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ORIGINAL ARTICLE

NapWell: An EOG-based Sleep Assistant Exploring the Effects of Virtual Reality on Sleep Onset

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Abstract

We present NapWell, a Sleep Assistant using virtual reality (VR) to decrease sleep onset latency by providing a realistic imagery distraction prior to sleep onset. Our proposed prototype was built using commercial hardware and with relatively low cost, making it replicable for future works as well as paving the way for more low cost EOG-VR devices for sleep assistance. We conducted a user study ($n = 20$) by comparing different sleep conditions; no devices, sleeping mask, VR environment of the study room and preferred VR environment by the participant. During this period, we recorded the electrooculography (EOG) signal and sleep onset time using a finger tapping task (FTT). We found that VR was able to significantly decrease sleep onset latency. We also developed a machine learning model based on EOG signals that can predict sleep onset with a cross-validated accuracy of 70.03%. The presented study demonstrates the feasibility of VR to be used as a tool to decrease sleep onset latency, as well as the use of embedded EOG sensors with VR for automatic sleep detection.

Keywords Virtual reality · Sleep onset · Electrooculography

1 Introduction

Sleep, like eating and drinking, is biologically imperative to all living beings, while also carrying other benefits like improving one's memory and cognitive abilities (Milner and Cote 2009). Power naps specifically show us that sleeping can improve alertness, productivity, and mood which is especially useful in scenarios like night shift work or prolonged driving sessions (Mednick et al. 2002). However, many modern technologies prevent us from taking a nap by providing mental stimulation, sudden notifications, as well as modifying light-based cues (e.g. increased blue-light after sunset which can promote alertness). Many efforts have been made to use technology to fall asleep faster, from pharmacological agents to mechanical and physiological efforts such as cortical electrical stimulation and acoustic stimulation (Davis et al. 1939; Lee et al. 2019; Akert et al. 1951). However, while these technologies attempt to directly influence the nap time for a user, they do not control the environment the user sleeps in nor do they improve a users' sleep hygiene (how routine and effective sleep is for a person). One critical element to sleep hygiene in power naps is a proper nap environment, free of too much mental stimulation, little (if any) blue light, and be comfortable and/or familiar (Muzet 2007). This kind of environment may be hard to achieve in the physical world, especially in circumstances where a person is traveling, wishes to nap in a crowded space (e.g. an airport) or in an office or workplace. Most of us resort to imagery distraction to place ourselves mentally elsewhere to cope with such a situation (Harvey and Payne 2002). A common solution could be to simply wear noise-canceling headphones, or listen to some soft audio that suits the imagined environment.

In this work, we present a study to understand if VR environments can assist in imagery distraction by providing a virtual environment prior to the nap to decrease our sleep onset latency (time taken to transit from wakefulness to sleep). During the nap, we log the participants'

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eye movements using electrooculography (EOG) while employing a behavioral finger tapping task (FTT) task to detect sleep onset time ground truth. We also used the gathered EOG signal to train a machine learning model for automatic sleep onset detection. This allows us to conceptualize an all-in-one prototype VR head-mounted display (HMD) that can automatically detect sleep onset using embedded sensors in the HMD itself. Below are the contributions of this work:

1. We conducted and present results of a pilot survey ($n = 157$) to determine the sleep habits and preferred nap environments.
2. We present to our knowledge the first study ($n = 20$) exploring the effects of VR on sleep using both physiological and behavioral measures.
3. Our study shows that VR can significantly reduce sleep onset latency compared to no devices at all, and on average also provided longer sleeping time and lesser drowsiness onset latency.
4. We conceptualize a VR prototype with integrated EOG sensors and a machine learning model that can automatically detect sleep onset with a cross-validated accuracy of 70.03%.

2 Related Work

In this section, we look into the past decades of work that focused on understanding the parameters that influence our sleep quality and sleep pattern. HCI research has touched on improving sleep before, such as work by Liang and Ploderer (2016) and Ehleringer and Kim (2013) who investigated if commercial wearable devices improve sleep and the possibility of a wearable device to improve sleep quality for dementia patients, respectively. There are several good overviews regarding sleep assessment, the benefits of sleep, and pervasive technologies related to sleeping (Schmidt et al. 2012; Ibáñez et al. 2018). There are also some contactless sleep tracking works using smart home infrastructure (Adib et al. 2015). SleepThermo (Katsumata et al. 2019) was a wearable device that monitors body temperature with respect to sleep quality. Shirazi et al. (2013) use an alarm clock smartphone application to track and share sleep behavior. There are other works that use smartphones or fitness trackers for sleep quality tracking (Min et al. 2014; Choe et al. 2015).

Closest to our work, Kitson et al. explore lucid dreaming as a tool for introspection in Virtual Reality (Kitson et al. 2018). Semertzidis et al. (2019) also explore the pre-sleep state, yet in a much more artistic and qualitative evaluation. We see our work as being complementary to this research, as we are evaluating sleep onset and utilize EOG (compared to EEG in Semertzidis et al.'s study). In this work, we mainly focus on the various sleep detection methods used and VR's effect and immersion on the human mind.

2.1 Sleep detection

When someone falls asleep, several markers are present such as a decrease in attention and change in physiological signals (Ogilvie 2001). In most related work, methods to detect sleep onset largely fall into two categories; physiological and behavioral-type methods (Scott and Lack 2017). Physiological detection refers to the use of physiological signals such as electrooculography (EOG), polysomnographic (PSG) (gold-standard for sleep studies), electroencephalogram (EEG), and so on to detect sleep onset. Detecting sleep onset can be a complicated and costly process, usually conducted only at traditional sleep labs with expensive PSG equipment and a trained specialist. PSG detects sleep onset specifically based on a reduction of alpha waves and the dominance of low voltage waves (Berry et al. 2012). However, there has been some related work on using simple EEG electrodes which are cheap and easily accessible to detect sleep onset (Zhang et al. 2014). EEG has also proven to be reliable enough to even detect microsleep (Rothkrantz 2016). However, signals from EEG require intense filtering due to noise. Otherwise, other more invasive methods are required, such as implants through the skull for a better signal-to-noise ratio. There have also been low-cost approaches with relatively high accuracy, such as the use of commercially available heart rate sensors (Okamura et al. 2016). However, one of the earliest approaches used to detecting sleep is to recognize the rapid eye movements (REM) via electrooculography signals (Boukadoum and Ktonas 1986). Both EEG and EOG are non-invasive measures; however, EEG signals try to measure the brains potentials though a thick skull and are thus affected by the wearer's full physical and physiological state. In contrast, EOG senses the electrical potential difference between the cornea and the retina only, leading to overall less noisy signals. When coupled with a head-mounted wearable, this will cause more issues for EEG as well, since a minor shift in electrode placement due to the straps on the head will lead to noisy signals once again (Gupta et al. 2020). EOG need only be in contact with the user's face. Furthermore, AR/VR head-mounted displays are often in contact with the face, making EOG a more logical approach. EOG has also proven to be able to outperform EEG-based methods in sleep stage classification (Rahman et al. 2018).

