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Visual behavior of racing bike cyclists in multi-tasking situations

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ABSTRACT

Distracted biking can have serious repercussions for the rider such as accidents. The purpose of the present experiment was to determine the effect of visually monitoring two parameters, the cadence, and the heart rate on a bike computer fixed on a racing bike, and simultaneously detect hazardous traffic situations. Individuals (n = 20) were instructed to ride a racing bike that was fitted onto a roller trainer. After conducting a bicycle step test to assess the maximal heart rate (HF_{max}), participants were assigned to a within subject-design on a separate day. They were instructed to perform the riding task in two single-task conditions (only watching the traffic at the video with occluded or without occluded bike computer), two multi-tasking conditions (monitoring the cadence of 70 RPM or 90 RPM, monitoring the heart rate, and observing the traffic) and one control condition (no instructions). Percentage dwell time of the eye movements, the constant error from the target cadence, keeping the heart rate in an interval of 50% - 70% of the HF_{max}, and percentage of the recognized hazard traffic situations were analyzed. The analysis indicated that monitoring the parameters on the bike computer induced no significant decline in perceived hazardous traffic situations.

Cycling consists of several simultaneous tasks such as pedaling, keeping balance, and steering the bike along the road (Magill & Anderson, 2017). Additionally, since cyclists are actively engaged in traffic, for safe cycling the traffic must be visually monitored (Guo et al., 2023; Mwakalonge, White, & Siuhi, 2014). Today most bikes have a computer mounted on the stem or handlebar. Bike computers are an important equipment for cyclists. They provide information about the route or the kilometers ridden. Especially in a sport-related context, athletes monitor parameters of their physiological and biomechanical demands during exercise and competition to distribute their metabolic resources with the aim to maximize their performance (see Dobiasch, Krenn, Lamberts, & Baca, 2022). In order to process the information from the bike computer and the information from traffic, the cyclists must divide their visual behavior on the one hand to recognize possible hazardous traffic situations and on the other hand to monitor physical output information from the bike computer to adjust the cycling behavior to keep/maintain the performance (Pfeifer, Leinen, Puhl, & Panzer, 2023). Even though, athletes have extended practice in pedaling, keeping balance and steering the bike, the attentional demands for these types of tasks are low. However, the processing of traffic information and information from the bike computer requires visual attention. This situation necessitates the detection of the traffic changes and of processing the alternating display information from the bike computer. This creates a typical multi-tasking situation for athletes, which can be visually and cognitively distracting and increases the risk of hazardous traffic situations (Goldenbeld, Houtenbos, Ehlers, & DeWaard, 2012).

The empirical findings in the context of detecting hazardous traffic situations and monitoring the bike computer on a racing bike

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are ambiguous. In an experiment from Yang and Wu (2017), cyclists ride a racing bike in a virtual environment. The cyclists were instructed to watch video clips with hazardous traffic situations and concurrently monitor the cadence. Their results provided empirical evidence that visual control of the bike computer distracted the riders' visual behavior to detect hazardous traffic situations. In another related experiment, Pfeifer, Leinen, Puhl and Panzer (2023) extended the findings from Yang and Wu to the analysis of eye-movements. In a within-subject design, cyclists were instructed to visually monitor the cadence of a bike computer and to perceive hazardous traffic situations in a virtual environment on a racing bike. They compared single-task (observing the traffic or the bike computer) and dual-task situations (monitoring the cadence and observing the traffic). It should be noted that, in contrast to a street bike, athletes on a racing bike have an elongated upper body position, and riders have to lift/stretch their heads to visually control the road traffic. Following the analysis of eye-movements their results provided empirical evidence that riders prioritized their visual behavior on the hazard traffic videos. Furthermore, the cyclists showed no performance impairments between single-task and dual-task situations evaluated by an awareness of risky traffic situations presented in the video clips. This suggests that cyclists attached a higher value to their cycling security than controlling performance output parameters. This finding is consistent with the priority task hypothesis proposed by Lemonnier, Brémond and Baccino (2015): visual attention resources are allocated to tasks in a graded manner associated with their priority. However, one of the mentioned limitations of the experiment from Pfeifer et al., (2023) was that only the output parameter 'cadence' had to be visually controlled by the riders. Another interesting research question is to know, what would happen if the number of parameters that have to be visually controlled at the bike computer increases and when the parameter frequently changes depending on the cadence? This alteration could have a major implication for the cyclists in which their visual behavior is burdened by the responsibilities of the bike computer scanning and traffic monitoring. A theoretical approach that seems to account fairly well for at least some of the observed effects is the Expectancy-Value Model of allocation of visual behavior. In order to explain visual behavior in multi-tasking, Wickens, Goh, Helleberg, Horrey and Talleur (2003) proposed that visual behavior depends on the expectancy and the value of task relevant information available from the different tasks in multi-tasking. Expectancy refers to the amount of relevant visual information in a perceptual field. The expectancy increases when the relevant visual information changes continuously. The relevance of a given task is characterized by its value. Scenes with higher values and higher expectancy are allocated with increased visual behavior. An interesting question is to know if visual behavior changes when the attentional demands increase by providing more and alternating visual information at the bike computer that had to be monitored by an athlete. It is of practical significance to ensure cyclists' traffic safety and to gather information about distracted biking to advance our understanding of visual behavior of cyclists to develop practice regimens to avoid serious repercussions for the rider.

