Head 'n Shoulder: Gesture-Driven Biking Through Capacitive Sensing Garments to Innovate Hands-Free Interaction

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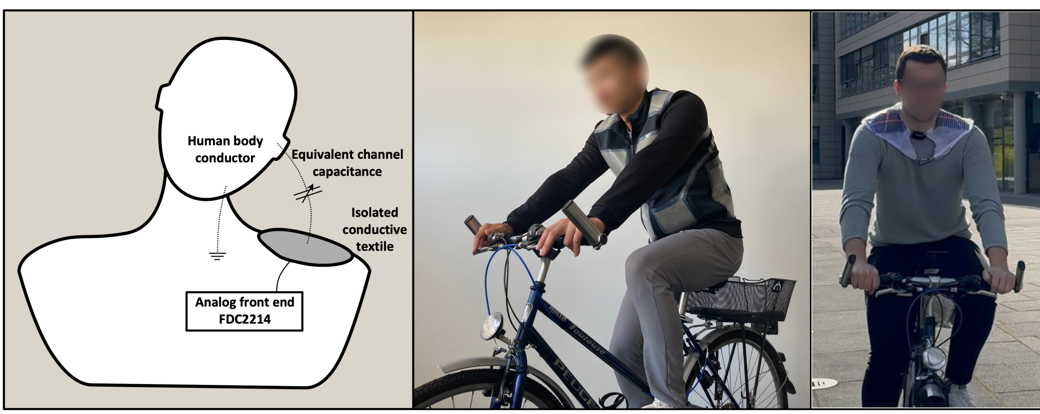

Fig. 1. *Head 'n Shoulder* implements capacitive sensing into upper-body garments to realize bike-safe gesture recognition.

Distractions caused by digital devices are increasingly causing dangerous situations on the road, particularly for more vulnerable road users like cyclists. While researchers have been exploring ways to enable richer interaction scenarios on the bike, safety concerns are frequently neglected and compromised. In this work, we

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propose *Head 'n Shoulder*, a gesture-driven approach to bike interaction without affecting bike control, based on a wearable garment that allows hands- and eyes-free interaction with digital devices through integrated capacitive sensors. It achieves an average accuracy of 97% in the final iteration, evaluated on 14 participants. *Head 'n Shoulder* does not rely on direct pressure sensing, allowing users to wear their everyday garments on top or underneath, not affecting recognition accuracy. Our work introduces a promising research direction: easily deployable smart garments with a minimal set of gestures suited for most bike interaction scenarios, sustaining the rider's comfort and safety.

CCS Concepts: • **Human-centered computing → Ubiquitous and mobile computing**.

Additional Key Words and Phrases: Bike Interaction, Bike Safety, Gesture Recognition, Capacitive Sensing

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1 INTRODUCTION

Cycling, as an eco-friendly alternative to traditional transportation, has seen a recent resurgence in popularity [4], especially fueled by the covid pandemic [1]. The general availability of E-Bikes has further increased this trend [45]. Yet, safety aspects often lag behind new bike technologies [7] and digital distractions are increasingly causing dangerous situations on the road [13, 14]. Using your phone during riding reduces alertness due to reduced peripheral vision and increased mental demand [15]. This greatly diminishes the required awareness of the environment and traffic [48] and increases the likelihood of accidents [39]. In 2019, the Netherlands even imposed a ban on phone usage during cycling [18].

Cyclists are engaging with digital devices for various purposes [33, 37], including navigation, communication, fitness tracking, and entertainment. Despite putting themselves in danger, riders may choose to neglect the safer "stop-to-interact" method and continue cycling while using digital devices, e.g., when interacting with the smartphone one-handed. Multiple methods for interaction while biking emerged over the past [40], such as custom button interfaces [53] towards more recent technologies like augmented reality [29, 35]. In this work, we challenge the necessity for such rich interaction scenarios on the bike.

Riding a bike, especially in city traffic, is challenging and requires the utmost attention from the rider. Yet, research still investigates more elaborate interaction opportunities with digital devices "while on the bike". We argue, that in such a safety-critical environment, the rider's safety and health should come first and propose a novel approach to bike interaction. To settle the motivation of this work, we consider the common cycling scenario: a cyclist on the road with one hand on the handlebar, the other hand occupied by a smartphone or smartwatch, and their eyes not fully focused on the road ahead. This behavior not only endangers the cyclist but also poses a risk to other road users. Our work focuses on fusing a viable set of interactions for digital devices with a bike-safe approach to not endanger and interfere with bike handling.

Our work outlines the development process, starting from the idea of how to design bike interaction with digital devices through hands- and eyes-free controls. For sensing movements and gestures, we embedded capacitive sensing technology into wearable garments, enabling the detection of upper-body movements and gestures. We subsequently explored possible layouts, shapes, and positions of capacitive sensor patches and created *Head 'n Shoulder*, a smart wearable built from a sports jacket with multiple sensing patches spread across the upper body.

Head 'n Shoulder is able to detect shoulder taps using one's cheeks, enabling complete hands- and eye-free input gestures. Further, the gesture movement does not interfere with the bike riding and does not require the rider to remove their hands from the handlebar. A Convolutional Neural Network (CNN) trained on a dataset collected from 10 participants is able to predict gestures with an average accuracy of 95% from capacitive time series data only. In an additional in-the-wild study, we confirmed *Head 'n Shoulder*'s detection accuracy on 14 participants and evaluated its usability and robustness. We paid particular attention to its impact on bike control, perceived safety and the feasibility of performing the gestures. Our results showed, that *Head 'n Shoulder* performed on par compared to buttons on the handlebar as a baseline, though participants expressed more safety concerns (compared to the baseline) due to the unfamiliar gestures.

In this paper, we contribute a technical design approach for hands- and eye-free interaction with digital devices while cycling. Our prototype *Head 'n Shoulder* enables users to perform basic interaction with digital devices suited for most viable scenarios without interfering with bike handling.

2 RELATED WORK

Secondary task interaction while riding a bike is challenging. Limited possibilities to interact with digital devices as well as a distraction from cycling [15] pose major obstacles. Consequently, research has not only looked into novel interaction modalities but also road safety aspects.