Behavioral detection, on the other hand, can be further divided into two categories; active and passive. Active behavioral detection refers to assigning a task that requires minimal effort for the participant to perform while trying to fall asleep. Once he/she stops performing it, that time is registered as the sleep onset time. It was first proposed by Blake et al. (1939) who asked his participants to hold a spoon when falling asleep. Once the spoon dropped, the time was recorded as sleep onset, which also correlates with a drop in alpha waves of the brain. Reaction time (RT) tasks are also often employed for this detection method (Liberson and Liberson 1966; Ogilvie and Wilkinson 1984). RT generally relies on audio feedback, where the participant needs to react to audio stimuli. However, one key issue with active behavioral detection is that there is a possibility for the stimuli to instead disrupt the process of falling asleep (Ogilvie 2001). This is evident, especially when employing RT because it promotes "readiness" from the participants, which increases arousal (Ogilvie and Wilkinson 1988). This resulted in the introduction of passive behavioral detection which refers to gathered sensor data from user behaviour, usually actigraphy which is the use of inertial sensors. Another approach used a pressure mattress to analyze the heat map of the user's sleeping posture and behaviour (Metsis et al. 2014). There have also been studies for detecting long-term sleep patterns using a combination of inertial, ambient light, and time data (Borazio and Van Laerhoven 2012). However, this does not mean that the passive approach is superior to the active, because the recent introduction of devices and applications that uses very discreet stimulus and requires very minimal response significantly reduces any disruption to sleep onset (Scott and Lack 2017).

Between physiological and behavioral sleep detection, both methods have a reasonable degree of accuracy. With PSG being the gold standard yet not easily accessible, behavioral methods have only shown a small difference of about 2 to 3 min (Connelly 2004; Lack and Mair 1995; Scott et al. 2018). This is due to a slight discrepancy that exists between sleep onset for physiological signals and behavioral activities. People can still possibly give a behavioral response to a stimuli even after PSG has determined sleep onset because most people only stop responding during the beginning of N2 sleep (Ogilvie and Wilkinson 1988; Ogilvie et al. 1989). One area where active behavioral sleep detection is potentially more beneficial than both physiological and passive behavioral methods is for short power naps, because the signals gathered using the other two methods require signal processing steps, whereas active methods are relatively instantaneous simply by observing the user's response to stimuli. However, it is still possible for actigraphy to detect naps with relatively high accuracy if the nap duration is at least 30 min (Kanady et al. 2011). Sleep onset time can be complex because it is a dynamic process marked by the change on both physiological and behavioral states at different points in time. In this study, we actually use an active behavioral task to first detect sleep onset when napping, then use that data as a label for a physiological-based detection, allowing our final prototype to the best compromise between them.

Regarding the factors that influence sleep, the primary reason that led us to want to understand the effects of VR towards sleep onset is due to imagery distraction in sleep studies. Imagery distraction was a proven method to help insomniac patients fall asleep (Harvey and Payne 2002). This is because imagery distraction occupies the cognitive space that prevents the participant from re-engaging with worrisome thoughts that causes insomnia. This brings us to the use of VR, which is very similar to imagery distraction in that, it is capable of placing us virtually into another space. However, it has, to our knowledge, never been used as a sleep-assist tool, though the closest literature we can find is for stress relief and meditation.

2.2 Sleep assist tools

There has been a myriad of methods employed by people to aid them in their sleep, either with the use of devices or through some form of sleep ritual. Typically, it is advisable to alter one's habit, such as not sleeping too late, doing more exercise, eat healthily and so on Brown et al. (2002), yet there will always be times where an external device or stimulus is preferable.

An eye or sleep mask is one of the most common tool to assist sleep. It does not serve as a stimulus, but rather to further block out light that can suppress melatonin. Studies have shown that a sleep mask can result in more REM time, shorter REM latency, less arousal, and elevated melatonin levels (Hu et al. 2010). It was also found to be able to reduce long awakenings for patients in intensive care units (Demoule et al. 2017; Yazdannik et al. 2014). Additionally, patients with acute coronary syndrome also found sleep masks to be a cheap and viable method over drug therapy to increase sleep quality (Daneshmandi et al. 2012). This has led to works like the Smart Eye Mask (Matsui et al. 2017) that integrated photo-reflectors into sleep masks to classify sleep stages. This method, however, adds bulk and weight onto the eye mask which was meant to be light and soft. Another potential negative impact of eye masks is that they press against the user's eyes, leading to possible discomfort on the eyes.

One of the most common tool is to use audio stimulus via binaural sounds to induce sleep. When an acoustic beat of two tones is played in each ear simultaneously, the generated binaural beat induces brain signals that can assist in sleep (Lee et al. 2019; MORALES-COBAS et al. 1995). Several researches look into this specific frequency, such as by Jirakittayakorn and Wongsawat (2018) who found that binaural beat at 3Hz and found sleep latency to be relatively shorter. A lot of these works, like the sleep mask, also specifically target those with health conditions that prevents them from sleeping. Pedemonte et al. (2014) used auditory feedback during sleep to treat participants with idiopathic tinnitus and found significant changes in the brain activity. Audio feedback remains a popular choice for sleep assistance because the responsiveness of the auditory system during sleep is still partially preserved (Peña et al. 1999).

