

gPhysics—Using Smart Glasses for Head-Centered, Context-Aware Learning in Physics Experiments

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Abstract—Smart Glasses such as Google Glass are mobile computers combining classical Head-Mounted Displays (HMD) with several sensors. Therefore, contact-free, sensor-based experiments can be linked with relating, near-eye presented multiple representations. We will present a first approach on how Smart Glasses can be used as an experimental tool for head-centered, context-aware, wearable-technology-enhanced, and inquiry-based learning in physics education. Therefore, we developed an app that is based on the Google Glass platform and designed to perform educational physical experiments on the topic of acoustics. Its initial application is intended for high-school students whose task is to study the relationship between the frequency of the sound generated by hitting a glass of water and the amount of water in the glass. The core idea is to have Google Glass automatically measure both the water fill level with the camera and the sound frequency with the microphone, and incrementally generate a fill level/frequency graph in the HMD. We designed an educational setting and studied its effect on cognitive and affective variables with an intervention-control-group design. While the intervention group analyzed the fill level/frequency relationship with the Google Glass platform, control group 1 worked on the phenomenon using the same platform implemented on a tablet PC. Control group 2 analyzed the phenomenon using a tablet PC with a typical mobile-based education platform. We used a two-way ANCOVA to study learning outcome, wondering, curiosity, cognitive load, and experimentation time as dependent variables of 46 high-school eighth-graders together with group membership and gender influence as independent variables. While the positive effects of using Google Glass as a mobile lab on wondering and curiosity as well as a positive trend for experimentation time were detected, no differences were analyzed for learning achievement. Although students have a higher cognitive load when working with Google Glass compared to other devices, the cognitive load level is very low in general.

Index Terms—Wearable computers, physics education, student experiments, acoustic measurements, wearable sensors, image recognition



1 INTRODUCTION AND RATIONALE

SMART Glasses are a new class of wearable systems that extend the original vision of head-mounted displays (HMD) toward a broader concept of head-centered interaction and sensing (overview of current projects: [1]). Devices like Google Glass [2] are full-blown mobile computers that combine an HMD, a headphone, a multi-touch trackpad, head motion and eye-blink sensing, a microphone, first person camera, significant amount of FLASH storage, and variable communication capabilities. So, on the one hand, Smart Glasses allow the analysis of physical data, which encompass or influence the device (e.g., sound, acceleration) and which can be presented with different kinds of representation to the user, such as with pictures, tables, graphs, equations, etc. On the other hand, they enable users to seamlessly blend their interactions in the physical and

digital worlds, fusing and manipulating information from both worlds with minimal interference with other activities. With these features, two aspects could be brought together: contact-free, sensor-based experiments with relating, near-eye presented multiple representations. Combining experiments as a central key of teaching and learning science with multiple representations as a key aspect in learning and problem solving, especially in science education [3], facilitates context-aware, ubiquitous, just-in-time learning activities [4], [5].

Using internal sensors of everyday modern communication technology as experimental tools has become an extremely dynamic trend, especially in physics education (brief summary: [6]; column for examples on high-school level: [7]; pilot studies in high-school and university curricula: [8], [9]). However, applying Google Glass as an experimental tool for experiments in physics education classroom is completely new. Based on previous work [10], [11], [12], [13], [14], [15], [16], [17], [18], we will demonstrate in this paper how Google Glass, as an example of Smart Glasses, can be used as an experimental tool for head-centered, context-aware, wearable-technology-enhanced, and inquiry-based learning in physics education.

This paper is structured as follows: *first*, we will discuss why Google Glass serves as a suitable example of Smart Glasses as an experimental learning tool. Therefore, we will

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give a brief overview of previous works that have studied the use of Google Glass as a learning tool in general and present the theoretical framework for using such Smart Glasses as a suitable and effective *experimental* learning tool in particular. *Second*, we will present the technological and educational approach of the gPhysics-project which is based on the mentioned rationale. Therefore, we implemented a Google Glass app which is based on the Google Glass platform and designed to perform an educational physical experiment on the topic of acoustics. The initial application is intended for high-school students whose task is to examine the relationship between the frequency of the sound generated by hitting a glass of water and the amount of water in the glass. The core idea is to have Google Glass automatically measure both the water fill level (with the camera) and the sound frequency with the microphone, and incrementally generate a fill level/frequency graph in the head-mounted display. To confirm and correct measurements, we provide a choice between a hands-free head motion/eye-blink interface or the Google Glass touchpad. Our vision is to enhance physics teaching and learning and develop possibilities for utilizing Smart Glasses—such as Google Glass—to (1) reduce the “technical” effort involved in conducting the experiments (measuring, generating plots, etc.) and to (2) allow the students to interactively see/manipulate the theoretical representation of the relevant phenomena while, at the same time, interacting with the phenomena in the real world. To study this, we will present, *third*, an intervention-control-group study which was based on the mentioned theoretical framework. We will discuss the materials, methods, and results of this empirical study. While the intervention group (IG) analyzed the fill level/frequency of a water/glass relationship with the Google Glass platform, control group 1 (CG 1) worked on the phenomenon using the same platform implemented on a tablet PC. Furthermore, we provide a second control group (CG 2) which studied the same phenomenon with the best possible, mobile-based analysis methods that were previously available. We used a two-way ANCOVA to study learning outcome, curiosity, cognitive load, wondering, and experimentation time as dependent variables of high-school eighth-graders together with group membership as an independent variable. At the end of the paper we will discuss the gPhysics approach, the results of the study, and give conclusions for further works.

2 GOOGLE GLASS: A SUITABLE AND PROMISING EXAMPLE OF SMART GLASSES AS EXPERIMENTAL LEARNING TOOL

The educational properties of wearable technologies have been explored by Bower and Sturman, who mention in [1] that there is considerable literature investigating the development and use of wearable technologies across a range of fields. But—except for some minor work—there is a lack of research into the use of wearable technologies in education. So we will first present the studies on the use of Google Glass in educational settings before discussing Google Glass as a suitable example of Smart Glasses, especially as an *experimental* learning tool.

2.1 Previous Studies on Google Glass in Educational Settings

Recently, wearable technologies (such as Google Glass) have been used in medical training role-play activities to provide a first-person viewpoint and recordings [19]. Recordings were then used to observe the amount of time participants spent focusing on different information sources, the level of attention paid to the patient, and other metrics that informed reflective learning and group debriefing. The first-person viewpoint in the role-play and the novel observations that led to discussion on items were not typical in role-play tasks completed without the wearable device. The hands-free nature of the device meant that it did not interfere in the role-play in any way. This led the research team to conclude that wearable devices could offer unique advantages in role-play-based learning contexts with few negative consequences.

Further studies on medical education report the positive effects of broadcasting a procedure onto a mobile phone as a viewer, replacing expensive and often cumbersome existing equipment [20] or of video-recording students during standardized patient encounters, providing a novel perspective for the analysis and evaluation of their interpersonal communication skills and nonverbal behaviors [21]. As well as being used by trainers to broadcast to trainees, some case reports have suggested that Google Glass may be used by trainers to instruct trainees wearing Google Glass—so-called ‘telementoring’. Studies have reported success in orthopaedic shoulder surgery [22] and in training people to acquire simple views during cardiac ultrasonography [23].

Another implementation describes the use of Google Glass to provide art gallery visitors with augmented information while looking at paintings [24]. The study aims to assess how Google Glass enhances visitors’ learning outcomes within the art gallery environment. The analyzed data reveal that Google Glass helps visitors to enhance their knowledge and understanding of paintings.

Coffman and Klinger [25] provided teachers and students with access to Google Glass to use during educational psychology and organizational behavior classes. They found that the technology could be seamlessly integrated into the lessons to take pictures of student work, video-record class activities, access the Internet, and poll students for responses to questions. Based on their preliminary explorations with Google Glass, they identified the main potential of the technology as its ability to spark interest and creativity, facilitate collaboration, and improve feedback. The issues associated with the use of the technology were technical challenges as well as related privacy concerns.

To sum up, so far the reported implementations and studies of Smart Glasses, such as Google Glass, in educational settings have focused more on general and “traditional” applications such as recording actions, presenting and sharing information, also with elder learners. Furthermore no project has provided a concept that could be implemented in regular high-school curricula. So, the previous concepts have not exploited all possibilities of Smart Glasses, having neglected to examine implementation in the regular curricular context—at least in high school—and are limited to very specific use cases.

With this project, we consider the above-mentioned challenges [26], [27], [28], [29] concerning future, context-aware,

ubiquitous learning activities and are responding to the recent call in this journal “for more productive research into seamless, ubiquitous, and contextual learning” [30].

2.2 Google Glass as Experimental Tool: Theoretical Background

As Smart Glasses such as Google Glass are wearable systems with full-blown mobile computers that combine a “traditional” HMD with different sensors (e.g., headphone, multi-touch trackpad, head motion and eye-blink sensing, microphone, camera, etc.), they allow the analysis of physical data which encompass or influence the device (e.g., sound, acceleration) and which can be presented to the user in different kinds of representations such as pictures, tables, graphs, etc. Furthermore they enable users to seamlessly blend their interactions in the physical and digital worlds, fusing and manipulating information from both worlds with minimal interference with other activities. With these features, two aspects could be brought together: contact-free, sensor-based experiments with relating, near-eye presented multiple representations.

This approach could be based on fundamental cognitive theories. Competent handling of multiple representations is supposed to be significant for learning and problem solving in physics [31], [32]. This applies especially to the topic of acoustics, as multiple representations are important for learning content with oscillograms, frequency spectra, etc. A psychological model for understanding the cognitive processes while working with multiple representations is offered by the Cognitive Theory of Multimedia Learning (CTML; [33]) and the Cognitive Load Theory (CLT; [34]). Referred to as CTML, the generation of a mental model of the learning content requires an active part in information processing. The presentation format of the learning material is essential and can be structured into text/picture or classified according to dynamics and interactivity [35]. Students’ learning is improved by presenting text/equations and pictures/graphs/videos instead of learning with text/equations alone. While using the pictorial and verbal/auditory channels simultaneously, sensory and representational differentiations are connected. As a result, cognitive load is reduced. So greater capacity of working memory is available for forming mental representation models according to CTML and, therefore, learnability is increased. By presenting experimental and theoretical data, students can compare predicted theoretical results with real experimental data. They immediately receive feedback on their assumptions and their calculations. Such prompt feedback on results fosters learning [36].

Second, besides enhancing cognitive variables, our approach could be integrated into motivational frameworks: using Smart Glasses as an instrument for measurement and analysis allows students to play a more active role in problem-solving processes. They become involved in the experiment, gather and analyze experimental data themselves, and hence experience autonomy, which is said to foster motivation in general [37], [38] as well as curiosity and wondering, as special features of motivation, in particular [39], [40], [41], [42], [43]. So we assume that a closer connection between theoretical exercises and experimental tasks allows students to experience

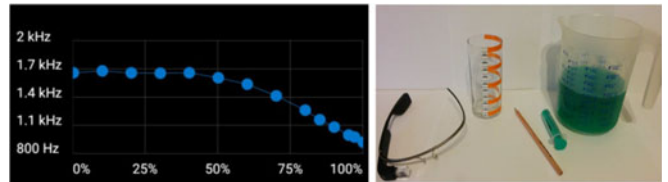


Fig. 1. The gPhysics acoustic experiment: The frequency/fill level relationship of a water glass (left) and the related experimental material (right).

autonomy in the problem-solving process and, thus, fosters motivation in general.

Furthermore, the implementation of teaching practices that involve phenomena related to students’ everyday lives could improve their learning process and increase their motivation (context-based science learning, [44], [45], [46], [47]). Therefore using mobile devices as an experimental tool to study everyday phenomena follows context-aware, ubiquitous just-in-time learning activities [4], [5], [26], [27], [28], [29], [30] and provides a dual link to context-based science learning: studying phenomena and using experimental tools that are both related to students’ everyday lives [8], [48].

3 GPHYSICS PROJECT

With the gPhysics project we provide contact-free, sensor-based, and context-based experiments with relating, near-eye presented multiple representations for different topics of regular high-school, college and university curricula. Combining experiments as a central key to teaching and learning science with multiple representations as a key aspect on learning and problem solving, especially in science education [3], should facilitate context-aware, ubiquitous, just-in-time learning activities [4], [5]; [26], [27], [28], [29], [30]. In this paper we will start with a first experiment in acoustics: studying the tone of a water glass.

3.1 The gPhysics Acoustic Experiment

Based on Section 2.2, we designed a concrete experiment which is part of many high school physics curricula and relates to a well-known everyday phenomenon: when water is filled in a glass, the frequency of the tone becomes lower. This happens because as water is added, more mass is added to the water glass. More mass results in a smaller/lower vibrating frequency, and less mass produces a faster/higher vibrating frequency of the wall of the glass. But instead of the supposed obvious relationship—the more water in the glass, the higher the tone—this everyday phenomenon is much more complicated (see Fig. 1, left). The basic intention of this experiment is to make the real relationship obvious.

The students study:

- the relationship between the water fill level in the glass and the frequency of the generated tone and
- the relationship between the water fill level in the glass and the frequency of the induced tone by damping the vibration of the glass with an additional mass

while hitting the glass with a wooden peg (Fig. 1).

The core idea is to allow the students to fill the glass and test the frequency while at the same time having Google