Extending previous research from Pfeifer et al., (2023) the current experiment aims to determine the effect of visually monitoring parameters on a bike computer fixed on a racing bike, and simultaneously detect hazardous traffic situations. To increase the expectancy the amount of relevant visual information on the bike computer was increased. Riders were instructed to visually monitor and maintain the preset cadence of 70 or 90 RPM and a physiological parameter, the heart rate in a moderate interval between 50% and 70% of the maximum heart rate (HF_{max}) as an indicator for the physical demands and the training loads. The procedure emphasized to visually monitor each task with equal priority (monitoring the cadence and heart rate and observing the traffic videos and naming the hazardous situations). Considering the theoretical assumptions of the Expectancy - Value model of Wickens et al. (2003), we hypothesized that the increase in the amount of relevant and constantly changing visual information on the bicycle computer is associated with increased visual behavior. Therefore, the perception and the naming of the hazardous traffic situations should be reduced. To increase the physical demands and changes in the heart rate and the cadence, the pedal frequency was changed from 70 RPM to 90 RPM. In this situation, the athletes have to adjust their cadence and probably to shift in another gear to stay within the preset heart rate interval. This increases the expectancy because athletes have to monitor the visually changing information on the bike computer more often and longer, which reduces visual control of the traffic situations and affects negatively hazard perception.

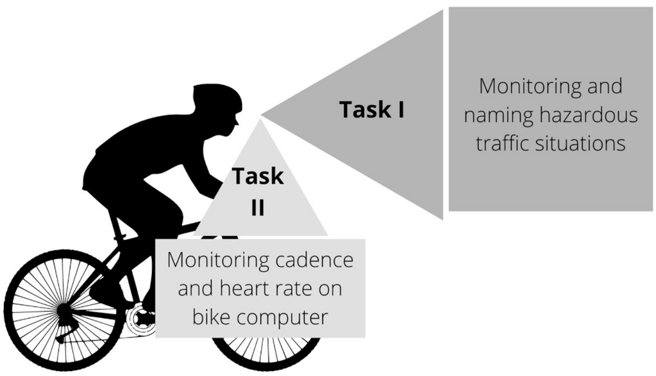

Fig. 1. Illustration of the experimental set-up. A cyclist on a racing bike instructed to monitor the video clips with the hazardous traffic situations as a primary task and the secondary task to monitor the cadence on the bike computer.

1. Methods

1.1. Participants

Undergraduate students of sports sciences ($N = 20$; females 8; males 12) with a mean age of 21.40 yrs. (SD = 2.81 yrs.) volunteered to participate in the experiment. Participants received class credit for their participation. All participants used their bikes/racing bikes at an average of 1.05 h/week (SD = 1.35 h) but did not participate in official bike races. None of the participants had an eye impairment. The experiment was conducted in accordance with the Declaration of Helsinki and the guidelines were approved by the Ethics committee of the University (Faculty of Human and Business Science). All participants provided and signed informed consent before participating.

1.2. Apparatus

The apparatus consisted of a roller trainer (Tacx™ Flux 2 Smart T2980 virtual reality trainer). The Tacx 2.0 (T1990.02) software controlled the performance of the athletes. A racing bike (frame size M) was fitted to the roller. The racing bike has a 22-gear system. In a virtual environment, the traffic environment was projected on a 2 m × 2 m screen by a video projector (temporal resolution was 60 Hz; spatial resolution was 1024 × 1280 pixels) located 2 m in front of the athletes onto a projection screen at eye-level (see Fig. 1). Hazard traffic situations were presented in video clips in full-frame modus with a duration of 1 min. To increase uncertainty of the provided hazardous traffic situation in the videos, some clips were recorded without containing a hazardous traffic situation. Therefore, in each video clip none, one, or two hazardous traffic situations were presented. For the current study, video clips were collected in real-life traffic environments. The videos were recorded in the morning on the way to work and in the evening on the way home. This increased the likelihood that the traffic density was higher and that the individuals were encountered with different traffic situations. The videos included different types of traffic environments in the city and outside the city: cars and cyclists share the road, intersections, separated cycling paths and sidewalks, and a path where the pedestrian and the cyclist share the route. Furthermore, some hazardous traffic situations were enacted and recorded on a university campus with volunteers during the day to achieve a comparable traffic density to the real-life traffic. According to Mantuano, Bernardi and Rupi (2017), hazardous traffic situations were defined as follows: (1) when a car approaches at an uncontrolled intersection (e.g. intersection without traffic lights where cyclists have to constantly monitor the intersection to see if they can cross without a traffic risk), (2) when cars suddenly stop, and the driver gets out which increases the likelihood of dooring, (3) or when a parked car suddenly starts (see also Kovácsová et al., 2018). We digitally recorded 26 video clips with a GoPro 8 (30 fps) camera. The camera was fixed on the helmet of the cyclist. Therefore, the hazardous traffic situations were recorded from first person view (cyclists' perspective). In a pilot study, we determined the inter-rater reliability. For this, we calculated Cohen's Kappa (Cohen, 1960). The resulting κ-value was 0.65, which indicated a substantial agreement of independent rates to the hazardous traffic situation provided in the video clips (McHugh, 2012).