2.1 Interaction While on the Bike

Recent work by Porcheron et al. [37] showcases the activities and use of technology by bike riders while on the move. Cyclists make use of different technologies (smartphones, smartwatches, earphones, ride computers) for different purposes [37]. Here, road safety oversight, bike-control ability, and the digital device fight for the rider's attention. To provide safer methods of interacting, multiple research works have investigated customized input methods that are suitable while riding a bike [27].

Using hand gestures is a widespread approach and aligns with natural turn-taking signals [10]. Yet, gestural input often requires riders to remove at least one hand from the handlebar. Consequently, investigations into the feasibility of micro gestures [46, 55] confirmed that riders do desire a safe grip on the handlebar. Likewise, Woźniak et al. [53] presented *Brotate* and *Tribike*: two hand-activated input methods on the handlebar allowing for eyes-free interaction. Both their methods significantly reduced the cognitive effort of interacting with a connected smartphone. Their rotatable handle (Brotate) enabled users to ride with increased steadiness.

Apart from gestural and hand-activated input, researchers considered voice-activation [44], albeit suffering from environmental limitations. Vechev et al. [50] proposed several tapping gestures, where users would make contact with areas of their body for interaction, and Matviienko et al. [35] investigated the use of mid-air input for augmented reality. Yet, both approaches suffer from inherent safety risks while cycling, having to remove the hands from the handlebar. In *Notibike* [29], this problem is addressed by leveraging gaze-based target selection, ensuring hands-free interaction.

These past works offer insights into critical areas of improvement for interaction while cycling. Most notably, related works focused strongly on enabling hands-free (cf. [29]) and eyes-free interaction (cf. [53]). Two aspects that are essential for safe bike riding. In our work, we want to combine these two aspects and propose a minimal — but viable — set of input gestures sufficient for everyday interaction with digital devices while on the bike.

2.2 Safety Technology While on the Bike

Safety during cycling has been an ongoing research direction, ranging from proactive systems [12] to prevent accidents and dangerous situations, to reactive warning systems for the riders themselves [52]. Dancu et al. [12] presented a system that provides the cyclist with projected visual information and additionally includes projected visual cues for other road users to alert them of the rider's turn-taking — a proactive approach to bike safety. Reactive systems commonly involve some way to sense incoming danger and warn the rider in a timely manner. Here, research focused on investigating suitable modalities (visual, auditory, tactile) to notify the cyclist and compared their effectiveness [52]. The system is often integrated into cycling gear, such as the helmet [51]. Apart from investigating the safety of individuals, related work considered the collective of cyclists, proposing taxonomies to quantify cycling safety [36] as well as leveraging their combined sensor input to monitor bike behavior [25].

2.3 Wearable Sensing for Contact and Gestures

While head-mounted inertial measurement units (IMUs) can be used to detect head movements [8, 41, 42, 54, 56], they are not particularly suitable for the cycling scenario due to the dynamic motions and vibrations during the cycling activity. Single IMU-based systems also cannot detect the interactions between head and shoulders. Capacitive sensing is a versatile wearable sensing modality and has been used in the head area for facial expression and head gesture detection [34]. Typically each capacitive sensor channel is a piece of conductor material and behaves as a proximity and contact sensor for other conducting entities like the human body. The sensing conductor can also be flexible, and the capacitance output also changes with the deformation of the sensing material. While the output of capacitive sensors is a combination of proximity and self-deformation, the temporal patterns are often unique to specific activities and interactions, which can be distinguished through machine learning and pattern recognition methods. In [26], a capacitive-based neckband was developed for detecting head gestures and postures, with 79.1% accuracy for 15 head gestures. Dobrea, et al. [17] also presented a capacitive sensing system integrated into a necktie to recognize head gestures as control inputs for wheelchair users, reaching 75% accuracy under leave-out validation. With a modified theremin as the capacitive sensing hardware with conductive wires in a jacket, Bello, et al. [6] demonstrated capacitive sensing can detect 20 upper body gestures with 97% accuracy using deep learning.

Related work has demonstrated that capacitive sensing is a powerful sensing technology able to distinguish numerous gestures. With the design of *Head 'n Shoulder*, we leverage this potential. In contrast to related work, we put special emphasis on safety aspects when cycling, focusing on a minimal — yet viable — set of head gestures suited for most interaction scenarios on the bike.

3 METHODOLOGY

A lot of factors determine safe bike riding, such as experience, ground conditions, traffic and fatigue [48]. Thus, introducing secondary tasks during bike riding always poses a potential safety risk [14]. To design for mobile interaction, two design aspects should be considered: the relation of the interaction to the locomotion and how much it could inhibit the latter [33].

To minimize, possibly inhibiting, physical movements, we focus on augmenting the rider instead of the bike and place emphasis on developing a hands- and eyes-free interaction system. As such, we investigate body movements that are executable while keeping both hands on the handlebar and keeping one's view on the road. At the same time, the body movements should not interfere with the riding itself. This excludes exaggerated body movements and lead us to focus on minimal movements that are still detectable by sensors.

Changing posture through moving while bike riding impacts intended bike ergonomics. There is a large corpus on correct postures depending on bike type, intended use and body anatomy. Small changes, e.g. handlebar placement, can have a big impact on spine curvature and pelvic tilt, among others [3]. Effective adjustments to find the right riding position are essential [9]. Likewise, meddling with the optimal position can lead to pain and discomfort [16]. On the other hand, a dynamic posture during riding is favorable, allowing the rider to balance and react to the bike's behavior. A dynamic posture involves the repeated activation of different muscles, distributing tension and load [47]. Consequently, using change of posture as a means of interaction is feasible and supports an active riding style.

With these limitations in mind, we established three primary objectives to guide our design and implementation process:

(1) *Steady Bike Control*: We want to ensure that cyclists can keep both hands securely on the handlebars while using our system. Maintaining control over the bike is crucial.
(2) *Minimal Signal Interference From Cycling*: We aim to prevent any signal interference from the bike's steering or motion. Cyclists must feel confident that our system seamlessly integrates with their biking experience without introducing distractions.
(3) *Freedom of Wardrobe*: Interacting with *Head 'n Shoulder* needs to be possible regardless of season, weather, or body type. Recognizing the diversity in user preferences and clothing choices, we want our system to be transferable to various outfits, from sportswear to casual clothing. Placing *Head 'n Shoulder* on the rider also allows frequent bike changes, such as rentals.

Our investigation is focused around two studies. In the first study (Section 4), we evaluate the technical feasibility of selected sensor placements in correspondence with upper-body gesture interaction through a lab evaluation. Subsequently, we improved the design of *Head 'n Shoulder* based on these results and conducted a second in-the-wild study (Section 5) with additional usability analysis.

4 STUDY I - TECHNICAL FEASIBILITY EVALUATION OF *HEAD 'N SHOULDER*'S GESTURES

In this first study, we focus on designing *Head 'n Shoulder* and evaluating its capabilities in recognizing gestures. We first introduce the sensing modality for our prototype and highlight its suitability to be integrated into garments. Further, we elaborate on the design of *Head 'n Shoulder*'s gestures and the respective sensor placements. A technical feasibility evaluation concludes this first study.

4.1 *Head 'n Shoulder* - Hardware and Jacket Design

At the heart of our system lies multi-channel capacitive sensing, a technology chosen for its non-invasive nature and suitability for detecting body movements and gestures through multiple textile sensing patches placed on loose-fitting garments. The deformation or touch of conductive patches embedded into garments causes the capacitance to change by the wearer's movement, which in turn can be used to link the capacitive change towards movement reconstruction or gesture recognition without the requirement of placing the sensor directly on the user's skin. To gather the capacitance change from the conductive sensing patches, we use a data acquisition unit (DAU) inspired from [57] which is based on two FFDC2214 4-channel 28-bit capacitance-digital converter [28] to gather 8-channel data in total and an Adafruit Feather Sense for merging the signal into a data package for transmitting it to a terminal device via Bluetooth Low Energy for further processing or storing of the data.

We configured the DAU to sample at 30Hz to keep power consumption low and the sensing sensitivity high enough without risking side effects such as cross-talking due to the multi-channel setup. For sensing the capacitance of the conductive patch, the DAU uses a virtual ground as a

(a) Frontal patches of *Head 'n Shoulder* on chest and belly.

(b) Shoulder patches connected to the DAU.

Fig. 2. Sports Jacket equipped with 8-channel capacitive sensing patches routed to the DAU placed on the back to explore possible bike-safe gestures.

reference due to the lack of grounding through the biking scenario. Additionally, since such virtual ground can be floating, we added a metal patch on the inside of the garment to the DAUs ground line to further enhance the signal stability due to the larger conductive mass.

To embed conductive textile sensing elements seamlessly into clothing, we utilized a heat transfer process as presented in [21]. Conductive textiles from Shieldex® (Shieldex® Porto RS) [43] are heat-pressed onto the *Head 'n Shoulder* sports jacket that forms the base for our smart sensing wearable. Small stripes of the same material are used to route the sensing patches to the sensing unit on the backside of the jacket. Furthermore, we placed transparent plastic covers on top to prevent any short circuits while touching the patches. The goal was to ensure that these elements do not compromise comfort for the user. We've also taken care of determining the shape and size of these patches to strike a balance between functionality and user comfort. Contrary to the assumption larger patches are less comfortable due to their size, it is rather the opposite: the larger the patches, the easier it is for the user to interact with them, but this also means a potentially greater risk of introducing noise through unintentional movements, which can reduce the accuracy of the system. A suitable design was established through preliminary experiments and adaptions, trading off comfort and functionality and as such, sensing precision and patch size and placement [20].

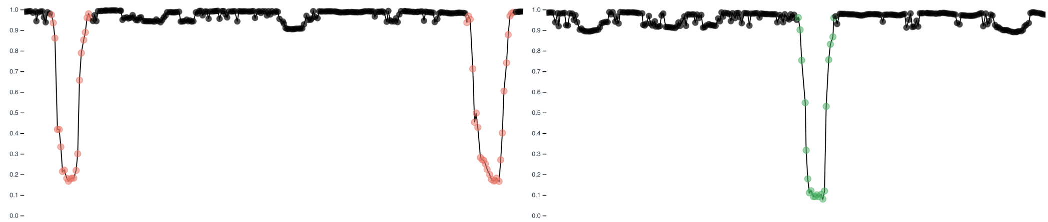
4.2 Detecting Gestures with *Head 'n Shoulder*

Designing gestures suitable for cycling presents a unique challenge. These gestures had to be distinguishable from regular bike movements to avoid confusion. Based on our knowledge of similar capacitive sensing projects related to Human-Activity-Recognition, we used a sportswear jacket and applied eight conductive patches with heat transfer to it [38]. Keeping the biking scenario in mind, we decided to place the patches only on the upper body part of the jacket, since the cyclist's arms are already occupied by steering the bike. The first *Head 'n Shoulder* prototype is shown in Figure 2. Our investigation of patch placements revealed the complexity of distinguishing between intentional gestures and natural bike-related motions based solely on the deformation of sensing patches. To optimize gesture recognition accuracy, we conducted preliminary experiments by checking the signals gathered from each patch.

We investigated two basic strategies and evaluated their feasibility. First the movement strategy, which involves interpreting body movements through the deformation of patches. In this case, patches should be placed in body joint positions to gather the biggest deformation. While we assumed to get insights into the cyclist's body posture, we experienced the signal amplitude for deforming the patch to be weak and susceptible to interference in preliminary experiments. Though this strategy is valuable for capturing nuanced movements, it is inappropriate for scenarios that require distinguishing the gesture from basic cycling movements. In contrast, touch-based gestures require physical interaction with specific patches. This approach offers more robust signal strength, allowing us to distinguish the basic cycling movements from the interaction gestures more easily. Here, a simple touch of a conductive patch leads to a drop in the capacitance signal with much higher amplitude than the nuanced movement detection of the other scenario. We discovered that strong and robust sensor signals can be found at the shoulder patches. These patches were strategically placed to align with the cyclist's shoulder and neck, facilitating natural and unambiguous gesture recognition when touched.

After promising initial tests on ergonomics and signal quality, we introduce "shoulder tapping" as the most promising gesture, specifically designed to allow hands- and eye-free control. Compared to previously investigated gestures, shoulder-tapping adapts to the biking activity by executing gestures through and with bike-independent body parts. The gesture involves a simple tap on the shoulder by the user's cheek, allowing them to maintain full control over their bikes. This is either accomplished by moving the shoulder upwards towards the cheek, or tilting one's head to lower the cheek towards the shoulder (see Figure 7). Both approaches are equally feasible and we saw participants usually execute a combination of the two. In order to generate noticeable signal changes for each shoulder tap gesture, users are required to gently touch the patch. However, as opposed to buttons requiring pressure to overcome the button resistance, there is no need to apply excessive pressure onto the patch since capacity changes are enabled through the conductivity of the human body. Moreover, typical cycling movements comprise few shoulder movements, minimizing the risk of noisy sensor signals. To facilitate practical interaction, we implemented multiple gestures using the left and right shoulder patches. These gestures include "left", "right", "both", and "double-tap". Here, we drew inspiration from common devices like in-ear headphones [11], ensuring that our gestures — and combinations thereof — can cover the bandwidth required for viable interaction scenarios. By keeping the set of gestures small, we ensure that participants can learn and utilize the gestures easily. It also ensures robustness and less risk of incorrect input or distraction while biking. The subsequent linking of gestures to relevant interactions on the end device can be freely selected as with other input devices.

In Figure 3, we visualized a short section of the left and right signal gathered from our prototype and scaled it into the range 0 to 1 to outline the strong signal for detecting the gestures. Due to the nature of capacitive sensing, every channel operates on different frequency levels in order to decrease interference between channels. Additionally, the conductivity of the wearer's body and the placement due to different body shapes can influence the frequency base level further. Therefore, normalization of all capacitive channels into the range between 0 and 1 is a crucial step to provide meaningful signal data for the further interpretation of gestures. As shown in the figure, compared to the baseline signal jittering around 0.9 to 1 due to the cycling movement, the orange and green data points show the clear signal drops down to the range of 0.1 to 0.2 which we labeled as the gesture "left" and "right" respectively.



(a) Left Shoulder Patch Signal (b) Right Shoulder Patch Signal

Fig. 3. Signal of *Head 'n Shoulder*, "left" gesture labeled orange and "right" gesture labeled green.

4.3 Experiment Setup and Procedure

In order to carry out an experiment that simulates real cycling and enables the recording of data in a supervised and safe environment, we set up a stationary bike mount that allows dynamic resistance change to simulate slope and gradient. With this setup, the data still contains the signal noise from cycling movements and steering without risking the safety of the participants in real traffic scenarios. Further, to evaluate the gathered data afterwards, the experiment lab setup enables the thorough collection and supervision of gathered data for later evaluation. External lab influences or connections to the ground were eliminated to simulate the mobility approach of the system. Ethical approval for the study was obtained from the Ethics Team of the German Research Center for Artificial Intelligence.

After providing informed consent, we asked each of our ten participants (7 male, 3 female) to cycle for 10 to 15 minutes on the bike while wearing the *Head 'n Shoulder* jacket in two sessions. The garment has European clothing size L, whereas participants stated their sizes from S to L.

During the experiment, we recorded the capacitive data of the two shoulder patches and the camera footage as a reference for labeling the data afterwards. The participants were instructed to arbitrarily execute the gestures to gather the natural gesture execution without the experiment conductor's influence and to additionally get feedback regarding their impressions of the gestures' ease of use. The "shoulder tapping" (see Section 4.2) involved three gestures: left and right for touching the respective shoulder with your cheek as well as using both shoulders at the same time. Users initially reported that using both shoulders is uncomfortable and hard to perform. Especially depending on their physique and body constitution, one might have difficulties to properly touch both sides of shoulder patches at the same time. Therefore, this gesture is less present in our dataset, and the focus for the participants was on the "left" and "right" gestures.

We note that the double-tap gesture is artificially created and realized by introducing an additional layer on top of the neural network's prediction by monitoring the time interval between two detected taps. This way, with only two main gestures, the system's versatility can be extended to present systems like in-ear headphone touch gestures.

Additionally, participants were asked to add clothing on top or below the *Head 'n Shoulder* jacket to simulate the various wardrobes when cycling. Depending on the material and the thickness of the clothes covering the capacitive patches, the signal can be damped since the clothing is less conductive than the participant's body itself. We added a sweater, a rain jacket, a combination of both, and a helmet with straps at the cheeks for a smaller set of four participants to generate versatile scenarios throughout an extended dataset.

4.4 Gesture Prediction Accuracy

To evaluate the accuracy of *Head 'n Shoulder* and the recorded dataset, we developed a classifier based on the common Convolutional Neural Network model [30, 31]. The model consists of two one-dimensional convolutional layers followed by one fully connected layer. Together with weak dropout layers of 0.1 added to every main part of the CNN, this architecture is sufficient to generalize the dataset. The input is two channels, namely the left and right capacitive shoulder patch signal in the form of time series data. We selected a sliding window approach with a size of 30 data points to cover the average duration of a gesture with approximately one second due to our initial sampling rate of 30 Hz. The model predicts the probability of four classes, which are the labels "left", "right", "both" and the "null" class. As already mentioned, we excluded the "double-tap" from the prediction itself, since it can be generated later on by merging two consecutive predictions. With this approach, we ensure that all gestures are independent of each other and within the defined sliding window.

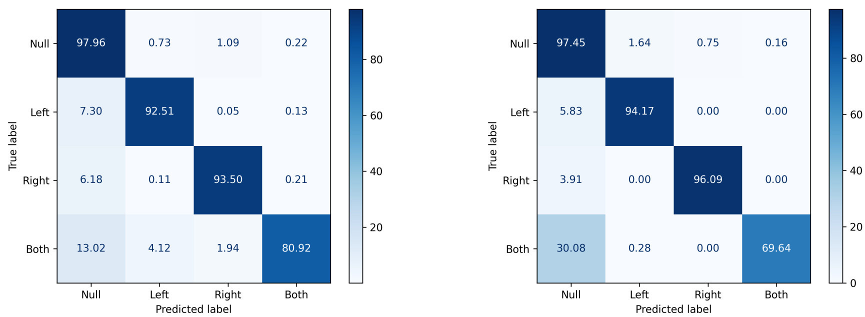
The results of our trained classifier are analyzed by applying leave-one-person-out cross-validation. The correlation between model architecture and signal quality was analyzed visually and numerically to detect issues and outliers in order to maximize the performance [24]. Across all participants, the accuracy ranged between 93% to 98% percent, resulting in an average accuracy of 95% for our *Head 'n Shoulder* prototype to predict the gesture. Figure 4a shows the confusion matrix across all participants for our set of three gestures and the null class. *Head 'n Shoulder* achieves satisfying accuracy across the two main gestures "left" and "right" and the "null" class between 92% up to 98% accuracy. As already suspected by the user feedback, the accuracy for the "both" gesture is slightly lower at around 80%. The reason for that is the lower occurrence in the dataset and the larger variance for this gesture when participants tried to touch both of their shoulders at the same time. The false positive classifications can be interpreted as a hallucination of the system to trigger a non-existent gesture. Throughout our test, these values were very low. For the false negative, meaning the system did not detect the touch properly, we can derive the slightly increased false classification from improperly executed gestures. Especially since we did not instruct the participants on how to execute the gestures, the false classifications predominantly represent too slight touch or only approaching the patch without proper contact.

Additionally, we trained the model again excluding only the data where participants wore clothes on top of the sensor patches. This allowed us to validate if our model still performs well if arbitrary covering is worn on top of *Head 'n Shoulder*, despite it not being specifically trained for this scenario. The results are shown in the confusion matrix of Figure 4b using leave-session-out cross-validation. While the accuracy for the gesture for "both" dropped over 10% compared to the previous results, again due to the problematic execution of the gesture, we determined the accuracy for the "left" and "right" gestures was still significantly above 90%. This result manifests our idea of transferring the technology into other textiles, by integrating *Head 'n Shoulder* into different garments regardless of their materials or even wearing additional clothes on top due to changing weather conditions.

4.5 Implications

Based on our study, we determined a suitable set of upper-body gestures (shoulder taps) that can be performed with relative ease, yet they are distinct enough to elicit a strong signal-to-noise ratio for the capacitive sensor. Recognizing shoulder taps is robust across participants, achieving an average accuracy of 95% and still works even with clothing on top of *Head 'n Shoulder*.

However, we also found that the jacket design is not optimal as it only allows specific clothing sizes and is not applicable during hot days. Consequently, we decided to update our prototype,



(a) Confusion matrix for *Head 'n Shoulder*. (b) Confusion matrix for covered shoulders patches.

Fig. 4. Evaluation of CNN trained on the whole dataset (left) and only for covered shoulder patches (right).

taking into account the functional sensor design and placement while reducing clothing overhead (see Section 5.1).

5 STUDY II - USER EXPERIENCE EVALUATION THROUGH AN IN-THE-WILD STUDY

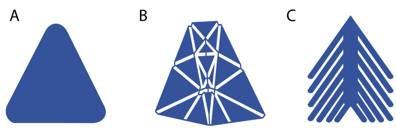
In this second study, we focus on evaluating the usability and user experience of *Head 'n Shoulder*. We first address lesson learned from our first study to improve the design of *Head 'n Shoulder*. Subsequently, we confirm its technical feasibility in detecting shoulder taps, while simultaneously investigating usability in an in-the-wild study.

5.1 Improved version of *Head 'n Shoulder*

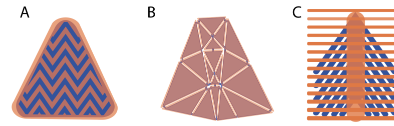
To enhance the everyday usability of *Head 'n Shoulder*, we envisioned several future designs enhancing real-world applicability by simplifying the garment from a jacket into an optimized shoulder cover. While the design focuses on comfort, usability, and robustness, we kept technical requirements, such as sensor placements and configurations identical. Based on these aspects, we have developed different patterns that are as close as possible to the initial smart jacket while showcasing the accompanying inclusion of design elements. The three sensor patch variants are presented in Figure 5a, depicting the original shape (Variant A) as present in *Head 'n Shoulder*. Further, Variant B introduces a polygonal structure and Variant C has a spring-like subdivision.

To stabilize the connection with the textile, for adding robustness but also flexibility, we aim to add different cover patterns using thermal transfer foil. This foil does not isolate the sensor, hence contact still results in a strong capacitive signal change. The different patterns are shown in Figure 5b for the different sensor patch variants. For instance, adding gaps increases the flexibility of the sensor patch. In Variant A, adding the isolation includes gaps whereas Variant B is fully isolated. Its polygonal structure allows a kind of folding that can adapt better to the shoulder shape. Variant C increases flexibility through the spring-like structure resulting in thin protrusions aligning with the shoulder. The inversely attached isolation adds stability to support the structure.

From the design perspective, the color and shape of the isolations are based on the movement axes that are covered and further stabilize the durability of the conductive tracks and the sensing. The patterns created here were developed to showcase the possibilities to improve simplicity and functionality in an appealing design.

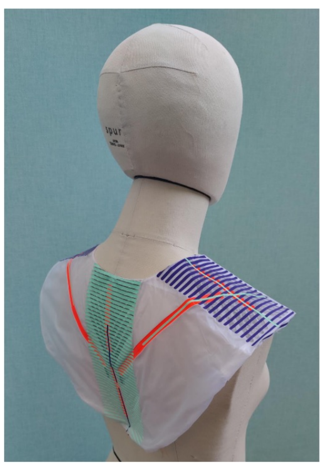


(a) Conductive Sensing Patches



(b) Transfer foil as cover for robustness and flexibility

Fig. 5. Three drafts to fuse design and technology within textile conductive sensing patches.



(a) Shoulder Cover with spring-like subdivision

(b) Shoulder Cover with polygonal shaped patches

Fig. 6. Design of the improved *Head ’n Shoulder*.

With this updated design of *Head ’n Shoulder*, we enhance its real-world applicability by simplifying the garment from a jacket into an optimized shoulder cover to improve usability, robustness, and comfort. Figure 6 visualizes the implementation of the spring-like (Variant C) and the polygonal patch design (Variant B). The third patch on the back works as a stabilizer for the hardware’s capacitive virtual ground as discussed before to stabilize the data acquisition without interfering or cross-talking the capacitive channels. The system’s technology is mimicked to the first *Head ’n Shoulder*, except that the design presents a solution that might be more suitable for everyday use. This updated version allows for greater freedom of clothing choice, as it can be worn as an additional layer on top, in between, or underneath.

Through initial tests, we investigated the robustness and signal quality of the newly created prototypes. We selected the spring-like subdivision prototype as our final design to conduct additional studies. The conductive sensing patch based on the spring-like layout provides sufficient flexibility to align with the natural 3-dimensional shape of the shoulder. Moreover, if the material snuggles to the user’s body, clean and robust signals can be gathered due to the minimized movement of the whole prototype.

Table 1. Custom questions to assess bike safety, control and interaction. From *strongly disagree* to *strongly agree*; all visual analog scale (0 to 100). Note: for the *Head 'n Shoulder* condition, we substituted interaction with gestures.

Perception of the Interaction	
Q1	Performing the interaction negatively impacted my bike control.
Q2	I felt safe while riding the bike.
Q3	Performing the interaction did distract me.
Q4	I was able to fully concentrate on riding the bike.
Q5	I was able (physically) to perform the interaction accurately.
Q6	I was able to perform the interaction immediately.

5.2 Study design

Study II focuses on evaluating the real-world feasibility of *Head 'n Shoulder*. As such, we introduced a baseline interaction method through buttons on the handlebar on either side. In a within-subject design with the type of interaction (either button or *Head 'n Shoulder*) as an independent variable, we measured the usability of the two conditions during a short bike ride of 10 minutes on average using a set of custom questions (see Table 1) and the UMUX-Lite questionnaire [32]. The area for the experiment was closed up from regular traffic, ensuring the participants safety while giving them freedom to select the route.

We further evaluated the robustness of *Head 'n Shoulder*'s detection algorithm by comparing it with the results from Study I, especially focusing on a non-updated model architecture and training from Study I evaluated on data collected during Study II.

5.3 Apparatus

As discussed in Section 5.1, we selected the shoulder cover with spring-like conductive patches as the most promising solution to provide robust sensor signals together with comfort and design implementations. The design was the outcome of a workshop with smart-fashion designers, supporting our work of *Head 'n Shoulder* towards real-world applicability. We mimicked the hardware from the jacket with an identical DAU setup. However, due to the changing design and positioning in conductive patches, the operation level of each patch changes between prototypes. To resolve issues in this sense, we apply the same signal preprocessing as for the old prototype. By normalizing the data into the range between 0 and 1 and subtracting each channel's operating mean signal, we obtain a data-cross comparison between prototypes and their respective capacitive channels.

Towards proper analysis of the new design in real-world scenarios, we designed an Android 12 based app, exclusively designed to shift the lab-based experiment from Study I to an in-the-wild experiment. The functionality of the app accommodates the features from the previous JavaScript to gather the capacitive signals from the shoulder cover's DAU. Additionally, since experiment instructors may not be available to supervise the experiment all the time if participants cycle around, we implemented a visual and audio-based instruction provider in the app. A randomized trigger instructs the participant to either apply the left or right tap gesture. Compared to the previous experiment, we can thus balance the occurrence of the two touch gestures. Figure 7 shows the in-the-wild experiment with the updated *Head 'n Shoulder* system, especially highlighting how participants raise their shoulders and tilt their head to execute the gesture.

Due to the user feedback from the previous study, especially regarding the complaints about executing the both tap gesture, we removed it from Study II. To conduct a user study between common button interaction and *Head 'n Shoulder*, we added two single buttons to the left and right side of the handlebar to mimic the intended usage of left and right shoulder taps with button press events.

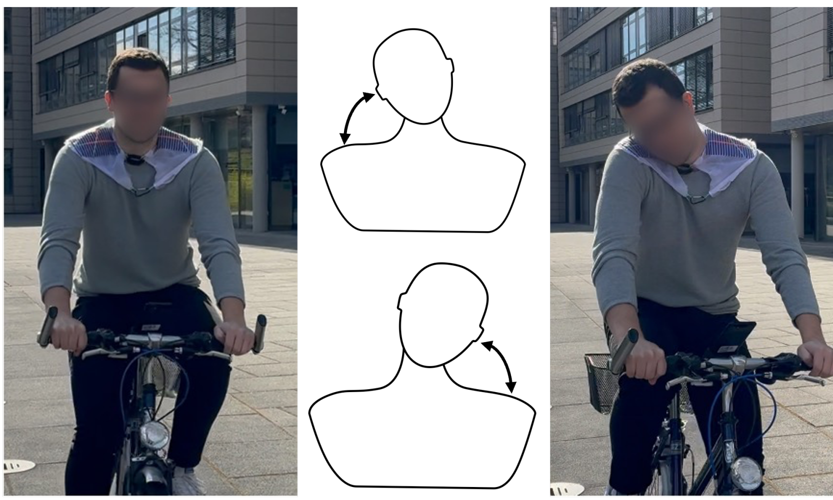


Fig. 7. The *Head 'n Shoulder* prototype of Study II in-the-wild, showing the movement of shoulder raise and head tilt to touch the patch.

5.4 Participants

We recruited 22 participants (Female=8, Male=14; Mean age=28, SD = 4.5) through mailing lists and word of mouth. 14 participants participated in our first study. Participants reported an average bike riding experience of $\bar{x} = 52.7$ ($s = 25.8$) measured on a visual analog scale (0 to 100).

5.5 Procedure

After providing informed consent, participants were introduced to either of the two interaction methods in randomized order: the buttons on the handlebar and the improved version of *Head 'n Shoulder*. They subsequently performed a first bike run with their first condition. We collected ground truth by instructing participants to perform respective gestures through an auditory signal that they received from a smartphone. Participants received a gesture request on average every 10 seconds. After finishing their first run (approximately 10 minutes), the participants completed the questionnaire containing custom questions on perceived bike control and safety (Table 1), as well as the UMUX-Lite questionnaire [32]. In the second bike run, participants were using the other condition and likewise answered the same questions at the end of the run. All bike runs were performed on a pre-set course to minimize safety hazards. Participants were asked to ride their bikes the way they are used to cycle so that our dataset contains the missing balancing act from previous Study I. Overall, the study duration did not exceed 30 minutes. Ethical approval for the study was obtained from the Ethics Team of the German Research Center for Artificial Intelligence.

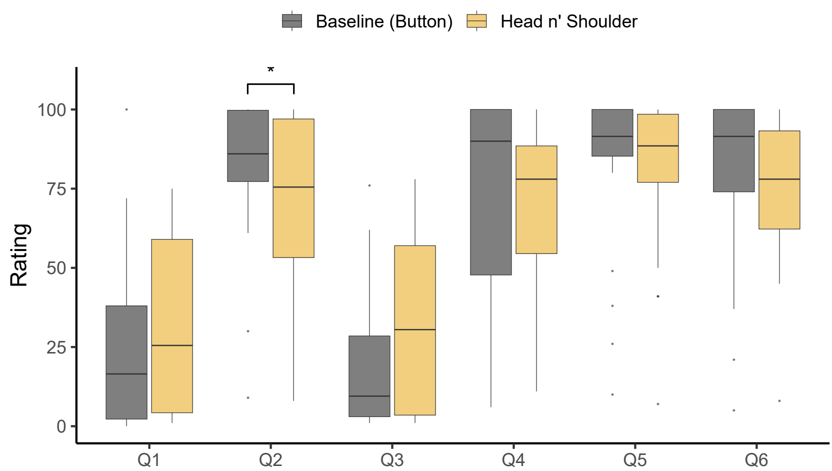


Fig. 8. Ratings for questions Q1-Q6 (see Table 1). Q2 ("I felt safe while riding the bike.") showed a significant difference between the conditions (marked with *).

5.6 Results

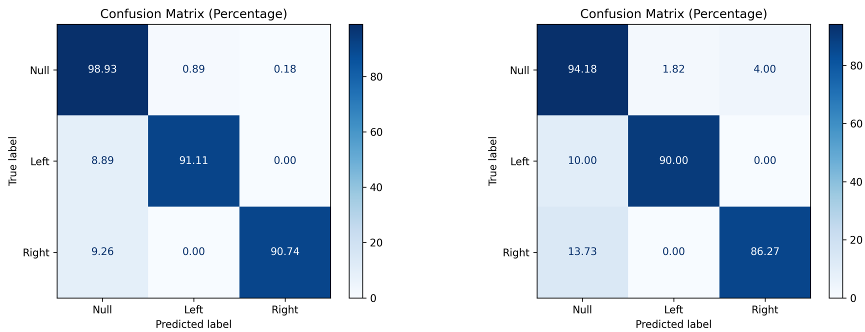
5.6.1 User Feedback. We report on our custom questionnaire (see Table 1), usability score as measured by UMUX-Lite and the stated comfort rating for *Head 'n Shoulder*.

Custom Questionnaire (Bike Control & Safety, Interaction Performance). For each condition, we measured perceived bike control and safety as well as gesture interaction through custom questions (see Table 1). A Wilcoxon signed-rank test (normality could not be confirmed) showed a significant difference between the two conditions for Q2: "I felt safe while riding the bike".: $V = 156, p < .05$. No other significant differences were found. Figure 8 shows all custom questions. Both conditions scored low on perceived distraction (Q1, Q3). Participants also gave high scores for being able to perform the interaction without issues (Q5, Q6). There is some indication that performing either interaction impacted bike riding to some degree leading to a lower perception of safety, more so for *Head 'n Shoulder* (Q2); and concentration loss (Q4).

Usability (UMUX-Lite). We further analyzed the UMUX-Lite scores for both conditions and calculated the parity values for the System Usability Scale (SUS). Using Bangor et al. [5]'s rating scale, both conditions can be classified as "good", with scores of 74 and 83 for *Head 'n Shoulder* and button interaction, respectively. A Wilcoxon signed-rank test revealed a significant difference between the two conditions ($V = 101, p < .05$).

Perceived Comfort of Head n' Shoulder. After the run with *Head 'n Shoulder*, we asked participants about their perceived comfort with the device: "I felt comfortable wearing the device". The answer was recorded on a visual analog scale (0 to 100). *Head 'n Shoulder* scored a high average comfort rating of $\bar{x} = 70.0(s = 25.8)$.

User Opinion. After the experiment, we openly asked the participants about their opinion and their experience. Overall, participants agreed to utilize such system in their everyday biking activity to handle smartphone interaction. They commonly liked the design and functionality especially



(a) Confusion matrix of Study II dataset.

(b) Confusion matrix for training on old and evaluating on new dataset.

Fig. 9. Evaluation of CNN architecture (identical to Study I) trained on the new dataset of Study II (left) and cross-evaluated through the new and old dataset combined.

the simplicity of use. Additionally, the lightweight shoulder cover obtained positive feedback, as it can be worn independently from the user clothing and does not bother during the activity.

5.6.2 Algorithmic Robustness. Similar to the technical evaluation from Study I, we trained the identical machine learning model based on the convolutional classifier with the new dataset gathered from Study II. The same training strategy and hyperparameter were applied to provide a comparison between in-the-wild and lab environments.

We applied leave-one-person-out cross-validation across all 14 participants from Study II. As shown in Figure 9a, the results show similar results to Study I, highlighting the robustness against disturbances introduced by the biking activity. Due to the enhanced design, flexibly covering the shoulders only, the prototype is less affected by participants' movements. This proves that compared to the previous iteration in Study I, we could improve the overall accuracy across all participants by 2% points up to 97% in total. The slightly increased false negative classifications can be traced back to the increased skill requirement to handle the balancing on the bike while executing the gestures. However, the results are still in acceptable range, especially the more important false positive errors are less than 1%.

Additionally to the classic evaluation for leave-one-person out cross-validation of the new dataset, we trained the model on the dataset of Study I and evaluated it on the dataset from Study II. As shown in Figure 9b, promising results can be found for the classification, with an average accuracy of 92%. Since training and evaluation data are gathered from different prototypes, we can confirm the robustness of *Head 'n Shoulder* hardware and the designed software pipeline.

6 DISCUSSION

Our work investigated the potential of *Head 'n Shoulder* as an alternative gesture detection system using hands- and eyes-free gesture recognition. Based on the promising results and the system's robustness, we discuss the implications of *Head 'n Shoulder* for future systems to establish capacitive sensing in the scope of enhancing bike interaction and safety.

6.1 Robust and Accurate Detection Enabled Through Capacitive Sensing

In our evaluation, *Head 'n Shoulder* achieved an overall accuracy of 95% for three distinct head gestures in Study I. Our updated version (Section 5) is even more accurate (up to 97%) while offering a lighter clothing option. This is mainly due to the positioning of the patches to minimize interference with the cycling movement and the use of touch gestures instead of tracking gestures through joint movements only. For this strategy, the basic left and right gestures yielded very promising results, though the use of both shoulders was less accurate. Hence, we removed this option in Study II as it was not practical. For both technical evaluations, we scored a very low false positive rate of < 1%, limiting the chance for false triggers. This highlights the suitability of capacitive sensing during active movements, such as cycling. We also confirmed its high robustness, as neither clothes worn on top of *Head 'n Shoulder*, nor environmental influences could significantly impact its performance. More so, we were able to train a prediction model using only data collected in our lab study (Study I) and still achieved a high prediction accuracy showcasing *Head 'n Shoulder*'s ability to generalize.

6.2 Capacitive Sensing for Wardrobe and Bike Freedom

Capacitive sensing does not involve direct physical touch with the conductive material. Rather, it is possible to touch the sensing patch even though it is covered with multiple layers of garments or plastic shielding. Participants reported that *Head 'n Shoulder* was comfortable to wear and its accurate prediction allows users complete wardrobe freedom, deciding on arbitrary garments below or on top of *Head 'n Shoulder*. Moreover, the technology of *Head 'n Shoulder* enables its integration in various types of garments, e.g., through conductive thread and fabric patches. For the cycling scenario, this allows the adaption of the user's wardrobe to changing climate and weather conditions while maintaining the full potential of *Head 'n Shoulder*. Since it works independently of the bike and is completely body-worn, it inherently supports the trend of bike-sharing with changing bikes [19].

6.3 Gestures of *Head 'n Shoulder* Subject to Design Constraints

While our technical evaluation of *Head 'n Shoulder* showed very promising results, its usability was not appreciated that much by our participants. In comparison with a simple baseline using the button on the handlebar, they were more concerned about their safety while cycling and rated *Head 'n Shoulder*'s usability significantly worse though still as "good" [5]. As feedback, most of them argued to feel safer when keeping their head straight during gesture execution due to the stable viewpoint and improved balance. Especially for elderly people, a shoulder-only movement offers less distraction and imbalance than head movements [2]. These findings show that while our sensing method is aligned with cycling, participants struggled with the novel way of interaction not derived from common cycling actions. In comparison, *Brotate and Tribike* [53], deliberately designed the interaction in line with cycling paradigms in mind. In this work, we used a different design methodology, approaching the idea of augmenting the rider through sensors. While our given gesture set is not optimal yet, it provides a good foundation to further investigate upper-body gestures for interaction during cycling.

6.4 Enabling Self-Contained Hands- and Eyes-Free Interaction While on the Bike

Compared to button-based solutions (cf. [53]), *Head 'n Shoulder* does not require touching additional buttons on the handlebar due to its hand-free solution, neither does it impact the user's gaze (cf. [29]). However, its usability as mentioned previously is still limited. Nevertheless, its small technical footprint (entirely contained in the jacket/shoulder cover) allows easy deployment. In order to fully integrate the system into real-world biking scenarios, *Head 'n Shoulder*'s slim CNN architecture enables real-time inference through embedded devices since the energy-footprint for training and inference was minimized [23]. Instead of having to pass the raw data to an external computing device, the hardware integrated into *Head 'n Shoulder* is capable of processing the data and performing inference directly, producing a compatible output format to map the head gestures to HID commands [49]. As such, *Head 'n Shoulder* is a self-contained system that can be further utilized to link downstream tasks with the proposed head gestures. In combination with an additional layer taking care of consecutive gestures during a short time frame, we can realize a sufficient number of distinct gestures, similar to modern in-ear headphones. Here, we implement *Head 'n Shoulder* as a human-interface device (HID) to link gesture detection to specific controls on digital devices as presented in [22]. Doing so, allows general-purpose input for a variety of applications, e.g., enabling media control for any playback app similar to Bluetooth headphones. Capabilities can be extended to answering phone calls, navigation control and voice activation. Further, in line with bike locomotion, *Head 'n Shoulder* provides a natural mapping to left and right turn-taking signals, possibly integrated into smart wearables (e.g., LEDs in clothing), increasing visibility [10] and safety during turning.

7 CONCLUSION

Interacting with and controlling digital devices while on the move can be a challenging — even dangerous — endeavor, especially while riding a bike. We advocate that secondary tasks during cycling increasingly demand more and more cognitive attention from riders and pose an inherent risk if the rider's attention is split between the road and their smartphone. In this work, we presented our smart *Head 'n Shoulder* prototype through two iterations, leveraging the potential of capacitive sensing to enable hands- and eyes-free interaction with digital devices during cycling. *Head 'n Shoulder* uses a minimal set of gestures sufficient for everyday interaction with digital devices. The system is robust and achieves an overall accuracy of 95% in the first iteration, regardless of whether users wore garments on top of the jacket. In an updated design iteration of *Head 'n Shoulder*, we highlighted the technology potential as a ubiquitous smart wearable suited for everyday use by any cyclist while enhancing the accuracy to 97% and investigating the user feedback.

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