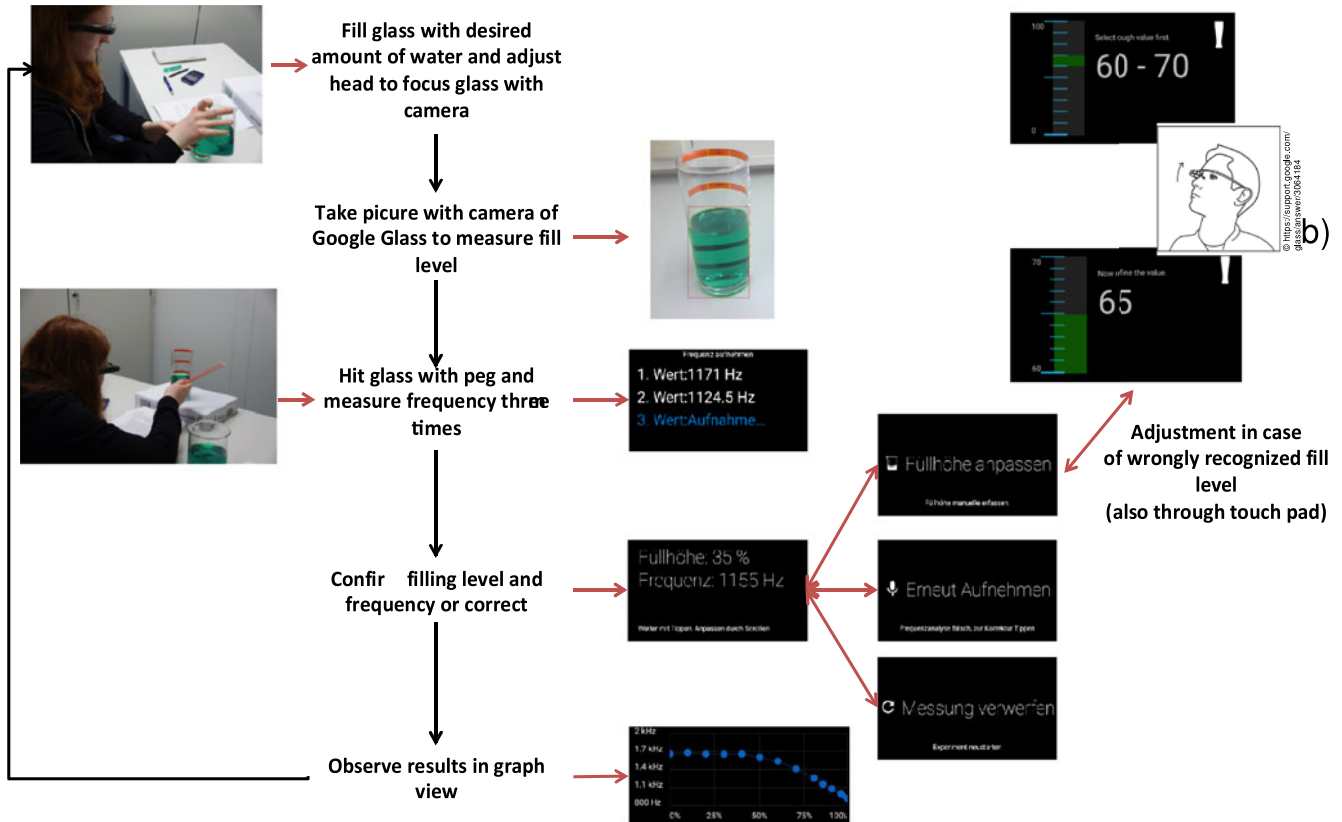


Fig. 2. Steps to perform water-glass experiment with the Google Glass gPhysics app.

Glass incrementally generate the graph showing the relationships mentioned above. Noticeably, the phenomenon to be detected by students is that the pitch does not correlate linearly with the fill level (see Fig. 1, left), although this is what they would assume on the basis of everyday experiences, and that this relationship can be influenced with a damping mass. Until the water glass is nearly filled half, the pitch changes less when a fixed amount of water is added compared to when the water glass is nearly full. Thus the student can view the results on the display as the experiment evolves (while he fills/removes water into/from the glass).

3.2 Hypothesis

Based on the theoretical framework discussed in Section 2.2, the gPhysics system (see Section 4) should offer the possibility to work actively with different representational formats simultaneously (e.g., bar graphs, graphs, values). The experimental process students have to process should be multimedial (text and picture), multimodal (audiovisual), and interactive. The physical context of the considered experimental process integrates these representations into a consistent framework.

We therefore study the following hypothesis:

Learning with the gPhysics system on Google Glass (intervention group IG) fosters

- wondering,
 - curiosity, and
 - learning achievement,
- and reduces
- cognitive load and
 - experimentation time

compared to learning with the gPhysics app on a tablet PC (control group CG 1) and compared to studying the phenomenon in a traditional learning environment with the best possible mobile learning system (control group CG 2).

4 GPHYSICS SYSTEM IMPLEMENTATION

4.1 The gPhysics App

We developed a Google Glass app (gPhysics) that implements the above idea through a series of steps shown in Fig. 2. To create a comparable case, we ported the application to run on Android tablet devices. As an example, we will explain the steps required to perform the experiment based on the Google Glass app. In Section 4.5 we will highlight the differences with the tablet app.

Having started the gPhysics app, the first activity is to adjust the fill level of the glass. We chose a computer vision approach to automatically estimate the fill level of the glass. The camera live stream is shown in the Google Glass display. To initiate estimation of the fill level, the user needs to adjust the camera to focus on the glass with his/her head first. Double-blinking with the right eye or a tap on the touchpad starts the estimation by taking a picture with the camera and starting the processing. Having estimated the fill level of the glass, the user is forwarded to the frequency measuring activity. He/she can start hitting the glass with the peg at any time. To detect the water glass frequency, we use the built-in microphone of Google Glass. Next, the user is forwarded to a confirmation screen which displays the estimated fill level and the measured frequency and asks for



Fig. 3. Binary mask of green pixels (left) and extracted fluid component contour line and bounding rectangle (right).

confirmation. If the two values are correct, a double-blink or a tap gesture on the touchpad of the device leads the user to the graph view. If one of the values or even both values are not correct (e.g., if the fill level has been estimated inaccurately or the frequency is incorrect due to background noise during the measurement), the user can correct them separately or, alternatively, discard both and go back to step 1 (if the fill level is obviously incorrect due to a malfunction of the visual recognition system). The three options can be accessed by scrolling through a horizontal three-item menu either by forward/backward swiping on the touchpad or by moving his or her head to the left or right, respectively.

The fill level is corrected by adjusting a vertical slider to the correct value. Once again, selection can be made by using a head gesture (up/down head movement and double-blinking for confirmation) or a touchpad (left/right scrolling and tapping for confirmation) interface. At this point, we do not go back to visual estimation, as this alternative method of selection is not as error-prone as visual detection. If the frequency is not measured correctly (which is generally the case if the three measurements that the system performs for each frequency are not consistent), the user is directed back to the frequency measuring activity. Finally, measurements (fill level, frequency) are visualized on a graph view which plots the fill level along the x -axis and the frequency along the y -axis. Using a horizontal three-item menu, the user has the possibility to delete existing entries in the reverse order that they were created including the latest point, to reset the whole graph, or to accept the new entry and go back to step 1 to record a new measurement. As described before, the menu can be navigated either by using head gestures or the touchpad of the Google Glass device. Fig. 2 summarizes the procedure described before.

On Google Glass, we implemented the application with the Glass Development Kit (GDK) which is an add-on for the Android SDK. It enabled us to build Glassware that run directly on the Google Glass device (as opposed to the Google Glass Mirror API which does not allow full hardware access and interaction). The visualization and input (including eye-blink and head motion detection) are based on the provided routines and require no further explanation. Thus the two core components of the gPhysics app are the visual recognition of the glass fill level (see Section 4.2) and the tone frequency measurement (which had to take into account the filtering out of higher harmonics; see Section 4.3). Additionally, we implemented a logging system to record the interactions of the user with the application and information about every measurement made during a single round of the experiment (see Section 4.4).



Fig. 4. Binary image of orange pixels (left) and extracted strip components (right).

4.2 Automatic Fill Level Detection from Images

First it has to be noted that the purpose of this work was not to develop a novel video processing method that could work under complex real-life conditions. Instead, we intended the experiments to be performed in a controlled lab environment, where colored water and glass with clear markings can be used and the background can be kept largely free of clutter. We used a bright green fluid created with green food coloring and five orange strips with their upper edges aligned with the 100, 75, 50, 25, and 0 percent level markings, respectively. Figs. 3 and 4 show examples of glasses filled with some fluid.

In all following descriptions, we will refer to this setup. The actual image processing was implemented with OpenCV computer vision libraries and essentially consisted of two stages: the detection of the fluid color component and, the detection of the colored labels and estimation of the fill level. The entire detection ran directly on the Glass device or on the tablet, respectively.

4.2.1 Detection of the Fluid Color Component

Initially, the input image from the camera (for demonstration purposes we will use the images in Figs. 3 and 4 as examples) was converted from RGB to HSV color space, which is commonly used for color segmentation purposes. Next, the HSV image was thresholded and post-processed, applying morphological operators to clean it up. To localize the fluid color component, we computed the contours of connected components in the mask image and filtered out those that were insignificantly small. From the remaining significant ones, we assumed that the biggest contour corresponded to the fluid component and computed its bounding box. If no appropriate component existed, we assumed the fill level to be 0 percent.

4.2.2 Detection of the Colored Labels and Estimation of the Fill Level

For the remaining part of the algorithm, all further image processing was restricted to subimages covering only the area above the bounding box (region of interest) of the (merged) fluid color component. The HSV image was thresholded again to create another binary mask containing orange pixels of the color labels this time. Next, cleaning up, contour extraction, and component filtering were performed in a similar way to described above.

If no orange contour was found at all, the algorithm assumed that the glass was full and displayed a fill level of 100 percent. Otherwise, the mean points of the remaining contours were computed, projected to the vertical line going

through the center of the region of interest, and the components were merged together if their projected mean points were closer to each other than a certain threshold. This merging step is necessary if the contour of a color label is not detected as a whole, but is fragmented into two or more color components. From the merged contours, we computed the mean distance d_{mean} between two adjacent ones, filtering out those that were either too far away from each other or too close, comparing the distance between the upper edges of their bounding rectangles. From the resulting set of extracted color labels, the fill level was determined by assuming one of the following two cases: if n is the overall number of color labels that are fixed to the glass and m the number of extracted (visible) color labels.

1. If $m = 1$, the fill level is estimated as

$$f = \frac{h_f}{h_{total}} \cdot 100\%,$$

where h_f is the height of the bounding rectangle of the fluid color component in pixels and h_{total} is the vertical distance of the upper edge of the only color label bounding box and the lower edge of the fluid component bounding rectangle in pixels.

2. If $m > 1$, the fill level is

$$f = \left(1 - \frac{m-1}{n-1} - \frac{d_{fluid}}{d_{mean}} \right) \cdot 100\%,$$

where d_{mean} is the mean distance in pixels between the extracted color labels as explained before and d_{fluid} is the distance between the upper edge of the bounding box of the color label and the upper edge of the fluid bounding rectangle. Thus, the first term $(m-1/n-1)$ generates a coarse estimation based on the number of covered bars, while the second uses the amount of space to the last visible bar to refine the estimate. We have found this two-stage method to be more robust than an estimate based merely on the fraction of the glass height covered by the colored fluid.

4.3 Frequency Measurement

To detect the water glass frequency, we used the built-in microphone of Google Glass and the Android tablet PC. The main requirement for detecting water glass frequency in real time is to achieve a robust, resource-saving, and accurate algorithm. The resonant frequency detection algorithm is a multi-step pipeline process that forwards the provisional results to the next stage following the following series of steps:

1. Reading the audio buffer.
2. Applying Fast Fourier Transformation.
3. Filtering frequencies between 650 Hz and 2,000 Hz.
4. Detecting frequency with highest magnitude based on power spectrum.
5. Validating detected frequency with a magnitude threshold (0.5).
6. Detecting sequential ascending, resonant, and descending values in window sequence.
7. If sequence is valid: computing resulting frequency value.
8. If sequence is invalid: searching for new valid sequence.

The audio buffer is read continuously (every few milliseconds). Each audio buffer window is transformed by the Fast Fourier Transformation (FFT) into the frequency domain. The frequency with the highest magnitude based on the power spectrum is retrieved. Harmonic frequencies are not detected as they are quieter than the fundamental oscillation. Only frequencies between 650 Hz and 2,000 Hz are analyzed, which is the known frequency range of the water glass. A validation step is performed to ignore sound input with a broad frequency spectrum in the allowed frequency range. If the frequency is lower than the empirically determined threshold (0.5), it is rejected. While the water glass is being tapped, the algorithm detects ascending frequencies, lingering peaks with similar frequencies (as the water glass is in resonance) and descending frequencies (as the water glass stops the resonance frequency). If the ascending, descending, and then in-between frequencies (with very similar frequencies) are detected, the average value of the in-between frequencies is computed. If the in-between frequencies are distinct (i.e., speech is recognized), the recognition is reset and the search for ascending frequencies is restarted.

4.4 Logging

While the experiment is being performed, the application creates a comprehensive log file recording the interactions of the user with the app and the results of the measurements. This allows us to understand in detail how the application is used (e.g., which input modalities are applied or how much time a user spends on a certain screen).

In detail, a log file contains the following entries:

- The timestamp of the start of the experiment (created as soon as the user starts the experiment).
- The timestamp of the end of the experiment (created when the user finishes the experiment using the “End experiment” option in the graph view).
- The overall time needed for the experiment.
- The list of individual measurements performed during the experiment with each entry containing detailed information about the measuring process and the application usage.

For each of the measurement entries we record:

- The time spent per screen. We log the time the user spends on each screen (camera, frequency measurement, confirmation, fill level correction, graph).
- Additionally, input modalities (tab, swipe, blink, head turn left/right, up/down) which are used to interact with the application are recorded per screen.
- The estimated fill level and, if relevant, the chronologically ordered list of fill level corrections (a user may correct the fill level more than once if he/she has made a mistake).
- The processing time needed to automatically compute the fill level from the input image. This value is necessary to compare the experiment execution times with the Glass and the tablet app as the processing speed of the Google Glass hardware is essentially slower.
- A list of frequency measurement triples with each entry containing the three measured frequencies.

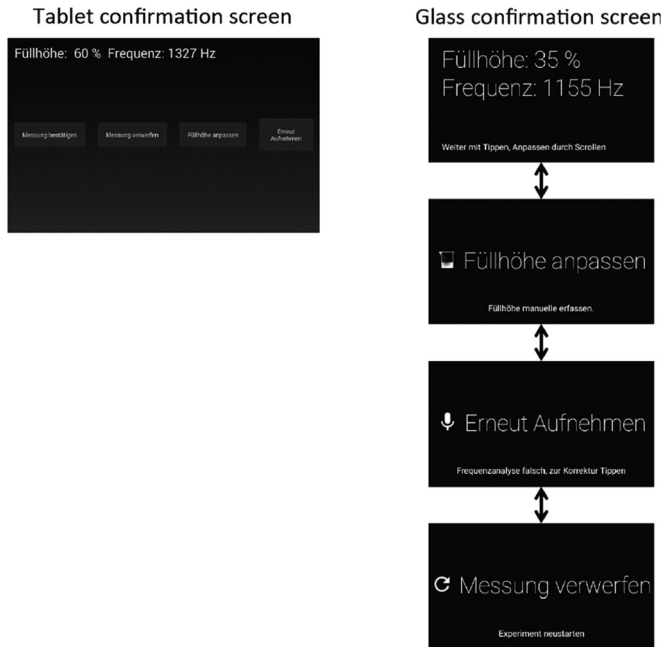


Fig. 5. gPhysics App on Android tablet/smartphone (left) compared to its Google Glass implementation (right).

The list usually contains only one entry unless the user decided to measure the frequency again.

- A flag indicating whether the user deleted the measurement afterwards in the graph view.

4.5 gPhysics App: Differences between Google Glass and a Tablet

The gPhysics app was first developed for Google Glass. To have a comparable case for our study, we implemented a slightly adapted application to run on Android tablet/smartphone devices. While the core functionalities (automatic fill level detection from images, frequency measurement using the built-in microphone, and logging) are equivalent to the Glass app and share the same code base, the main differences are in the layout and the available input modalities for interacting with the application (see Fig. 5). These differences are due to the inherently distinct nature of the devices.

The Glass app uses the standard card-based layout offered by the Glass development kit. Each entry of the option menu is displayed as a separate view of the confirmation screen (adjust fill level, measure frequencies again, restart measurement), which can be accessed by swiping on the touchpad or turning one's head to the left or right. The chosen option can then be selected by double-blinking or tapping the touchpad. On the same screen of the tablet app, however, we simply use buttons placed below the values to confirm or to start an option (e.g., correction of the fill level). The audio and video recognition algorithms on the tablet are identical with the ones that run on Google Glass.

4.6 gPhysics App: Limitations

The aim of our work was not to implement a final, robust platform but to investigate the potential of context-aware Smart Glasses for inquiry-based learning in physics education. Consequently, the gPhysics system is a prototype with

a number of limitations. *First* there are the hardware constraints of Google Glass, in particular with respect to its processing speed and the quality of its camera. The *second* limitation is the complexity of optical fill level recognition. It was implemented using standard algorithms which were good enough to demonstrate the potential benefit of using Google Glass, but not necessarily sufficiently robust and highly reliable. While the latter is not a fundamental problem, the engineering effort required from the point of view of computer vision would be significant. *Finally*, interaction with Smart Glasses is an active research field in wearable computing. Thus, while the interaction modalities that we chose are based on significant previous general experience and initial specific experiments, there is certainly scope for further improvement. Within this project, we have accounted for the above limitations by explicitly capturing their impact as described in Sections 5 and 6 (predominantly by looking at how different aspects increased the execution time). The understanding we acquired about the relevance of different types limitation is a significant result of the experiments described in this paper; an improved version of the experiments can only be developed based on an understanding of that result.

5 MATERIAL AND METHODS

The hypotheses mentioned in Section 3.2 were examined with an intervention-control-group study design with the following independent variables (see Fig. 6):

- intervention group (IG), in which students used Google Glass as an experimental tool and the gPhysics app to conduct the water-glass experiment (Fig. 6, left),
- control group 1 (CG 1), in which students used a tablet PC (Android) as experimental tool and the gPhysics app to conduct the water-glass experiment (Fig. 6, middle)
- control group 2 (CG 2), in which students used a tablet PC (iPad mini) as an experimental tool and the app SpectrumView [49] to measure sound frequency. In order to assess a new innovation for educational instruction, the innovation should be compared with the method that is presumed to be the best possible one until now as a baseline. Measuring acoustic phenomena with a tablet PC is currently the best possible conventional mobile learning system (traditional tablet PC group; Fig. 6, right; see [8]). The app SpectrumView is an iOS app which is available in the app store and typically used to analyze and visualize frequencies in real time in physics classrooms [10]. It provides a real-time spectrogram view of audio data measured with the in-built or an external microphone in order to observe trends in the frequencies present in the recording environment. So CG 2 was the "baseline" of the study.

Learning achievement, curiosity, wondering, cognitive load, and experimentation time were measured as dependent variables (see the following sections). Note that the IG differed from CG 1 only in the use of a wearable versus a mobile system as experimental tool. Students in CG 2, on the other hand, measured the acoustic signal of a tone using



Fig. 6. Experimental procedure in the intervention group (IG; left), control group 1 (CG 1; middle), and control group 2 (CG 2; right).

the iOS app SpectrumView which generates a spectrograph. This group collected the fill level value with a measuring tape fixed to the side of the glass, sequentially entered the tone frequencies and fill levels in a table, and constructed a diagram with the measured data by themselves.

5.1 Study Sample and Study Design

The investigation was conducted with three eighth-grade classes of a German high school. In total, the tested sample included 46 students, who were randomly sampled in three groups: 19 students in the IG (37 percent female, 63 percent male; age: 13.05 ± 0.71 years), 13 students in CG 1 (31 percent female, 69 percent male; age: 13.00 ± 0.58 years), and 14 students in CG 2 (36 percent female, 64 percent male; age: 13.00 ± 0.55 years).

Before initiating the intervention, we gathered the students’ grades in Physics, Mathematics, and German and administered pre-test measures (questionnaires; see 5.2) on familiarity with the use of smartphones and tablet PCs, curiosity concerning smartphones and tablet PCs and concerning Google Glass, and pretests on achievement consisting of curriculum-based, multiple-choice items on the topic of acoustics (duration: 45 minutes). Then students were shown how to use the mobile device and apps separately in each group in a 45-minute session.

This introduction included a presentation of the relevant functions of the devices and their apps (duration: 15 minutes) followed by a 30-minute period during which the students autonomously practiced with five different measurement examples that we provided. After the introduction, the students in the three groups individually studied the relationship between the fill level of the water glass and the resulting tone as well as between the water fill level in the glass and the frequency of the generated tone by damping the vibration of the glass with an additional mass (see Fig. 6). Therefore they conducted three experiments. In the first experiment they studied the relationship between the fill level of the glass and the resulting tone. The second experiment was a repetition experiment to reproduce the first study, and in the third experiment the students examined the relationship between the water fill level in the glass and the frequency of the generated tone by damping the

vibration of the glass with an additional mass. In this case the vibration was damped with an additional hair tie fixed to the top of the water glass. While the overall experimental procedure was identical in each group, the actions differed in some details because the devices and their apps needed to be handled differently (see Section 5.2).

After the experimental procedure, we administered post-test measures (questionnaires) on their state of curiosity about formal and informal learning with a tablet PC as well as with Google Glass, on wondering, cognitive load, and learning achievement respectively for comparison with the pre-test measures (duration: 45 minutes). An overview of the study design is presented in Table 1.

5.2 Instruction Material, Questionnaires, and Analytical Methods

The students of the three groups individually conducted the three experiments to study the fill level/frequency relationship and its dependency on damping (see Section 5.1). The instructions of the experiments were presented on a worksheet for the students (see Tables 2 and 3).

We measured wondering, cognitive load, and curiosity with well-established questionnaires (see [34]; [50]). The two latter variables were related to both the devices and the experiments as pre- and post-test measures. Each questionnaire had a six-point Likert-type scale and the score of each questionnaire was normed to [0;1] (resp. 0–100 percent).

TABLE 1
Study Design

Time	gPhysics Google Glass group (IG)	gPhysics tablet PC group (CG 1)	traditional tablet PC group (CG 2)
45'	Pre-test measures		
45'	Introduction to use...		
	<i>Google Glass and the gPhysics app</i>	<i>tablet PC and the gPhysics app</i>	<i>tablet PC and SpectrumView</i>
45'	Study the fill level-tone frequency relationship with...		
	<i>Google Glass and the gPhysics app</i>	<i>tablet PC and the gPhysics app</i>	<i>tablet PC and SpectrumView</i>
45'	Post-test measures		

TABLE 2
Experiment Instructions for Google Glass Group (IG)
and Tablet PC Group (CG 1) Using the gPhysics App

1. Fill the glass with an amount of water.
2. Determine the water fill level by visual recognition; in case of invalid measurement, use head movement to set water fill level.
3. You are now in the measuring menu. Hit the glass with the wooden peg until the app has detected the tone three times. Note: In case of invalid measurement, repeat step 2 und step 3.
4. In case of valid tone detection, the current frequency is added to a diagram displaying water fill level (x-axis) and frequency (y-axis).
5. Choose the option 'Add new entry' and repeat the procedure until 12 frequencies have been correctly detected.
6. Have the displayed graph checked by the instructor.
7. Repeat the procedure one time.
8. After repeating the first experiment, fix a hair tie to the top of the water glass and repeat the procedure again.