A Garmin® Edge1030 bike computer (height = 11.4 cm; width = 5.8 cm) was fixed to the center of the bicycle handlebars stem. The average viewing angle of 10.86° was determined from the sagittal plane using the trigonometric functions of tangent and arctangent with a head distance of 60 cm from the bicycle computer. The bike computer monitored the data with a temporal resolution of 1 Hz. Eye movements were recorded with mobile Tobii glasses 2 eye-tracking system (Tobii Technology AB, Danderyd, Sweden). The gaze position was determined by pupil tracking and recorded with a temporal resolution of 30 Hz and a spatial resolution of 0.5° over the range of the visual angle between the leftmost and rightmost edge. The eye-tracking system was calibrated for each participant following three video clips using Tobii Studios 9 calibration dots. A minimum of 4-star rating out of 5-stars (highest) for accuracy and tracking was pursued. During the whole experiment, participants were required to wear the mobile eye tracker and to avoid touching the glasses. The experimental procedure took approximately 60 min for each participant, including the admission and the breaks between each video and condition for calibration.

1.3. Tasks and procedure

The experiment consisted of two testing days: The first day contained an incremental cycle ergometer step test to assess the HF_{max}, and on the second day athletes had to perform the multi-tasking situation while cycling on a fixed racing bike. To avoid fatigue the two test days were separated by a minimum of 48 h. After entering the testing room on day one, the participant read and signed the informed consent. Then they read the written instructions. Following this, they were instructed to put on cycling shoes with a two-bolt cleat system and the saddle height was positioned at the racing bike with the heel-to-pedal method. The instruction was to place the heel on the pedal and pedal backwards to reach the six o'clock position. In this position, the knee should not be completely straight (Bini & Diefenthaeler, 2010). The step test was conducted on a cycling ergometer (Cyclus 2, RBM elektronik-automation GmbH, Leipzig). The incremental test protocol started at 50 W or 100 W, depending on gender and body weight. The cadence was set between 70 RPM to 80 RPM throughout the test. Workload was increased by 50 W within every 3 min until athletes' volitional exhaustion. The heart rate was continuously measured by the Cyclus system and saved at the end of the 3 min step in an Excel file. The incremental cycle ergometer step test was conducted by a trained person. For the second test day athletes returned to the laboratory. Now the apparatus was the Tacx™ Flux 2 Smart T2980 roller trainer. As on test day one, athletes read the written instructions. Following this, participants had to put on the cycling shoes and the saddle height was again positioned at the racing bike. Further, they had to put on a cycling jersey with a backside pocket to keep the data logger from the eye-tracking system. Then they were required to put on the eye-tracking glasses and the calibration procedure was started. To keep the position between the head and the bike computer constant, participants were instructed to sit in a road rider position and to place their hands at the handlebar above the brake handle. At this position, the individuals had an elongated upper body position. Participants were required to pedal with a self-paced frequency for three minutes to get familiarized with the seat position. Further, they were instructed to choose a comfortable gear for the beginning. If they considered pedaling required too much force and they could not stay within the required heart rate interval of 50% to 70% from the HF_{max} and the required cadence they were allowed to shift the gear. In a within subject-design individuals were instructed to perform the riding task in five different conditions: (1) single-task condition (only watching the traffic in the video, the bike computer was occluded; STO), (2) single-task condition (only watching the traffic in the video, the bike computer was not occluded; STnO) (3), a multi-tasking condition (monitoring the cadence of 70 RPM and the heart rate interval of 50% to 70% from the HF_{max} and observing the traffic; MT70), (4), a multi-tasking condition (monitoring the cadence of 90 RPM and the heart rate interval of 50% to 70% from the HF_{max} and observing the traffic; MT90), and (5) a control condition without any instructions where to look but pedaling the cadence of 70 RPM (CO70). In the multi-tasking conditions, the cyclists were instructed to monitor the provided information on the bike computer and to observe the traffic in the video clips with equal emphasis. The STnO condition was included to control the instruction to monitor only the videos. The bike computer was occluded. The STO condition was included to control the instruction to monitor the traffic videos while the bike computer was not occluded. Each condition lasted 3 min with 3 different video clips of one minute each. The order of the conditions was incompletely balanced. The video clips were randomly selected from all possible 26 digitized clips to minimize that the participants after the completion of the experiment exchange information about the specific contents and the hazardous situations. