version of the STAI questionnaire again, as well as the self-developed questionnaire, and a demographic questionnaire. Altogether, this session took between 40 and 50 minutes. The data, automatically recorded by each application, were then stored on the laptop's storage after the session.

All materials and methods were approved by the Ethics Committee of Ulm University and were carried out in accordance with the approved guidelines. All participants gave their written informed consent.

E. PARTICIPANTS

In total, 60 participants were recruited (see Table 1), whereby most of them were recruited at Ulm University and Software Companies. The study included students from various

TABLE 1. Sample description and comparison between low and high performers in baseline variables.

Variable		Low performer (*n*=31)	High performer (*n*=29)	*P* value
Gender, n(%)				
	Female	7 (*23%*)	3 (*10%*)	
	Male	24 (*77%*)	26 (*90%*)	.302[a]
Age Category, n(%)				
	<25	1 (*3%*)	5 (*17%*)	
	25-35	27 (*87%*)	21 (*72%*)	
	36-45	0 (*0%*)	2 (*7%*)	
	46-55	1 (*3%*)	0 (*0%*)	
	>55	2 (*6%*)	1 (*3%*)	.099[a]
Highest Education, n(%)				
	High School	3 (*10%*)	5 (*17%*)	
	Bachelor	7 (*23%*)	6 (*21%*)	
	Master	21 (*68%*)	18 (*62%*)	.692[a]
Mental Rotation Test, Mean (SD)				
	Correct Answers	3.03 (*1.40*)	5.31 (*0.76*)	.001[b]
	Wrong Answers	2.19 (*1.47*)	1.21 (*0.56*)	.000[b]
Spatial Hearing Test, Mean (SD[c])				
	Correct Answers	4.39 (*1.09*)	4.31 (*1.00*)	.467[b]
	Wrong Answers	1.61 (*1.09*)	1.69 (*1.00*)	.940[b]

[a]Fisher's Exact Test

[b]Two-sample t-test

[c]SD = Standard Deviation

subjects [30], such as computer science, physics, or psychology. Ten female participants and 50 male participants joined the study, whereby the majority was between 25 and 35 years old. Recruited professionals were mainly software developers, not necessarily with a focus on smart glasses. The target group of immersive analytics (e.g., data scientists, production workers) has most probably no experience with smart glasses. Study participants willing to participate were instructed according to the developed study design, which was explained to them before. The participants were classified to the groups high and low performers according to the mental rotation test. Altogether, our classification resulted in 31 low performers (7 female and 24 male) and 29 high performers (3 female and 26 male).

F. STATISTICS

Matlab R2017a, RPY2 [31], and SPSS 25.0 were used for statistical analyses. Frequencies, percentages, means, and standard deviations were calculated as descriptive statistics. Low and high performers were compared in baseline demographic variables using Fisher's exact tests and t-Tests for independent samples. For RQ1, RQ2, RQ3, and RQ5, linear multilevel models [32] with the full maximum likelihood estimation were performed. Hereby, two levels were included, where level one represents the repeated assessments (either in outlier detection or cluster recognition), whereas level two represents the participants. The performance measures (except errors) were the dependent variables in these models. In RQ 1, we also used Fisher's exact tests for the error probabilities. The STAI scores were evaluated using t-Tests for dependent samples for RQ4. In RQ5, the effect of 2D vs. HoloLens was explored, using McNemar's test for the error probability. All statistical tests were performed two tailed; the significance value was set to $P < .05$.

G. DATA AVAILABILITY

The raw data set containing all collected data that was analyzed during this study is included in this paper (and its supplementary material).

III. RESULTS

This section discusses the results of the conducted study.

A. BASELINE COMPARISON BETWEEN LOW AND HIGH PERFORMERS

Table 1 summarizes the sample description and comparisons between low and high performers in baseline variables. No significant differences were found. Descriptively, the low performers had a higher percentage of female participants than the high performers and the high performers were younger than the low performers.

B. RESULTS FOR RQ1

Concerning the errors for cluster recognition, the performance did not differ significantly for the 2D approach (4 errors for low performers, 2 errors for high performers, $p = .672$) and the 3D approach (8 errors for low performers, 2 errors for high performers, $p = .082$) between high and low performers. In Table 2, high performers were compared to low performers across the eight tasks of the outlier detection task using the HoloLens. Hereby, the high performers were significantly quicker to solve the tasks than the low performers ($p = .013$). Moreover, the high performers required a tendentially shorter walking distance ($p = .071$) to solve the tasks. The multilevel models did not converge for the 2D / 3D cluster recognition to explore differences between high performers and low performers, with respect to time in 2D and 3D cluster recognition.