2.3 VR for stress relief, therapy, and meditation

The perceived environment and atmosphere can greatly influence a person's cognitive performance, mood, and physiology (Zhao et al. 2017). Even though studies regarding the use of VR on sleep is relatively rare to our knowledge, the most relatable use cases would be for stress relief, therapy, or meditation. For example, post-traumatic stress disorder (PTSD) can occur as a result of a disastrous event or experience and has been studied most in war veterans. PTSD symptoms include sleep disruptions (next to a multitude of other indicators). Studies with Vietnam War veterans in VR to desensitize the life-changing event showed that this treatment can significantly decrease their symptoms including sleep disruptions (Rothbaum et al. 1999).

There is also a lot of work using virtual reality and mixed reality for relaxation, stress relief, and mindfulness training (Kosunen et al. 2016; Amores et al. 2016; Roo et al. 2017; Bernardino et al. 2016). We see our work complementary, as we focus directly on naps and the impact of VR on napping properties.

Meditation can be relatable to naps because it requires the user to be in a calm state of mind. For example, RelaWorld (Kosunen et al. 2016) combines neurofeedback with VR as a meditation system to induce deeper relaxation, feeling of the presence, and a deeper level of meditation. For therapy, VR has consistently been used especially for exposure therapy for phobia treatment (Powers and Emmelkamp 2008), to mental and eating disorders (Ferrer-Garcia et al. 2013).

Both meditative experiences and therapy can also be combined, such as the development of the Meditation Chamber (Shaw et al. 2011). This device uses immersive virtual environments with biofeedback technologies (galvanic skin response and heart rate) to reduce stress and anxiety. The main negative feedback, though, was that the weight of the device hampers the experience. A recent work employed the use of VR for meditative walks as a way to treat chronic pain (Gromala et al. 2015). The developed virtual meditative walk (VMW) provides a peaceful environment with changing weather that depends on the user's physiological state.

The effects of VR on the human mind are primarily due to the sense of the presence it simulates, as this aids in perception and consciousness (Sanchez-Vives and Slater 2005). Cognitively, we know that we do not exist at a virtual space, but sub-consciously, we respond to it. Therefore, we wish to emulate this effect in our study on understanding the relationship between VR and naps. How can VR influence sleep onset time, and how to conceptualize a prototype HMD for this purpose?

3 Behavioural sleep and drowsiness onset detection

The first step in this work would be to detect sleep onset accurately. As seen from related work, it can be challenging to detect sleep onset without access to any specialized hardware. More lightweight detection as proposed by Okamura et al. (2016) use a smartphone application with the specific intention of detecting sleep onset. Their work uses finger tapping during a beep or vibration where, if the user does not do so after 4 indications, the system perceives the user to have fallen asleep and the application records the time. We used a similar approach, the finger tapping task (FTT) proposed by Casagrande et al. (1997). It is proven to be better than an auditory-based reaction task since it interferes less with the sleep onset process and thus reduces arousal.

We developed an FTT smartphone application, as shown in Fig. 2 that requires the user to tap the screen continuously. The smartphone was strapped to the participant's preferred hand using a velcro strap to make it effortless to hold and easily accessible (Ogilvie and Wilkinson 1988). The number of taps, tap rate, and time for each tap is then logged into the device. If the user does not tap for more than 300 seconds, then he/she is deemed to have fallen asleep (Casagrande et al. 1997). The user's tapping rate also allows for drowsy onset detection. Since each user taps their finger at their own pace, we first find their average tapping speed during their first 50 taps. The drowsy onset time is defined as when the average tapping frequency decreases tenfold. We find this estimation of drowsy onset time to be a suitable value because it falls into the range of time for Stage 1 latency (Casagrande et al. 1997). Sleep duration can be found by looking at the highest number of ms between a tap without any interruption.

Additionally, we log certain physiological signals from the user during their napping duration. We chose to use EOG sensing extracted from the JINS MEME smart glasses[1] as shown in Fig. 3, which is designed for everyday use Uema and Inoue (2017). Logging of the JINS MEME data is achieved via a Macbook running a Python script that received the data through Bluetooth with a sampling rate of 100Hz. To calculate EOG values, JINS combines

[1] https://jins-meme.com/en/.

the capacitance difference from the two nose pads for the horizontal EOG component, and the difference between nose pads and nose bridge for the vertical EOG component (Ishimaru et al. 2014). We log the EOG signal to develop a prototype that is able to detect sleep onset automatically. We present the experimental setup in the following.

4 Pilot survey

Before initiating the experiment, we first ran a survey to gather relevant data regarding peoples' general sleep behavior. The survey was deployed to social media platforms (Facebook, Twitter, WeChat, etc.) for a week. We successfully gathered data from a total of 157 participants (52 males) from 33 different countries (27.7% are from Indonesia, and 35.5% are from the Philippines). We found that 46.5% of the participants sleep for only 6 h every night, and 56.7% of them believe that their sleep quality can be further improved. 46.5% of the respondence find it difficult to fall asleep. 59.9% of them are relying on some form of activity or habit to fall asleep faster at night. One of the main causes is work or school-related stress, followed by a noisy environment.

Regarding naps, only 22.3% of them take naps very or quite often, with the majority of them being not that often. The reason for taking a nap or lack thereof is related to work. Too much work prevents nap time, while also causing some of them to be too tired to work continuously. When asked to imagine a place where they could fall asleep more quickly, the top five choices are their own room (73.1%), a hotel room (35.9%), by the clouds (17.3%), the beach (15.4%), and finally a lodge by the woods (14.1%) as shown in Fig. 4. We believe that their own room, or a hotel room scored the highest because most people find these places familiar. The other preferences are mostly natural surroundings, supported by literature (Felsten 2009). We use these results for the basis of our selected VR environments to assist naps. The survey also included the Epworth Sleepiness Scale (ESS) Questionnaire (Johns 1991), which showed an ESS score of 9.6 in average across our 157 participants. They fall into the normal range of ESS scores (majority not having any form of sleep disorder). We provided the link for the full results of our questionnaire (Bait 2019).

5 User study

To understand how VR can effect sleep onset, we design the experimental setup akin to taking a nap at work in the middle of the day.

5.1 Apparatus

For the hardware, we choose the Google DayDream View VR[2] headset with the Asus Zenfone AR[3] as our primary VR tool due to several reasons. A lightweight, wireless headset is essential to maintain the comfort of the user and to avoid any cable entanglement common with commercial VR devices tethered to a desktop computer. Secondly, the weight of the headset is also a primary concern. Since the DayDream View uses mobile VR, it is overall lighter than desktop connected HMDs. Finally, the DayDream View uses fabric and soft-like texture to ensure comfort for the user. The HMD is integrated with EOG sensors taken directly from a pair of JINS MEME smart glasses[4] (Fig. 3). The sensors' vertical position is adjustable so that it just rests on the participant's face and that it would be comfortable for different face shapes. The batteries are attached to the left side. The power and pairing button is attached to the right side of the HMD. A Macbook[5] is placed on a nearby table to read and log the EOG signals in real-time. The chair used in the study is the GTRacing Gaming Chair[6] that can recline backward until 90°. The phone used for the FTT is a Samsung Galaxy S8[7], though any Android phone running Android 5.0 and above should be compatible. For the VR conditions, the participants also used a pair of Sony Noise Cancelling headphones[8] that plays the audio of the virtual environment. Initially, we had the participants also use the Apple Watch[9] and Xiaomi Mi Band[10] for passive behavioral detection and compare the onset time with the FTT. However, pilot testing showed that they were unable to detect short periodic naps accurately. We, therefore, choose to exclude them.

5.2 Study design

The independent variable is the device used, with four distinct conditions: (1) napping without any device as a

[2] https://vr.google.com/daydream/.

[3] https://www.asus.com/Phone/ZenFone-AR-ZS571KL/.

[4] https://jins-meme.com/en/.

[5] https://www.apple.com/nz/macbook-air/.

[6] https://www.gtracingchair.com/.

[7] https://www.samsung.com/global/galaxy/galaxy-s8/.

[8] https://www.sony.co.nz/electronics/headband-headphones/wh-1000xm3.

[9] https://www.apple.com/apple-watch-series-5.

[10] https://www.mi.com/global/mi-smart-band-4.

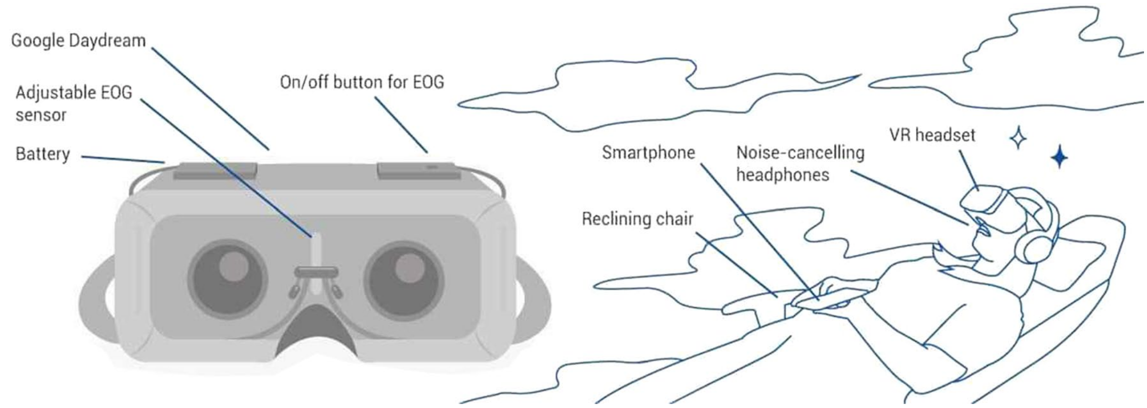

Fig. 1 (left) An illustration of the prototype that combines EOG sensors from JINS Meme with Google Daydream, (right) and a participant of the study using the prototype on a reclining office chair with a smartphone for a finger tapping task to detect sleep onset manually

Fig. 2 Screen capture of the FTT application logging the time stamp, tap number, and tap rate

baseline, (2) using a sleeping mask, (3) with a VR HMD showing the view of the study room itself (baseline for VR), and with (4) a VR HMD displaying the participant's preferred virtual environment (includes headphones playing audio of the selected environment). These conditions were chosen by taking into consideration how each items and devices are used conventionally, as opposed to the sensory feedback provided. For example, the sleeping mask condition does not include any form of audio feedback or earplugs as it is being used as a standalone item (Liang et al. 2015). A standalone VR experience, on the other hand, often includes both visual and audio feedback (Jerald 2015). For all conditions, the room light is left on to simulate an actual office working hour, as shown in Fig. 6.

For monitoring purposes, we avoided being in the same room as the participant when they were napping. Therefore, the FTT application was designed to send packets of data to a mobile device so that the tapping activity can be monitored remotely. When the tapping rate decreases, it indicates that the participant is feeling drowsy, and when it stops, it is an indication that the participant has fallen asleep.

Fig. 3 Prototype used for the study, with embedded, adjustable EOG sensors shown on the front view, and the battery and power switch on the top

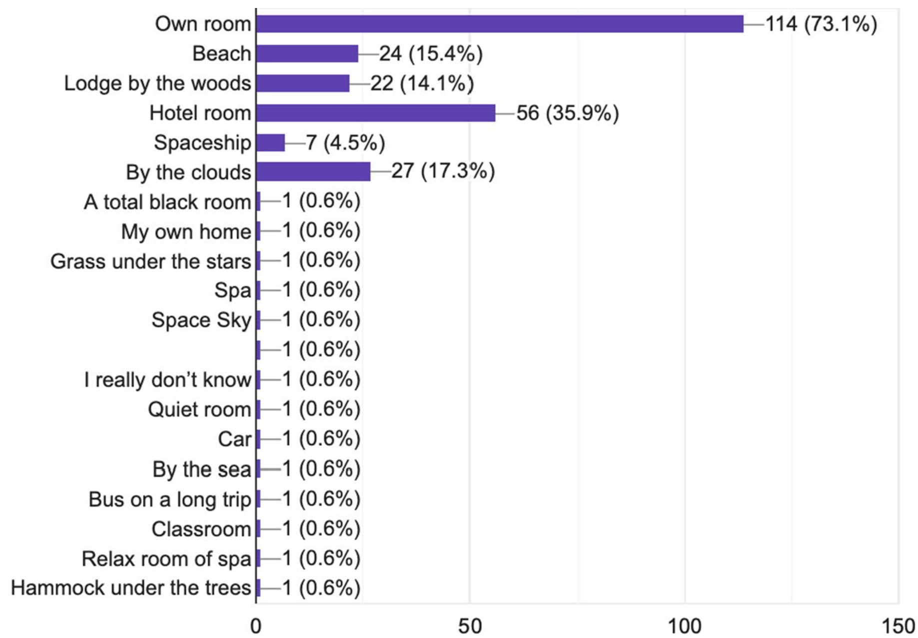

Fig. 4 Survey results regarding preferred locations to fall asleep easily with a sample size of 157

Fig. 5 Screenshot of the VR application, showing the (1) home screen with instructions to load the "own room" video into the application, (2) the main menu where the user can select using the DayDream controller, (3) the environment for the "study room" condition, (4) the "own room" condition which differs according to the participants' room, (5) the "hotel room", (6) the "by the clouds", (7) the "beach", and (8) the "lodge by the woods"

5.3 Virtual environments

The prepared virtual environments for the fourth condition are the top 5 results from the previously conducted pilot survey (see Section PILOT SURVEY). Figure 5 depicts the different environments. Each clip is at least 15 min in length so that the looping is not obvious. We initially tested with virtual environments built with a game engine, but the graphical quality needs to be on par with desktop-VR to achieve high realism. However, we got low framerates since it is just running off from a mobile phone. We, therefore, chose to use 360° video instead, which maintains realism

Fig. 6 The participants experiencing (left) the baseline condition with no devices, (middle) with the use of a sleeping mask, and (right) with VR (the "study room" and "preferred VR" condition)

while requiring low computing power. Participants who chose the "own room" environment were required to inform us at least a day before the experiment for the VR condition, where we lend the participant a 360° camera (the Ricoh Theta S) to capture a video of their own bed room. The video includes the ambient sound of the room as well. Once they did, we directly imported the environment into the VR application. Additionally, a blue-light filter was added into the environment to negate the effects of blue light on sleep onset (Green et al. 2017) (all conditions requiring the VR display to be on uses the filter). The dependant variable is the sleep onset time.

5.4 Participants

We recruited a total of 20 participants (7 female), aged between 22 to 29 (mean = 25.05, STD = 1.79) to participate in this within-subject study. The experiment itself is conducted in a regular office room to simulate naps in a working office environment. Each of the participants may freely wear any attire that they are comfortable with, and any restrictions were excluded. The room temperature is maintained between 25 to 28 degrees Celsius. The noise level of the study room itself is around 32dB, which is normal for a typical quiet room. Each participant was required to have at least 7 to 8 h of sleep the night before the experiment is conducted. Furthermore, we ensured that each of the experiments is conducted at least 3 h after the participant had a meal, to ensure that he/she would not be affected by caffeine, sugar, or alcohol intake (Okamura et al. 2016). The study was performed according to ethical rules and regulations of Keio University.

5.5 Procedure

Prior to the experiment, we ask the participants about their preferred VR environment among the available options (their own room, the hotel room, being among the clouds, by the beach, and a lodge by the woods). We also show them a short preview. If they chose the "own room" scenario, we lend a 360° camera to them for a recording for 15 min so that we can import it into the application during the experiment day.

On the experiment day, participants filled out a consent form detailing personal data saved and the experimental setup. The recorded video for the participant's room will be deleted at the end of his/her session. Each of them also came on four different days to participate for each of the conditions.

After we briefed them regarding the procedure, the participants lie down on the reclined office chair (see Fig. 1). We used an angle of 40° for the user study because it is an optimal angle for naps on a reclining chair as proven by Nicholson and Stone (1987). Depending on the assigned condition, we then put on the HMD, sleeping mask, or no device at all, onto the participant. The FTT phone was also securely strapped to the desired hand with velcro where they are instructed to continuously tap on the screen. A nearby Macbook was set up to record the logged EOG data, whereas the FTT data are stored directly in the phone. Each participant was given a maximum period of 1 hour for taking a nap. For participants who have fallen asleep, the FTT data will indicate this based on the duration between taps. However, if the participant did not fall asleep, we take the maximum allocated time of 1 hour for the duration.

6 Results and discussion

In this section, we divide the results into two main sections; the tapping data analysis to extract sleep onset latency, drowsy onset latency and sleeping duration, and the sleep onset classification accuracy. Of the 20 participants recruited, 8 of them chose their own room as the preferred VR condition. 5 participants chose the beach side, followed by another 5 who chose the lodge in the woods. Only 2 participants chose the hotel room environment.

6.1 Tapping data analysis

Figure 7 shows a sample result from a participant for the "preferred VR" condition. The red area represents the participant still being awake, the period between each taps being about 500 ms. This illustrates how a tap data generally look for a participant falling asleep. When they start becoming drowsy, the yellow region shows the taps slowing down, with the period between each tap being about 40,000 to 50,000 ms. This is aligned with our estimation that the tapping speed decreases by ten times the average tapping

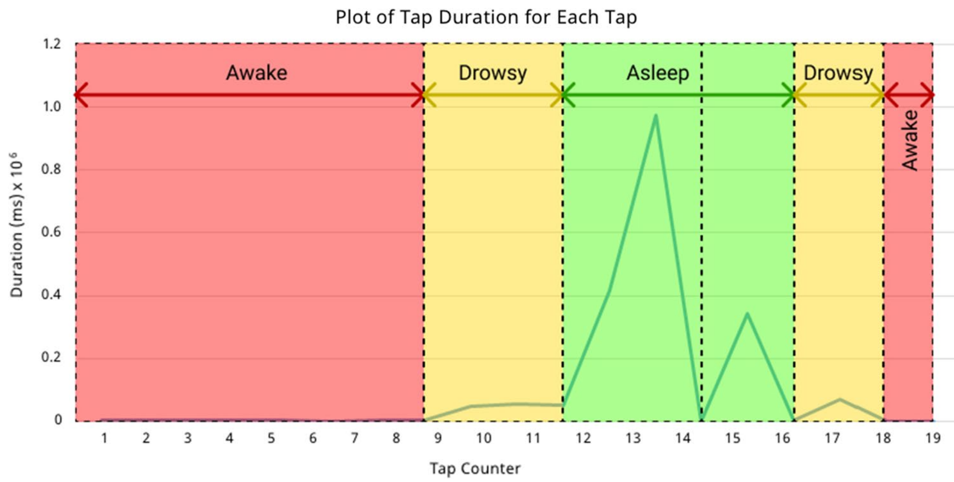

Fig. 7 A sample FTT result from a participant for duration between each tap. This is an extracted time window of about 33 min

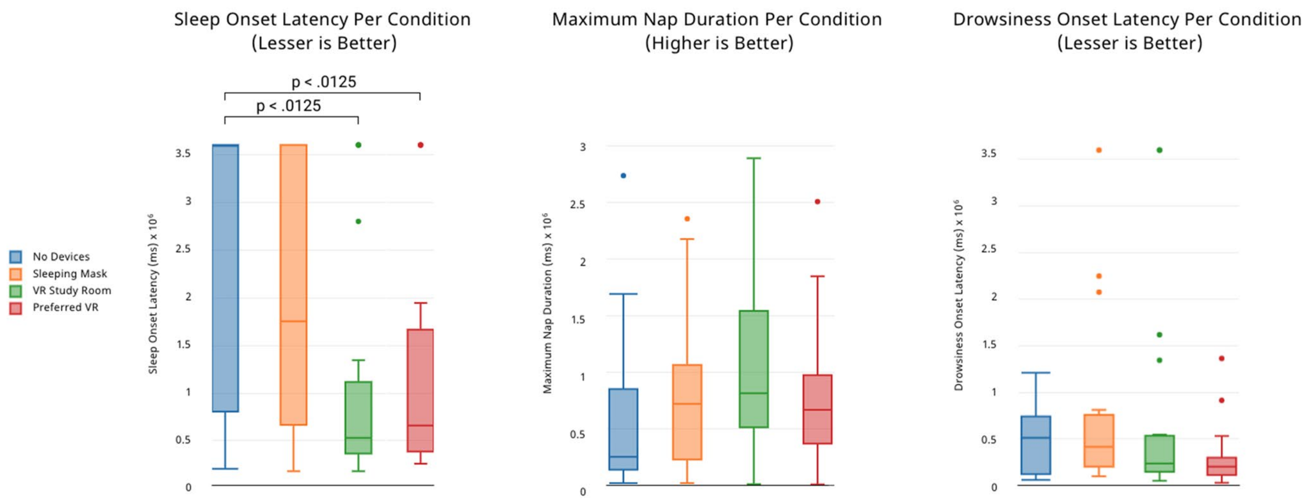

Fig. 8 Extracted results from the FTT, which shows the sleep onset latency (left), maximum nap duration (middle), and drowsiness onset latency (right) for all 20 participants

speed as it enters Stage 1 of sleep latency (Casagrande et al. 1997). In this stage, they have not fallen asleep yet, but are in the transitional phase between fully awake and fully asleep. Finally, the green region shows that the participant had fallen asleep, with the tap period being above 300,000 ms. Following the work by Casagrande et al. (1997), this study defines Asleep as when the inter-tap interval (ITI) is greater than 300,000 ms, Drowsiness as when the ITI is between 50,000 ms and 300,000 ms, and Awake as when the ITI is shorter than 50,000 ms. Figure 8 shows the ITI time course and the corresponding brain states (Awake, Drowsy, and Asleep) defined behaviorally.

The left chart of Fig. 8 shows the sleep onset latency data, the middle shows the maximum nap duration, and the right shows the drowsiness onset latency data for all 20 participants. The amount of participants that did actually fall asleep for each condition differs. For the “no device” condition, a total of only 8 participants managed to fall asleep. For the “sleeping mask” condition, a total of 13 participants successfully fell asleep. Finally, for both the “VR study room” and “preferred VR” conditions, a total of 17 participants managed to fall asleep. Looking at the results for sleep onset latency, the average time for falling asleep in the VR study room and preferred VR conditions are 1,089,950 ms (18.16 min) and 1,222,700 ms (20.38 min), respectively. These results are both faster than the time it took on average for participants to fall asleep for the conditions with no devices and wearing a sleeping mask, which took 2,553,550 ms (42.56 min) and 1,995,100 ms (33.25 min), respectively. We performed a Shapiro–Wilk test to determine the normality of our results. For the sleep onset time, we found that the results were significant ($p < 0.05$), meaning that we cannot assume normality in the data. Next, we ran the Friedman test and found that there was a statistically significant difference in sleep onset latency depending on the sleep condition ($x^2(2) = 18.648, p < 0.001$). Post-hoc analysis with Wilcoxon signed-rank test was conducted with Bonferroni correction applied, resulting in a significance level of $p < 0.0125$. The median (IQR) perceived effort levels for the conditions with no device, sleeping mask, VR view of study room and preferred VR environment were 60 min (13.14 min to 60 min), 29.21 min (10.69 min to 60 min), 8.84 min (6.04 min to 20.51 min), and 10.98 min (6.16 min to 30.96 min), respectively. There were no significant differences between the sleep conditions of no device with sleep mask ($z = -1.642$, $p > 0.0125$), the sleep mask with the VR study room ($z = -2.025$, $p > 0.0125$), or the VR study room with the preferred VR environment ($z = -1.16$, $p > 0.0125$), even though there is an overall reduction in sleep onset latency between no device with the sleep mask, and both VR conditions with the sleep mask. However, there was a statistical significant reduction in sleep onset latency between no devices with VR study room ($z = -2.765$, $p < 0.0125$) and no device with preferred VR environment ($z = -2.504$, $p < 0.0125$).

From these results, we can observe that being in VR does significantly decrease sleep onset latency, allowing users to fall asleep faster as opposed to without any devices. A participant mentioned that since the HMD feels similar to a sleeping mask, he/she feels inclined to keep his/her eyes closed most of the time while having them on. Since the rendered environment was exactly that of the physical space, there was nothing to further distract them or to examine further, such as a different environment which could potentially feel more exciting to view, at least for the first time. However, there was a lack of significance when comparing with the sleep mask, or with the VR baseline condition. A trend is visible where on average, there is a drop of sleep onset latency from no device, to the sleeping mask, and finally the VR conditions. When worn, both the sleeping mask and the use of VR effectively blocks any form of visual stimulus from the environment. However, VR includes a display that instead shows a different environment which may increase distraction, whereas the sleeping mask is simple but lightweight and comfortable, stated by a participant who preferred the sleeping mask. These factors contribute to the lack of significance between sleeping mask and VR. On the positive side, unlike the use of a sleeping mask that merely covers the eyes (Liang et al. 2015), VR is instead a combination of audio and visual stimulus, with content specifically designed to induce a sense of calmness, not unlike meditation or yoga (Gromala et al. 2015). Three participants did mention that the environment helped them imagine that they were there, which leads to better imagery distraction and sleep onset latency reduction. One participant claimed that he/she has been having a better sleep after participating in the experiment in preferred VR condition. Maybe the inclusion of a display for distraction and instilling calmness is useful for sleeping. Yet, further studies are needed to explore the effects of the displayed environment, such as by experimenting with lighter HMD, more content options, and softer padding. Our initial assumption was that participants who chose the "own room" option for the VR environment would be able to fall asleep faster compared to those who chose other environments, according to Fig. 4. However, our results do not indicate any significance between the "own room" and preferred VR" condition. This could be due to several factors, such as the VR environments being captured only with a 360° camera, thus lacking depth and realism to be perceived as the actual environment completely. Secondly, the videos used for all the environment were relatively pixelated and low resolution, further effecting the perceived realism negatively.

Next, we look at the nap duration time, where a longer duration indicates a longer rest time. On average, the participants slept for a maximum of 989,450 ms (16.5 min) and 779,238 ms (13 min) for the VR in a study room and preferred VR environment, respectively. Both these durations are higher than the conditions with no devices and sleeping mask, with a nap duration of 583,364 ms (9.72 min) and 778,734 ms (12.98 min), respectively. However, there was no statistically significant difference in nap duration depending on the sleep condition ($x^2(2) = 4.296$, $p > 0.05$).

Finally, we repeated the procedure for the drowsiness onset latency. On average, the participants show signs of feeling drowsy for the preferred VR environment after 296,800 ms (4.95 min). This is relatively faster than the other three conditions. Participants began to show signs of drowsiness after 490,000 ms (8.17 min), 731,000 ms (12.18 min), and 695,000 ms (11.58 min) for the no device, sleep mask, and VR of study room, respectively. However, there was no statistically significant difference in drowsiness onset latency depending on the sleep condition ($x^2(2) = 6.075$, $p > 0.05$).

P2 and P15 mentioned that they were able to sleep longer largely due to the presence of the background noise from the VR environments, since the visuals itself could not have any effect once they have fallen asleep. However, the VR content did help in making them feel drowsy faster, eventually leading to faster sleep onset. P1, who has no prior VR experience, did find the HMD to be heavy and made it harder to move around during sleep. However, he/she did mention that HMDs feel heavy in general, and not specific to our use case. When putting on the HMD, P5, P7, and P9 mentioned that the placement of the EOG sensors causes a slight discomfort to the face and chose to loosen the strap a bit more. Additionally, P5 mentioned that he/she could only sleep properly while in pajamas. Only P14 mentioned that he/she dislikes any form of noise as well as wearing any kind of device while sleeping.

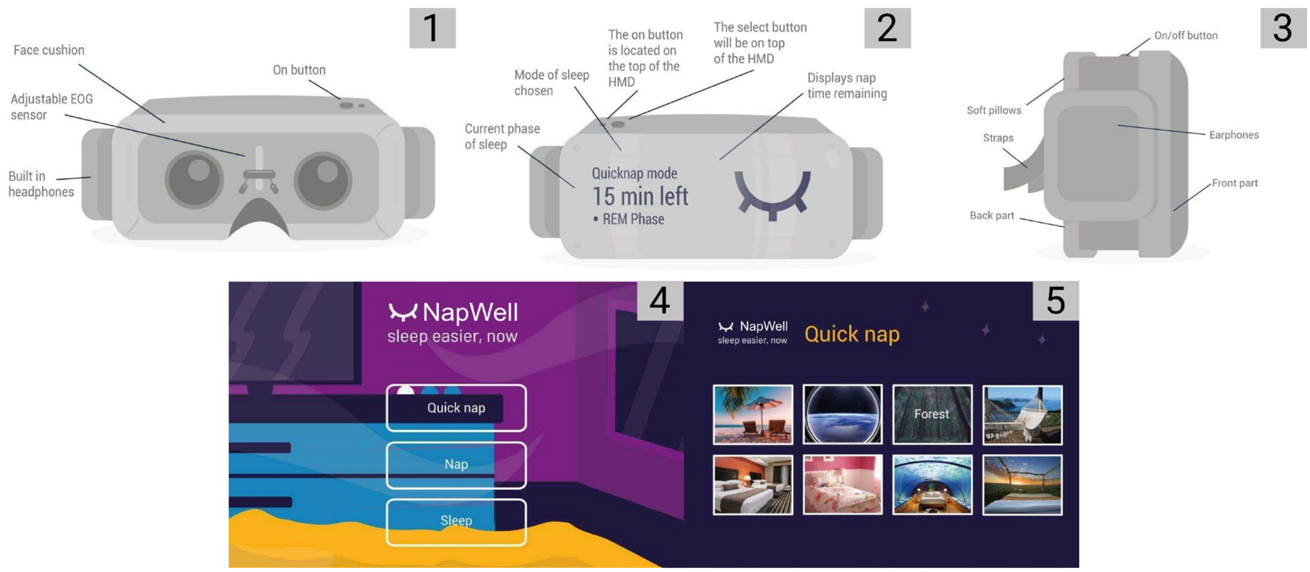

Fig. 9 Envisioned prototype with (1) adjustable EOG sensors and face cushion, (2) an outward display showing the sleep mode and remaining period, (3) integrated headphones, (4) the home screen showing several napping durations, and (5) the selection screen presenting 8 choices of VR environments

6.2 Sleep onset classification

In this section, we discuss further on the use of commercial EOG sensors to automatically detect sleep onset as our second main contribution. This solution allows an HMD integrated with it to be able to know when the user falls asleep depending on the eye movement, thus disabling the displayed content at the right time. This is an important issue to consider for a wearable sleep-assist tool. Even though our participants did not complain about this, it was previously found that audio or visual feedback still received after the onset of sleep increases the probability of arousal (Zhang et al. 2014). Yet, we look at this as the secondary contribution of the paper and an initial step towards conceptualizing NapWell as a working prototype. Even though the FTT procedure can be used to detect sleep onset, it is not ideal when suggesting NapWell as a standalone device. A prediction model would be able to achieve this automatically for the user.

We use the previously collected EOG data, as well as the data from the FTT application to label it for supervised learning. The raw data from the JINS MEME glasses are 3-axis accelerometer, 3-axis gyroscope, and EOG sensors at the left and right nose pad, for a total of 8 features. We then generated a sliding window with a period of 10 seconds which are non-overlapping for each of these features. Next, we calculated the mean, standard deviation, and variance for each of these features within that time frame, for a total of 24 features. To reduce the dimension of the data, we ran the principal component analysis (PCA) procedure until only 6 features remain. PCA essentially creates new transformed dimensions based on the original data and the desired amount of output dimensions[11]. This includes the most dominant trend from the data samples (Masai et al. 2018). After that, we filtered the features using the moving average filter. Finally, we fed the features with a train-test split of 80–20 into a logistic regression classification algorithm. The splitting was performed prior to PCA to avoid any biases from the test data, where we split depending on participant (data from 4 random participants out of 20 were selected as test data).

From the test results of our model, we obtained an accuracy of 82.88% with the full confusion matrix shown in Table 1 and details shown in Table 2. The errors in the

Table 1 Confusion Matrix

	Predicted Awake	Predicted Asleep
True Awake	596752	0
True Asleep	146196	110698

Table 2 Results of the main classification metrics

	Precision	Recall	f1-score	support
Awake	0.80	1.00	0.89	596752
Asleep	1.00	0.43	0.60	256894
Average/Total	0.86	0.83	0.80	853646

[11] https://scikit-learn.org/stable/modules/generated/sklearn.decomposition.PCA.html#sklearn.decomposition.PCA.fit_transform.

classification are mainly due to false positives of the detection. There are no false negatives. To validate the accuracy, we ran the model through K-fold cross-validation with $K = 6$ and obtained an average accuracy of 70.03%. Some of the contributing factors are due to the tightness of the worn HMD. To obtain better data with less noise, the HMD should ideally be as tight as possible. The misclassifications could possibly be due to if the HMD was loose on the head of the user for comfort as mentioned by some of the participants (the EOG not having full contact). To improve this in future works, we should make a signal check before starting the nap, to make sure the signal to noise ratio is better. Nevertheless, we believe this model can be further improved in future iterations.

6.3 Conceptual prototype

Based on the obtained results, this section conceptualizes it into a prototype. The key takeaway from the results are:

1. VR environments do improve sleep onset time. The "own room" VR option was the most popular choice.
2. embedded EOG sensors can detect sleep onset with relatively high accuracy, though one needs to adjust the EOG sensors

From these finding, we illustrated a HMD prototype shown on Fig. 9 that is meant to maximize comfort with soft face and ear paddings. The EOG sensor is sponge or textile-based so that it can be pressed firmly on the face without discomfort (Krishnan et al. 2018) and its position is highly adjustable to accommodate different faces. We also conceptualize an outward display showing remaining nap time, which could be useful at office environments. The user will first be presented with an interface that shows a room environment, with 3 separate options for different nap duration. After selecting an option, the next page shows up to 8 choices of virtual environments to choose from. The "own room" option will allow users to upload their own 360° video of their room if they have one. The system then automatically detects sleep onset based on a generalized pre-trained model suggested in section 6.2, without the need to perform the FTT procedure.

7 Limitations and future works

To further improve this study, we suggest experimenting with different kinds of HMD, as well as a higher resolution for the video. Even though Google Daydream itself is light (around 450 grams), the use of a mobile phone for VR display makes the content more pixelated. The EOG electrodes should also be softer, such as a sponge or textile-based material to be more comfortable (Krishnan et al. 2018). The use of a VR HMD for sleep undeniably adds bulk and weight to the user's face, though unlike a sleep mask, it does not press against the eyes directly. A custom HMD that mounts on the head and can be flipped down with minimal face contact, such as the Lynx[12] headset design, could help reduce weight and increase comfort. In the next phase, we plan to perform the user study for proper night sleep in a sleep lab. We also plan to use PSG equipment to obtain more accurate physiological signals that can ascertain the sleep quality of the participants.

When recruiting the participants, we ask that each of them have a gap of 3 h since their last meal, as proposed by Okamura et al. (2016). However, there are also studies that showed that sleep might be best induced when we are well fed and with low cognitive load (Wells et al. 1997). We also did not monitor what the participants did within that 3 h gaps; for example, some participants could have went for a jog, thus being more tired and susceptible to being sleepy. Future studies may include methods to measure a user's blood sugar and cognitive load level prior to the experiment.

As mentioned previously, the independent variable in the proposed experiment is not the different sensory feedback modality, but rather regarding the use of different device and its affect towards sleep onset. For our future works, we would like to extend this by investigating how each sensory feedback as well as the combination of feedbacks can affect sleep onset.

On the VR experience side, our study was only limited to five environments which we established from the pilot survey. Yet, each individual has their own specific preference regarding the VR environment they choose as their sleep assist tool. Therefore, future iterations of NapWell will look into (1) a VR environment creator that allows users to easily build and deploy their preferred environment, and (2) a method to easily share user-created content so that users of NapWell who share the same preferred environment can upload their creation to our dedicated servers to share with other users. Furthermore, we consider this work as a preliminary study towards using VR imagery to promote sleep. Future works can look into how each environment can be further manipulated based on the EOG data, such as adding dynamic relaxing imagery or other sleep-inducing patterns depending on the eye's saccades and blink rate.

8 Conclusion

We propose NapWell, an EOG-based sleep assistant that is integrated into VR HMDs to reduce sleep onset latency. We first conducted and presented a pilot survey from 157

[12] https://lynx-r.com/.

participants to establish the sleep habits and preferred nap environments of the general public. We then presented a user study that explores the effects of VR on sleep using both physiological and beahavioral measures. We found that VR can significantly reduce sleep onset latency compared to using no devices while also providing overall longer sleep time and lesser drowsiness onset latency. Finally, we conceptualized a low-cost VR prototype with integrated consumer-ready EOG sensors. Our machine learning model could detect sleep onset win a cross-validated accuracy of 70.03%. The conducted experiment and conceptualized prototype serve as a first step towards the broader concept of introducing VR as a sleep-assist tool. We showed that VR was able to influence sleep by reducing sleep onset latency during naps by augmenting the perceived environment of the user.

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