Table 4 presents a selection of different items from the paper-and-pencil tests. Furthermore the pre- and post-tests of learning achievement consisted of the same curriculum-based, multiple-choice items on the topic of acoustics. So we were able to use the pre-test data similarly to curiosity and cognitive load measures as a further covariate.

The experimental time required by the students to study the phenomenon for each experiment was recorded individually in each group. While the experimental times in the IG and CG 1 were measured by the gPhysics app (see Section 4.4), the time required for the students in CG 2 to complete the experiment was measured by the instructors.

As covariates, we collected curiosity trait (see above; [50]), the current school report card grades in Mathematics, Physics, and German as well as items concerning the familiarity of students with mobile devices. Together with gender and the pre-test data on learning achievement mentioned above, these measures allowed us to control for and analyze the possible influences of learner features on the effects of the intervention.

According to the variable plan and the intervention-control-group study design described above, we applied an Analysis of Covariance (ANCOVA; using SPSS version 20). The dependent variables consisted of wondering, cognitive load, curiosity, experimentation time, and learning achievement in physics. The independent variables were treatment (group membership) and gender; the covariates consisted of curiosity trait, grades from the current school report card in Mathematics, Physics, and German as well as items

TABLE 3
Experiment Instructions for Tablet PC Group Using
SpectrumView (CG 2)

1. Fill the glass with an amount of water.
2. Hit the glass with the wooden peg and record the spectrogram of the tone.
3. Read out the smallest frequency with the highest intensity.
4. Enter the measured value in the precasted table.
5. Repeat the procedure until 12 frequencies have been detected.
6. Transfer the value table in the precasted diagram.
7. Have the plotted graph checked by the instructor.
8. After repeating the first experiment, fix a hair tie to the top of the water glass and repeat the procedure again.

TABLE 4
Selection of Items from the Curiosity, Cognitive Load,
and Wondering Questionnaires

<i>Curiosity</i>
<i>(items in total: 6; item number on informal learning: 3; item number on formal learning: 3)</i>
- I would like to conduct further experiments with mobile devices.
- I would like to conduct further experiments with mobile devices.
<i>Cognitive load</i>
<i>(items in total: 17; item number on device: 7; item number on experiment: 10)</i>
- Solving the problem by conducting the experiment was easy.
- It was easy to use the mobile device for experimentation.
- I had no issue with understanding the physical principles related to the experiment.
<i>Wondering (items in total: 3)</i>
- I am surprised at the possibilities of using a smartphone/tablet PC/Google Glass as an experimental tool in physics.
- I wouldn't have expected that a smartphone/tablet PC/Google Glass offers the possibility to make precise measurements.

concerning the familiarity of students with mobile devices and the pre-test data on learning achievement. The reported measure of effect size is partial eta squared (part η^2): that is, the variance explained by a given variable of the variance remaining after excluding variance explained by other predictors, with the usual size categorization (see [51]: small effects: $0.01 < \text{part } \eta^2 < 0.06$; medium effects: $0.06 \leq \text{part } \eta^2 < 0.14$; large effects: $0.14 \leq \text{part } \eta^2$).

6 RESULTS

Table 5 presents the descriptive data of the study variables. Following [52], we included only covariates in the ANCOVA calculation which correlated significantly with the dependent variable (see Tables 6 and 7).

The three groups therefore differed significantly with large effect sizes concerning the variables wondering ($F(2, 46) = 6.02$; $p < .01$; part $\eta^2 = 0.23$) and curiosity state (in total as well as concerning formal and informal learning; CS(total): $F(2, 46) = 10.17$; $p < .001$; part $\eta^2 = 0.36$; CS(formal): $F(2, 46) = 6.94$ $p < .05$; part $\eta^2 = 0.27$; CS(informal): $F(2, 46) = 8.11$ $p < .01$; part $\eta^2 = 0.31$; see Table 6). The effects concerning wondering as well as curiosity state with regard to informal learning, and curiosity state in total are related to the higher value of each dependent variable in the intervention group—consistent with the related hypothesis in Section 3.2 (see Fig. 7). Thus the CS-formal value differed only between the gPhysics groups and the SpectrumView tablet group, but not between the two gPhysics groups.

The variables wondering and curiosity state (total) were also dependent on gender aspects. While female and male students differed significantly in their degree of wondering with medium effect size independent of their group membership ($F(1, 46) = 3.94$; $p < .05$; part $\eta^2 = 0.09$), this could also be analyzed concerning the variable curiosity state (total) related to the interaction between group membership and gender ($F(2, 46) = 3.62$; $p < 0.05$; part $\eta^2 = 0.16$). Both effects are related to the higher value of male students compared to their female counterparts. Furthermore the

TABLE 5
Descriptive Data (Mean *M* and Standard Deviation *SD*)
of Dependent Variables and Covariates in %

Variable	IG (<i>M</i> / <i>SD</i>)	CG 1 (<i>M</i> / <i>SD</i>)	CG 2 (<i>M</i> / <i>SD</i>)
<i>Dependent variables</i>			
Wondering ^a	75.44/6.07	56.41/5.88	46.67/8.24
Curiosity state device (total) ^a	84.6/2.9	78.1/3.7	64.3/3.4
Curiosity state device (informal) ^a	86.2/3.0	84.6/2.9	70.3/3.4
Curiosity state device (formal) ^a	82.9/4.4	69.6/5.5	55.6/5.1
Cognitive load (total) ^a	24.4/3.4	13.5/4.1	15.0/2.5
Cognitive load (device) ^a	20.5/4.2	15.9/4.9	16.4/2.9
Cognitive load (experiment) ^a	29.9/3.0	10.1/3.3	13.1/2.2
Experimentation time ^b	Exp. 1: 17.5/4.3 Exp. 2: 13.5/2.8 Exp. 3: 12.8/3.2	Exp. 1: 11.2/1.8 Exp. 2: 8.8/1.4 Exp. 3: 10.18/2.4	Exp. 1: 22.5/2.2 Exp. 2: 16.5/15.7 Exp. 3: 15.7/1.6
Learning achievement (post-test) ^a	51.8/2.8	55.9/3.6	60.6/3.3
<i>Covariates</i>			
Familiarity ^a	80.7/12.4	76.4/18.0	81.7/13.4
Curiosity trait ^a	78.7/13.8	68.8/18.0	74.3/23.7
Grade in Physics ^c	2.89/0.81	2.75/1.06	2.79/1.12
Grade in Mathema-tics ^c	2.68/1.00	2.75/1.14	2.64/1.15
Grade in German ^c	2.79/0.87	3.08/0.79	2.71/0.83
Learning achievement (pre-test) ^a	45.3/12.9	38.8/14.7	42.9/12.9

^a Data in %; ^b data in minutes; ^c in Germany school grades range from 1 to 6 whereby 1 means “very good” and 6 “very bad”.

covariate curiosity trait had a significant and medium to large influence on the dependent variables of curiosity state (CS(tot): $F(1, 46) = 9.78; p < 0.01; \text{part } \eta^2 = 0.21$; CS(form): $F(1, 46) = 12.69; p < 0.01; \text{part } \eta^2 = 0.25$; CS(inform): $F(1, 46) = 5.21; p < 0.05; \text{part } \eta^2 = 0.12$). Therefore, besides the correlation of curiosity trait and curiosity state, it shows that the differences between the groups in their degree of curiosity state explained between 12 percent (CS(inform)) and 25 percent (CS(form)) of variance of the curiosity state variables.

TABLE 6
Analysis of Covariance (ANCOVA) of the Dependent
Variables Wondering and Curiosity

Variables	df	WON F(part η^2)	CS(tot) F(part η^2)	CS(form) F(part η^2)	CS(inform) F(part η^2)
Main effects					
Group membership (GM)	2	6.02** (0.23)	10.17*** (0.36)	6.94* (0.27)	8.11** (0.31)
Gender	1	3.94* (0.09)	0.61	3.39	0.20
Gender x GM	2	0.04	3.62* (0.16)	2.83	2.44
Covariates					
Curiosity trait	1	/	9.78** (0.21)	12.69** (0.25)	5.21* (0.12)
Error	40				

Note. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; WON = Wondering, CS(tot) = curiosity state in total, CS(formal) = curiosity state formal learning, CS(informal) = curiosity state informal learning.

TABLE 7
Analysis of Covariance (ANCOVA) of the Dependent
Variables Cognitive Load and Learning Achievement

Variables	df	CL(tot) F(part η^2)	CL(exp) F(part η^2)	CL(device) F(part η^2)	Achievement F(part η^2)
Main effects					
Group membership (GM)	2	4.12* (0.17)	0.91	14.47*** (0.42)	2.30
Gender	1	1.13	0.70	1.72	0.08
Gender x GM	2	1.28	1.49	0.53	0.04
Covariates					
Grade in Mathematics	1	/	/	/	7.45* (0.17)
Error	40				

Note. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; CL(tot) = cognitive load in total, CL(exp) = cognitive load of the experiment, CL(device) = cognitive load of the device.

The three groups also differed significantly and with large effect sizes concerning the variables cognitive load in total ($F(2, 46) = 4.12; p < .05; \text{part } \eta^2 = 0.17$) and cognitive load concerning the device ($F(2, 46) = 14.47; p < .001; \text{part } \eta^2 = 0.47$; see Table 7). These effects are also related to the higher value of these variables in the intervention group (see Fig. 8)—but in this case contradictory to the related hypothesis in Section 3.2 even though the cognitive load values are—all in all—very small.

Furthermore, the grade in Mathematics had a significant and large influence on the dependent variable achievement ($F(1, 46) = 7.45; p < 0.05; \text{part } \eta^2 = 0.17$). Therefore, besides the correlation of the grade in Mathematics trait with learning achievement in this topic, it shows that the differences between the groups regarding their grades in Mathematics explained 17 percent of the variance of learning achievement in acoustics.

The results of the cognitive load variable were also reflected by differences in experimentation time: The three groups differed significantly with large effect sizes concerning the experimentation time in all three experimental procedures. Fig. 9 shows that the IG (gPhysics Google Glass group) was faster than CG 2 (tablet PC with SpectrumView) which is partly consistent with the related hypothesis in Section 3.2. But the gPhysics group working with a tablet PC was even faster than the gPhysics Google Glass group, which contradicts the hypothesis in Section 3.2.

To analyze the contradictory hypotheses related to experimentation time for the gPhysics groups working with Google Glass and with a tablet PC in more detail, we used the

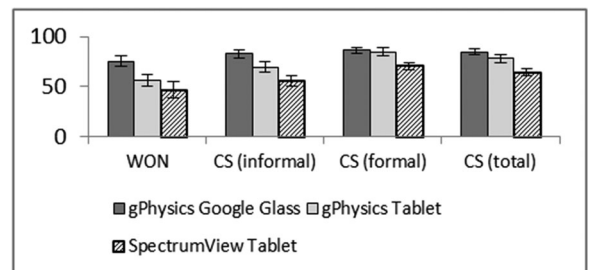


Fig. 7. Wondering and curiosity state of the three groups (mean values and standard error).

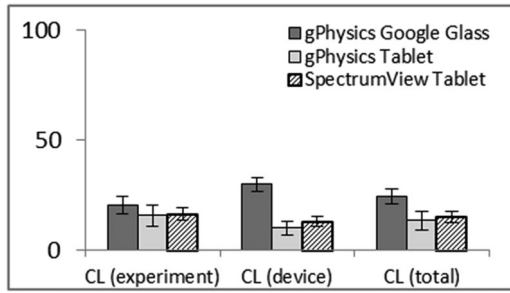


Fig. 8. Cognitive load of the three groups (mean values and standard error).

logging files of the gPhysics app. Table 8 shows that the fill level correction ratio for the Google Glass is almost twice as high and the mean of its image processing time almost five times higher than the corresponding variables for students working with the gPhysics tablet PC. To consider and compare only the experimentation time of the students in the two gPhysics groups, we subtracted the duration of image processing, of use of the camera, and of fill level correction from the total experimentation time.

Table 9 shows that in this case the differences in experimentation times between the gPhysics Google Glass group and the corresponding tablet PC group decrease substantially.

After correction, the gPhysics Google Glass group was faster at conducting experiment 3. This is the example with the largest degree of experimental interaction because the students had to fix and unfix the hair tie for each measuring point. No significant differences between the three groups were identified for the post-test of learning achievement and cognitive load related to the experiments.

7 DISCUSSION

As described above, the results clearly indicate that “outsourcing” all measurements (fill level and frequency) and plotting the graph with an electronic device significantly reduce the experimentation time and the cognitive load, while increasing wondering and curiosity. We thus reproduced and confirmed earlier findings [15], [16]. However, with the exception of wondering and informal curiosity, the effect does not relate only to wearable technology. Although both the Google Glass and tablet PC “automated” solutions outperform the traditional SpectrumView system, the tablet PC solution performs significantly better than

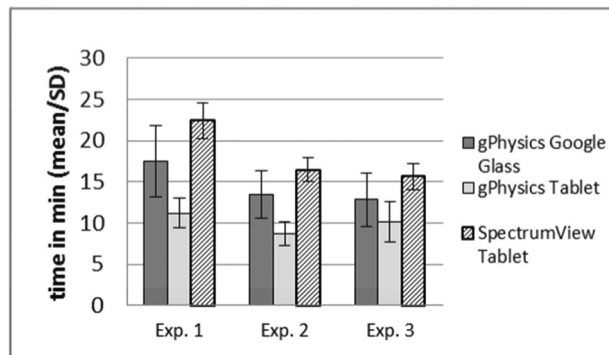


Fig. 9. Experimentation time of the three groups during the three experimental procedures (mean values and standard errors).

TABLE 8
Logging Data of the gPhysics Groups

Variable	Fill level correction ratio	Frequency correction ratio	Mean image processing time
Google Glass	63.8%	6.5%	10.8 s
Tablet PC	33.1%	12.5%	2.4 s

Google Glass with regard to both execution time and cognitive load.

Therefore, based on the findings of this study, we have to reject the hypothesis that learning with Google Glass as an experimental tool fosters learning achievement and reduces cognitive load and execution time. The key question is whether this is an artifact of the shortcomings of the Google Glass device, a question of students needing to grow accustomed to the technology, or a fundamental effect indicating that the advantage of wearable systems is not what it is widely believed to be.

To address the above question, Table 9 provides a more detailed breakdown of the experimentation time. It shows the experimentation time after (1) the image processing time has been subtracted, after (2) the time needed to align the camera with the glass has also been subtracted, and the (3) time finally spent adjusting mismeasured fill levels has been subtracted. Point (2) is motivated by the observation that, due to the slow response of the Google Glass camera combined with the unusual situation of using the head to align the camera, the students generally spent a lot of time on alignment. For all times in Table 9, the median of execution time is also given.

It is interesting to note that within the representation shown in Table 9 the execution time ratio goes from Google Glass being 1.77 slower than the tablet PC (experiment 2, mean, corrected for image processing only) to the Google Glass execution time being only 0.73 of the tablet PC time (experiment 3, all corrections, median). This is related to two effects: First, the hypothesis that the camera alignment time and fill level correction effort are significant factors that increase the execution time for the Google Glass condition is confirmed. Thus, while in the worst case the mean

TABLE 9
Experimentation Time Considering Processing Time (in Minutes) of Different System Sequence

	Time without...		
	...image processing (M/SD/Median)	...camera (M/SD/Median)	...fill level correction (M/SD/Median)
Experiment 1			
Google Glass	15.5/4.7/12.7	10.0/4.0/8.3	8.5/3.8/7.0
Tablet PC	10.0/1.7/10.8	6.9/1.8/7.6	6.5/1.9/7.0
Experiment 2			
Google Glass	13.5/2.8/10.7	7.4/1.8/6.7	6.1/1.5/5.7
Tablet PC	7.6/1.5/8.1	5.0/1.2/5.1	4.7/1.1/4.7
Experiment 3			
Google Glass	12.7/2.9/9.8	7.2/2.7/6.0	5.9/2.3/5.0
Tablet PC	8.9/2.2/9.7	6.8/2.4/7.3	6.4/2.4/6.8

time for Google Glass is 1.77 times higher than for the tablet PC (experiment 2), after the camera alignment and fill level correction times have been removed (for both), the worst case is only 1.29 slower. In the best case (experiment 3), Google Glass goes from being factor 1.47 slower to being faster than the tablet PC (mean execution time only 0.92 of the tablet execution time). Second, it can be seen that the median is much more favorable for the Google Glass system than the mean in all cases. This is in line with the observation that, while most students were quick in becoming accustomed to wearable technology, a minority had difficulties. In other words the shorter measured execution time of the tablet PC seems to be an artifact of students not being accustomed to Google Glass rather than a true advantage of the tablet PC platform. This is further supported by the comparison of execution times over the three experiments. For both the tablet PC and Google Glass, the execution time significantly decreases between the first and the second experiment. This is a clear indication of a learning effect with respect to the device. However, between the second and the third experiment, the execution time decreases for Google Glass only and increases for the tablet PC. This is an indication of a much stronger learning effect for Google Glass. Indeed, for the tablet PC, any learning effect gains are offset by the additional time needed to adjust the hair tie in experiment 3. However, for Google Glass, the learning effect remains visible. Consequently, Google Glass median execution times are significantly lower after having been corrected for camera alignment and fill level adjustment efforts (6.0 and 5.0 versus 7.3 and 6.8) for experiment 3. After having accounted for camera alignment and fill level adjustment, even the mean times are slightly faster. A shorter experimentation time means that the analytical variation of experimental parameters to explore a phenomenon can be increased, more representations can be produced and linked and, in turn, scientific expertise can also be increased. Due to the study design, the experimental procedure of the three groups has to be nearly equal. So the detected learning effects of Smart Glasses may not have reached their full potential because it was not possible to exploit all advantages of this approach, such as unrestricted experimentation with both hands, faster experimentation time, increased exploration possibilities, and representation production. It can therefore be expected that an educational setting that makes use of all advantages of such a system would result in larger effects on motivation *and* learning. Furthermore, the lack of increase in learning achievement with Google Glass compared to the tablet PC is connected with the higher cognitive load (required to operate the device and interact with it). Because of the technical limitations of today's version of Google Glass (see Section 4.6), students were more occupied with the device itself and distracted from the relevant learning content. These problems should be solved when this device is more powerful, because the cognitive load of the items relating to the software is very low (smaller than 15 percent) and does not differ significantly between the groups. This applies especially for applications that use the full potential of the device such as the gPhysics app (internal sensors to gather physical data, automatically detect fill level, and sound frequency, display of results just in time, seamless interaction of the user with the

app at each step). Although our approach is different to AR-/VR-approaches, the increase in learning outcome if the technology systems are optimized could be comparable [53]. And increasing cognitive effects by using Smart Glasses as an experimental tool could therefore also be expected, if the technology were optimized.

While we have to reject the hypothesis concerning learning outcome and cognitive load, we confirmed the hypothesis that learning with Google Glass fosters curiosity and wondering. This is remarkable on two accounts: *first*, the large effect sizes show that these effects are much more than novelty effects as a novelty effect would only induce small effect sizes (e.g., [54]); *second*, besides intelligence and effort (in the sense of willingness to exertion), intellectual curiosity is the third pillar of academic performance [42].

With regard to gender issues, our study shows that male students were more fascinated by the possibilities of mobile devices in general. This gender difference could also be identified with regard to curiosity state in total, especially for the male students who worked with Google Glass. The analyzed gender gap is consistent with earlier studies (e.g., [55]). Thus, for further applications of Google Glass in classroom settings, this aspect has to be carefully considered and counteracted with adequate methods (e.g., collaborative learning settings) or content (e.g., context-based instruction).

8 CONCLUSION AND FUTURE WORK

With the gPhysics project, we have provided a first successful approach for using Smart Glasses for contact-free, sensor-based experiments with relating, near-eye presented multiple representations for different topics of regular high-school, college, and university curricula. So using automated measurement and interactive plotting of the results on a digital device significantly increases wondering and curiosity while reducing the execution time and cognitive load. In the current experiment, the effect is stronger for a system implemented on a conventional tablet PC than on Google Glass. However, the results also provide a strong indication that this is due to the limitations of the current Google Glass device and the fact that students need to grow more accustomed to the wearable system rather than to fundamental limitations of the Smart Glasses concept. Overall, the results clearly support the case for the use of Smart Glasses as an experimental tool for science education.

Nevertheless, we did not measure an advantage for students learning with Google Glass with regard to their learning achievement. We used the most advanced method [8] as baseline in this study, making the comparison really competitive between the intervention and control groups. In other words, the students learn as much with Google Glass as with the most advanced method so far—and we have not yet exploited the full potential of Smart Glasses. In addition to this, fostering curiosity and wondering when learning with Google Glass stimulates variables which are well-known as a main pillar of academic performance in general. This should be really worthwhile and one of the predominant goals of every educational setting. The positive effects are also reflected by some of the comments which were added to the questionnaires by students. Although 10 percent of the students expect problems when Smart Glasses

are used in schools (e.g., “Maybe students could be distracted from the learning itself”), more than 85 percent also see the implementation of Smart Glasses as an opportunity for physics education (e.g., “Phenomena could be explored more often and more easily.”, “Maybe students feel more motivated, experiment more intensively, and learn more.”).

We are now working on new experiments that will remove the key limitations of the Google Glass device (the camera alignment problem and need for frequent manual adjustment of the fill level). We will also include more extensive possibilities for the students to become accustomed to the wearable devices. Finally, we are developing experiments in which the need to remain physically engaged with the experiment while conducting measurements is greater than in the current water glass setup. Such experiments are much better suited for leveraging the advantages of wearable systems.

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