C. RESULTS FOR RQ2

During the eight outlier detection tasks in HoloLens, the BoundingBox ($p < .001$), Pathlength ($p = .709$), PathVariance ($p < .001$), PathMean ($p < .001$), AngleVariance ($p < .001$), and AngleMean ($p < .001$) increased significantly from task to task (see Table 3). The recorded time ($p = .709$) did not change significantly from task to task in outlier's detection using the Hololens. Concerning cluster recognition using the Hololens, the recorded time ($p < .187$) did not increase from task to task (see Table 4). The change

TABLE 2. Results of the multilevel models for RQ 1 (Outlier detection in HoloLens).

Variable	Estimate	SE[a]	Result
BoundingBox for low performer across tasks	2.224	.438	t(60.00) = 5.08; p<.001
Alteration of BoundingBox for high performer across tasks	+.131	.630	t(60.00) = .21; p=.836
Time for low performer across tasks	20.919	1.045	t(60.00) = 20.02; p<.001
Alteration of Time for high performer across tasks	-3.863	1.503	t(60.00) = -2.57; p=.013
Pathlength for low performer across tasks	5.637	.613	t(60.00) = 9.19; p<.001
Alteration of Pathlength for high performer across tasks	-1.624	.882	t(60.00) = -1.84; p=.071
PathVariance for low performer across tasks	4.3E-4	4.7E-5	t(65.15) = 9.25; p<.001
Alteration of PathVariance for high performer across tasks	+4.3E-6	6.7E-5	t(65.15) = .063; p=.950
PathMean for low performer across tasks	.0047	5.3E-4	t(60.00) = 8.697; p<.001
Alteration of PathMean for high performer across tasks	+3.8E-5	7.7E-4	t(60.00) = .05; p=.960
AngleVariance for low performer across tasks	.0012	7.3E-5	t(85.70) = 16.15; p<.001
Alteration of AngleVariance for high performer across tasks	-2.7E-5	1.0E-4	t(85.70) = -.26; p=.796
AngleMean for low performer across tasks	.015	.001	t(60.00) = 14.27; p<.001
Alteration of AngleMean for high performer across tasks	-3.0E-4	1.5E-3	t(60.00) = -.20; p=.842

[a]SE = Standard Error

TABLE 3. Results of the multilevel models for RQ 2 (Outlier detection in HoloLens).

Variable	Estimate	SE[a]	Result
BoundingBox at first task	.984	.392	t(138.12) = 2.51; p=.013
Alteration of BoundingBox from task to task	+.373	.067	t(420.00) = 5.59; p<.001
Time at first task	19.431	1.283	t(302.08) = 15.11; p<.001
Alteration of Time from task to task	-.108	.286	t(420.00) = -.37; p=.709
Pathlength at first task	3.903	.646	t(214.81) = 6.05; p<.001
Alteration of Pathlength from task to task	+.271	.131	t(420.00) = 2.06; p=.040
PathVariance at first task	3.1E-4	3.7E-5	t(117.77) = 8.43; p<.001
Alteration of PathVariance from task to task	+3.5E-5	4.5E-6	t(455.00) = 7.90; p<.001
PathMean at first task	.0033	4.2E-4	t(88.98) = 7.66; p<.001
Alteration of PathMean from task to task	+4.1E-4	5.2E-5	t(420.00) = 7.81; p<.001
AngleVariance at first task	.001	5.7E-5	t(129.86) = 17.92; p<.001
Alteration of AngleVariance from task to task	+4.1E-5	6.5E-6	t(541.75) = 6.34; p<.001
AngleMean at first task	.0127	8.1E-4	t(82.17) = 15.52; p<.001
Alteration of AngleMean from task to task	+6.1E-4	9.0E-5	t(420.00) = 6.86; p<.001

[a]SE = Standard Error

of time from task to task in cluster recognition in the desktop approach is not reported since these multilevel models did not converge.

D. RESULTS FOR RQ3

With the help of spatial sounds, the users were able to solve the tasks in the outlier detection quicker than without using spatial sounds ($p = .020$, see Table 5).

E. RESULTS FOR RQ4

At the pre-assessment, the average state on the STAI scores were $M = 44.58$ ($SD = 4.67$). At post-assessment, it was $M = 45.72$ ($SD = 4.43$). This change did not attain statistical significance ($p = .175$). Descriptive statistics of the answers in the self-developed questionnaire are presented in Fig. 6. Hereby, the number of outliers for question *Support Sound* is remarkable.

F. RESULTS FOR RQ5

The HoloLens approach resulted in significantly faster cluster recognition times than using a desktop computer ($p < .001$, see Table 6). However, note that the speed advantage of the HoloLens was rather small (i.e., in a milliseconds range).

TABLE 4. Results of the multilevel models for RQ 2 (Cluster recognition in HoloLens).

Variable	Estimate	SE[a]	Result
Time at first task	9.450	.400	t(337.35) = 23.613; p<.001
Alteration of time from task to task	.130	.098	t(300.00) = 1.323; p=.187

[a]SE = Standard Error

TABLE 5. Results of the multilevel models for RQ 3 (Outlier detection in HoloLens).

Variable	Estimate	SE[a]	Result
BoundingBox without sound across tasks	2.459	.352	t(93.26) = 6.98; p<.001
Alteration of BoundingBox with sound across tasks	-.344	.316	t(420.00) = -1.09; p=.277
Time without sound across tasks	20.550	1.030	t(161.17) = 19.94; p<.001
Alteration of time with sound across tasks	-2.996	1.319	t(420.00) = -2.27; p=.024
Pathlength without sound across tasks	5.193	.545	t(121.81) = 9.54; p<.001
Alteration of Pathlength with sound across tasks	-.682	.604	t(420.00) = -1.13; p=.260
PathVariance without sound across tasks	.0004	3.5E-5	t(79.74) = 12.110; p<.001
Alteration of PathVariance with sound across tasks	+1.3E-5	2.2E-5	t(429.20) = .592; p=.554
PathMean without sound across tasks	.005	4.0E-4	t(73.66) = 11.35; p<.001
Alteration of PathMean with sound across tasks	+1.4E-4	2.5E-4	t(420.00) = .56; p=.575
AngleVariance without sound across tasks	.0012	5.4E-5	t(101.32) = 21.00; p<.001
Alteration of AngleVariance with sound across tasks	+3.3E-5	3.1E-5	t(648.56) = 1.07; p=.284
AngleMean without sound across tasks	.0145	7.8E-4	t(70.17) = 18.51; p<.001
Alteration of AngleMean with sound across tasks	+6.0E-4	4.3E-4	t(420.00) = 1.39; p=.166

[a]SE = Standard Error

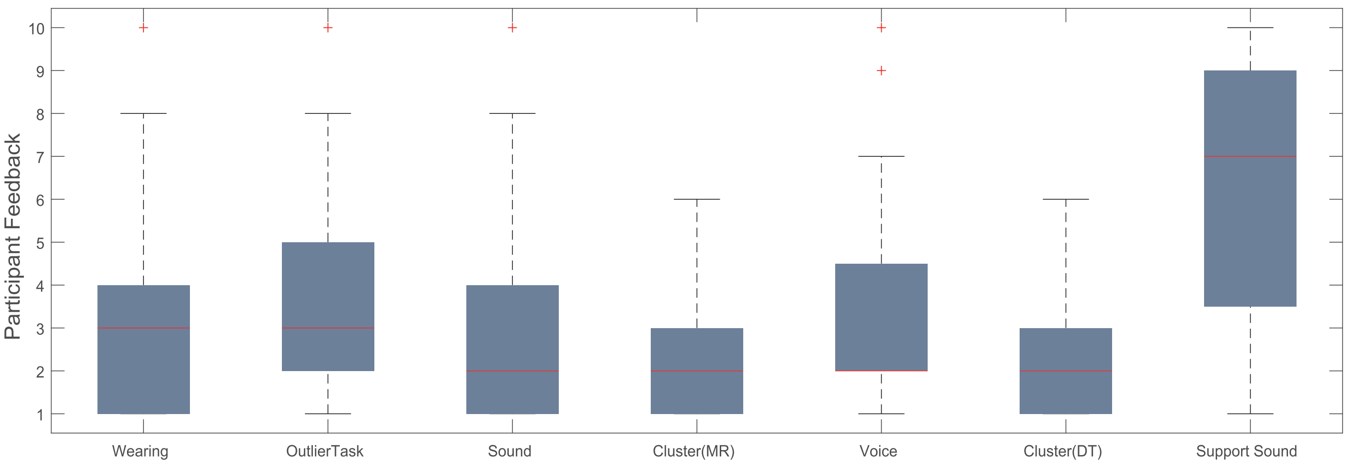


FIGURE 6. Box plots of questionnaire tasks.

When using the HoloLens, ten participants made errors. In contrast, six participants answered wrongly when analyzing the tasks with the desktop solution ($p = .344$).

IV. DISCUSSION

This study evaluated immersive analytic approaches for mixed reality. More specifically, several research questions were raised to address the usability of mixed reality for the accomplishment of visual analytic tasks. Hereby, the effect of spatial sounds, the benefit of a good spatial imagination ability, and the comparison against a traditional desktop approach were evaluated. In total, 60 participants took part and solved eight tasks for outlier detection and six tasks in the field of cluster recognition twice. High performers were classified

TABLE 6. Results of the multilevel models for RQ 5 (Cluster recognition in HoloLens).

Variable	Estimate	SE[a]	Result
Time with desktop across tasks	10.536	.228	$t(156.43) = 46.120$; $p<.001$
Alteration of time with Hololens across tasks	-.631	.286	$t(660.00) = -2.206$; $p=.028$

[a]SE = Standard Error

by using a mental rotation test. For *RQ1*, we found that high performers are quicker in outlier detection as well as in cluster recognition using the HoloLens compared to low performers. Note that our tasks were not domain specific. Also, other studies showed an advantage of high versus low performers in augmented reality, e.g., in the field of medical training [33]. In our study, we recognized a significant change of the measured movements patterns in outlier's detection using the Hololens (BoundingBox, Pathlength, PathVariance, PathMean, AngleVariance, AngleMean). The users learned that they can get a better overview and generate a better 3D perspective (RQ2) when moving around. Measurement patterns, such as the smoothness of a movement, have been also studied by augmented reality studies [34]. For *RQ3*, we measured a significant speed advantage in the outlier's task through the use of spatial sounds. It is evident that this effect is more valuable if the user's interface is too large to keep it always in the field of view. Again, the effects of spatial sounds are also addressed by other works in augmented reality settings, e.g., by [14], [35], and [36]. Its outstanding role in the handling of 3D user interfaces is always stressed by these works. For the HoloLens, the spatial sounds are limited to horizontal directions and unsuitable to direct the gaze to the bottom or the top. Moreover, even though the spatial sounds helped to solve the tasks quicker, the participants opinion of its usefulness was ambiguous (see RQ4). Some participants mentioned that they would like to start and stop the sound in order not to be not disturbed when they are in an orientation phase. Spatial sounds, in turn, could be applied very precisely and were even used in another use case to help blind users [37]. Referring to RQ5, the HoloLens results in faster responses in cluster recognition compared to a 2D desktop approach. To embed this result in the existing literature, the comparison of 3D visualizations to 2D representations was conducted several times ([18]–[20], or [21]), interestingly with different outcomes.

A. LIMITATIONS

The following limitations of this study [38] need to be discussed. First, the selection process of the participants limits generalizability. About 80% of all recruited participants were students or research associates. Note that the recruitment of students as a substitute in empirical studies is a general subject of discussions, where [30] argues in favor of recruiting them. Furthermore, the classification of recruited participants into low and high performers by using a mental rotation test administered via a desktop computer may be oversimplified, as it excludes prior knowledge in the field of augmented reality. We collected the prior knowledge concerning data analytics and augmented reality in a self-assessment questionnaire with questions asking for the number of days spent in this field. However, few people had prior knowledge with smart glasses and therefore it was impossible to choose this questionnaire as a suitable base for the division into the two groups. A combination of different aspects of mixed reality might lead to a more sophisticated expert score in future work. A possible threat to internal validity might be to have not covered enough variables to identify potential baseline differences between low and high performers. As immersive analytics include and affect many of the human senses, it might be difficult to cover and exclude all external influences. As another shortcoming, 60 participants are a rather small sample of participants. Moreover, the tasks were chosen domain independent and cannot be transferred to very specific settings and use cases. Despite these limitations, the strength of the study was that we provided a wide overview of the feasibility on immersive analytics.

B. SUMMARY

In summary, the results of this study underline the feasibility of immersive analytics in general. The main findings show that (1) high performers with a high mental rotation imagination ability are able to solve tasks quicker, (2) spatial sounds make immersive analytic less time consuming, (3) immersive analytics are a suitable alternative to desktop approaches. To the best of our knowledge, usability issues in the context of mixed reality have not been studied at this scale previously. Furthermore, this may serve as a valuable benchmark for the evaluation of immersive analytics in more general.

APPENDIX A
DEVELOPED QUESTIONNAIRE

The following questions were used as a subjective feedback:

- As how stressful did you experience wearing the glasses? (Short: Wearing)
- How stressful was the outlier's task? (Short: Outliers)
- As how stressful did you experience the spatial sounds? (Short: Sound)
- How stressful was the task finding clusters in Mixed Reality? (Short: Cluster(MR))
- How stressful was the task finding clusters in the desktop approach? (Short: Cluster(DT))
- How stressful was the usage of the voice commands? (Short: Voice)

- Did you feel supported by the spatial sounds? (Short: Support Sound)

APPENDIX B
CONFLICT OF INTEREST STATEMENT

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

APPENDIX C
AUTHOR CONTRIBUTIONS

BH conducted the study and wrote the paper; KK recruited participants; JS provided support on the ethics vote; MZ supervised the skin conductance measure; TP, WS, and MS calculated and supervised the statistical part; RP and MR provided resources. All authors revised the manuscript and approved its final version.

REFERENCES

[1] M. Aleksy, M. Troost, F. Scheinhardt, and G. T. Zank, "Utilizing hololens to support industrial service processes," in *Proc. IEEE 32nd Int. Conf. Adv. Inf. Netw. Appl. (AINA)*, May 2018, pp. 143–148.

[2] A. Hurstel and D. Bechmann, "Approach for intuitive and touchless interaction in the operating room," *Proc. J.*, vol. 2, no. 1, pp. 50–64, 2019.

[3] S. Bakker, E. Van Den Hoven, and A. N. Antle, "Moso tangibles: Evaluating embodied learning," in *Proc. 5th Int. Conf. Tangible, Embedded, Embodied Interact.*, Jan. 2011, pp. 85–92.

[4] H. Regenbrecht, G. Baratoff, and W. Wilke, "Augmented reality projects in the automotive and aerospace industries," *IEEE Comput. Graph. Appl.*, vol. 25, no. 6, pp. 48–56, Nov. 2005.

[5] H.-L. Chi, S.-C. Kang, and X. Wang, "Research trends and opportunities of augmented reality applications in architecture, engineering, and construction," *Autom. Construct.*, vol. 33, pp. 116–122, Aug. 2013.

[6] P. Milgram, H. Takemura, A. Utsumi, and F. Kishino, "Augmented reality: A class of displays on the reality-virtuality continuum," *Proc. SPIE*, vol. 2351, pp. 282–293, Dec. 1995.

[7] G. Evans, J. Miller, M. I. Pena, A. MacAllister, and E. Winer, "Evaluating the microsoft hololens through an augmented reality assembly application," *Proc. SPIE*, vol. 10197, May 2017, Art. no. 101970V.

[8] S. Izadi, D. Kim, O. Hilliges, D. Molyneaux, R. Newcombe, P. Kohli, J. Shotton, S. Hodges, D. Freeman, and A. Davison, "KinectFusion: Real-time 3D reconstruction and interaction using a moving depth camera," in *Proc. 24th Annu. ACM Symp. Interface Softw. Technol.*, Oct. 2011, pp. 559–568.

[9] B. Hoppenstedt, C. Schneider, R. Pryss, W. Schlee, T. Probst, P. Neff, J. Simoes, A. Treß, and M. Reichert, "HOLOVIEW: Exploring patient data in mixed reality," in *Proc. TRI/TINNET Conf.*, Jun. 2018.

[10] B. Hoppenstedt, M. Reichert, C. Schneider, K. Kammerer, W. Schlee, T. Probst, B. Langguth, and R. Pryss, "Exploring dimensionality reduction effects in mixed reality for analyzing tinnitus patient data," in *Proc. 4th Int. Conf. Virtual Augmented Reality Educ. (VARE)*, G. Bruzzone, G. Mendívil, and L. Gutierrez, Eds., 2018, pp. 163–170.

[11] T. Chandler, M. Cordeil, T. Czauderna, T. Dwyer, J. Glowacki, C. Goncu, M. Klapperstueck, K. Klein, K. Marriott, F. Schreiber, and E. Wilson, "Immersive analytics," in *Proc. Big Data Vis. Anal. (BDVA)*, Sep. 2015, pp. 1–8.

[12] A. Tang, C. Owen, F. Biocca, and W. Mou, "Comparative effectiveness of augmented reality in object assembly," in *Proc. SIGCHI Conf. Hum. Factors Comput. Syst.*, Apr. 2003, pp. 73–80.

[13] A. G. Taylor, "HoloLens hardware," in *Develop Microsoft HoloLens Apps Now*. Berkeley, CA, USA: Apress, 2016, pp. 153–159.

[14] J. Sodnik, S. Tomazic, R. Grasset, A. Duenser, and M. Billinghurst, "Spatial sound localization in an augmented reality environment," in *Proc. 18th Aust. Conf. Comput.-Hum. Interact., Design, Activities, Artefacts Environ.*, Nov. 2006, pp. 111–118.

[15] A. Härmä, J. Jakka, M. Tikander, M. Karjalainen, T. Lokki, J. Hiipakka, and G. Lorho, "Augmented reality audio for mobile and wearable appliances," *J. Audio Eng. Soc.*, vol. 52, no. 6, pp. 618–639, Jun. 2004.

[16] U. Neumann and A. Majoros, "Cognitive, performance, and systems issues for augmented reality applications in manufacturing and maintenance," in *Proc. Virtual Reality Annu. Int. Symp.*, Mar. 1998, pp. 4–11.

[17] R. S. Kennedy, N. E. Lane, K. S. Berbaum, and M. G. Lilienthal, "Simulator sickness questionnaire: An enhanced method for quantifying simulator sickness," *Int. J. Aviation Psychol.*, vol. 3, no. 3, pp. 203–220, 1993.

[18] A. Gracia and S. González, V. Robles, E. Menasalvas, and T. Von Landesberger, "New insights into the suitability of the third dimension for visualizing multivariate/multidimensional data: A study based on loss of quality quantification," *Inf. Vis.*, vol. 15, no. 1, pp. 3–30, Jan. 2016.

[19] D. Raja, D. Bowman, J. Lucas, and C. North, "Exploring the benefits of immersion in abstract information visualization," in *Proc. Immersive Projection Technol. Workshop*, May 2004, pp. 61–69.

[20] L. Arms, D. Cook, and C. Cruz-Neira, "The benefits of statistical visualization in an immersive environment," in *Proc. IEEE Virtual Reality*, Mar. 1999, pp. 88–95.

[21] M. Sedlmair, T. Munzner, and M. Tory, "Empirical guidance on scatterplot and dimension reduction technique choices," *IEEE Trans. Vis. Comput. Graph.*, vol. 19, no. 12, pp. 2634–2643, Dec. 2013.

[22] S. G. Vandenberg and A. R. Kuse, "Mental rotations, a group test of three-dimensional spatial visualization," *Perceptual Motor Skills*, vol. 47, no. 2, pp. 599–604, Oct. 1978.

[23] M. S. Masters and B. Sanders, "Is the gender difference in mental rotation disappearing?" *Behav. Genet.*, vol. 23, no. 4, pp. 337–341, Jul. 1993.

[24] V. Pulkki, "Spatial sound reproduction with directional audio coding," *J. Audio Eng. Soc.*, vol. 55, no. 6, pp. 503–516, Jun. 2007.

[25] R. J. Hathaway and J. C. Bezdek, "Visual cluster validity for prototype generator clustering models," *Pattern Recognit. Lett.*, vol. 24, nos. 9–10, pp. 1563–1569, Jun. 2003.

[26] M. B. Selleck, D. Burke, C. Johnston, and V. Nambiar, "Augmented reality integration of fused lidar and spatial mapping," *Proc. SPIE*, vol. 10666, May 2018, Art. no. 106660S.

[27] J. Choi, S. Park, and J. Ko, "Analyzing head-mounted AR device energy consumption on a frame rate perspective," in *Proc. 14th Annu. IEEE Int. Conf. Sens., Commun., Netw. (SECON)*, Jun. 2017, pp. 1–2.

[28] C. D. Spielberger, R. L. Gorsuch, and R. E. Lushene, *STAI Manual for the Stait-Trait Anxiety Inventory* ("self-evaluation questionnaire"), vol. 22. Palo Alto, CA, USA: Consulting Psychologist, 1970, pp. 1–24.

[29] S. Härtel, J.-P. Gnam, S. Löffler, and K. Bös, "Estimation of energy expenditure using accelerometers and activity-based energy models—Validation of a new device," *Eur. Rev. Aging Phys. Activity*, vol. 8, no. 2, pp. 109–114, Oct. 2011.

[30] M. Höst, B. Regnell, and C. Wohlin, "Using students as subjects—A comparative study of students and professionals in lead-time impact assessment," *Empirical Softw. Eng.*, vol. 5, no. 3, pp. 201–214, Nov. 2000.

[31] L. Gautier. *RPY2: A Simple and Efficient Access to R from Python*. Accessed: Feb. 15, 2019. [Online]. Available: https://sourceforge.net/projects/rpy/

[32] I. G. G. Kreft and J. de Leeuw, *Introducing Multilevel Modeling*. Newbury Park, CA, USA: Sage, 1998.

[33] E. Z. Barsom, M. Graafland, and M. P. Schijven, "Systematic review on the effectiveness of augmented reality applications in medical training," *Surgical Endoscopy*, vol. 30, no. 10, pp. 4174–4183, Oct. 2016.

[34] E. Nugent, N. Shirilla, A. Hafeez, and D. S. O'Riordain, O. Traynor, A. M. Harrison, and P. Neary, "Development and evaluation of a simulator-based laparoscopic training program for surgical novices," *Surgical Endoscopy*, vol. 27, no. 1, pp. 214–221, Jan. 2013.

[35] Z. Zhou, A. D. Cheok, Y. Qiu, and X. Yang, "The role of 3-D sound in human reaction and performance in augmented reality environments," *IEEE Trans. Syst., Man, Cybern. A, Syst. Humans*, vol. 37, no. 2, pp. 262–272, Mar. 2007.

[36] M. Hatala, L. Kalantari, R. Wakkary, and K. Newby, "Ontology and rule based retrieval of sound objects in augmented audio reality system for museum visitors," in *Proc. ACM Symp. Appl. Comput.*, Mar. 2004, pp. 1045–1050.

[37] J. R. Blum, M. Bouchard, and J. R. Cooperstock, "What's around me? Spatialized audio augmented reality for blind users with a smartphone," in *Proc. Int. Conf. Mobile Ubiquitous Syst., Comput., Netw., Services*. Berlin, Germany: Springer, 2011, pp. 49–62.

[38] R. Hyman, "Quasi-experimentation: Design and analysis issues for field settings (book)," *J. Personality Assessment*, vol. 46, no. 1, pp. 96–97, 1982.

BURKHARD HOPPENSTEDT studied computer science from the University of Ulm. He has been with the Institute of Databases and Information Systems as an External Research Associate, in cooperation with the ATR Software GmbH, since 2016. His research interest includes big data analytics (e.g., outlier detection and concept drift) in distributed systems and mixed reality, especially with the focus on predictive maintenance in an industrial context.

THOMAS PROBST studied psychology at Regensburg University. He received the Diploma degree, in 2009, and the Ph.D. degree in psychology from the Humboldt University of Berlin, in 2015. During the Ph.D. thesis, he was involved in psychotherapy monitoring, patient-therapist feedback, and decision support tools. He started his psychotherapy training and received the certification as a cognitive-behavior therapist, in 2013. From 2013 to 2015, he was a Research Assistant with Regensburg University and the Deputy Head of the Psychotherapy Outpatient Center. From 2015 to 2016, he was an Interim Professor of clinical psychology and psychotherapy and clinical psychodiagnostics at the University Witten/Herdecke. In 2017, he was an Interim Professor of clinical psychology and psychotherapy with the Georg-August-University Göttingen and a Research Associate with the University of Ulm. In 2017, he was appointed as a Professor of psychotherapy sciences with Danube University Krems, Austria. He is experienced in teaching courses on psychotherapy and psychodiagnostics, psychosomatics, digital health, and quantitative research designs.

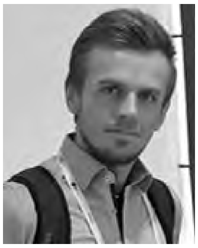
MANFRED REICHERT received the Ph.D. degree in computer science and the Diploma degree in mathematics. Since 2008, he has been a Full Professor with the University of Ulm, where he is currently the Director of the Institute of Databases and Information Systems. He was an Associate Professor with the University of Twente, The Netherlands. He was also a member of the Management Board of the Centre for Telematics and Information Technology, which is one of the largest academic ICT research institutes in Europe. His research interests include business process management (e.g., adaptive and flexible processes, process lifecycle management, data-driven, and object-centric processes) and service-oriented computing (e.g., service interoperability, mobile services, and service evolution). He has been a PC Co-CHAIR of the BPM'08, CoopIS'11, EMISA'13 and EDOC'13 conferences, and a General Chair of the BPM'09 and EDOC'14 conferences.

WINFRIED SCHLEE was born in 1978. He received the Ph.D. degree in clinical neuropsychology from the University of Konstanz, in 2009, where he introduced the concept of the Global Model of Tinnitus Perception to explain the neuronal mechanisms underlying the conscious perception of the tinnitus percept, and the Habilitation degree, in 2018. Since 2009, he has studied various factors influencing the conscious perception of tinnitus, among them the influence of age, stress and emotional arousal, the interference with auditory, electric and magnetic stimulations, and intrinsic neuronal moment-to-moment fluctuations of the resting alpha activity in temporal brain regions. In 2013, he joined the Tinnitus Research Initiative (TRI), where his current work focuses on discovering new methods for the treatment and measurement of chronic tinnitus. He is currently a German Neuropsychologist with the University of Regensburg. He studied psychology, statistics, and philosophy with the University of Konstanz and the University of Alabama at Birmingham. He is also a Chair of the European COST project "TINNET - Better understanding the tinnitus heterogeneity to improve and develop new treatments" and the European School for Interdisciplinary Tinnitus Research (ESIT).

KLAUS KAMMERER received the M.Sc. degree in media computer science from the University of Ulm, Germany, in 2014, where he is currently pursuing the Ph.D. degree with the Institute of Databases and Information Systems in cooperation with Uhlmann Pac-Systeme GmbH & Co., KG. His research interests include sensor data management, semantic web technologies, and context-aware business processes.

MYRA SPILIOPOULOU is currently a Professor of business information systems with the Faculty of Computer Science, Otto von Guericke University Magdeburg, Magdeburg, Germany. Her publications are on mining complex streams, mining evolving objects, adapting models to drift and building models that capture drift. She focusses on two application areas: 1) business, including opinion stream mining and adaptive recommenders, and 2) medical research, including epidemiological mining and learning from clinical studies. In the application domain of medical research, she works on modeling and predicting evolution of study participants with and without the target outcome. Her research on topic monitoring, social network monitoring, and analysis of complex dynamic data has been published in renowned international conferences and journals. Her current research interest includes mining dynamic complex data. She is regularly presenting tutorials on different aspects of complex data mining, and recently on medical mining. She is a member of the Presidium of the European Association of Data Science (EuADS). In Germany, she is a member of the Jury for the Best Ph.D. Award of the German Informatics Society. In 2018, she was a PC Co-Chair of the Applied Data Science Track in the ACM SIGKDD International Conference on Knowledge Discovery from Data (KDD'2018), London, in 2018. In 2019, she serves as a PC Co-Chair for the International Symposium on Computer-Based Medical Systems (CBMS 2019), in 2019. In 2019, she is a Guest Editor of the ECML PKDD 2019 Journal Track; this track is hosted by the *Data Mining and Knowledge Discovery* (DAMI) and the *Machine Learning* Journals of Springer. Since 2016, she has been serving as an Action Editor for the *Data Mining and Knowledge Discovery* Journal of Springer (DAMI). She is involved as a Senior Reviewer in major conferences on data mining and knowledge discovery.

JOHANNES SCHOBEL studied computer science from the University of Ulm. He received the Ph.D. thesis from the Institute of Databases and Information Systems, in 2018. He has been with the Institute of Databases and Information Systems, University of Ulm, as a Research Associate, since 2012. His current research interest includes mobile data collection. In particular, he focuses on end-user programming approaches to empower domain experts to create their own mobile data collection applications. In this context, he applies business process management techniques and end-user programming approaches to unravel new insights.



MICHAEL WINTER studied computer science with the University of Ulm. Since 2015, he has been a Research Associate with the Institute of Databases and Information Systems. He places a special emphasis on the comprehension of visual process models. In this context, he applies measurement methods and theories from cognitive neuroscience such as eye tracking and electrodermal activity, and psychology such as cognitive load theory to unravel new insights in this field. Therefore, he has developed a conceptual framework to foster and to assist novices and experts alike in the comprehension of process models. His research interests include business process management, statistical sciences, and human cognition.

ANNA FELNHOFER studied psychology at the University of Vienna. She received the Ph.D. degree in psychology in 2015; in the context of her thesis, she focused on the experience of presence, social stress, and social interactions in virtual reality. In 2015, she also received the master's training and was licensed as a Clinical Psychologist and a Health Psychologist. Since 2015, she has been a Research Associate (postdoctoral) with the Division Pediatric Psychosomatic Medicine, Department of Pediatrics and Adolescent Medicine, Medical University of Vienna. Her research interests include virtual reality treatment and digital media, and applied ethics in the context of pediatric psychosomatic medicine.

OSWALD D. KOTHGASSNER received the Ph.D. and Diploma degrees in psychological science. He has a certification as a Clinical Psychologist and a Health Psychologist. He was with the Department of Clinical Psychology, University of Vienna, and also as a Guest Researcher with TU Eindhoven. He is currently the Head of the Virtual Reality Intervention & Stress Research Laboratory, Department of Child and Adolescent Psychiatry, Medical University of Vienna. He is experienced with teaching courses on clinical psychology treatment, psychological assessment, and psychophysiological measures. His research interests include social stress and stress-related disorders, psychology in digital age, and virtual reality treatments.

RÜDIGER PRYSS studied at the Universities of Passau, Karlsruhe, and Ulm. He received the Diploma and Ph.D. degrees in computer science from the University of Ulm, in 2015. In his Ph.D. thesis, he focused on fundamental issues related to mobile process and task support. He was a Consultant and a Developer in a software company. Since 2008, he has been a Research Associate with the University of Ulm. He is experienced with teaching courses on database management, programming, service-oriented computing, business process management, document management, and mobile application engineering. He was a Local Organization Chair of the BPM'09 and EDOC'14 conferences.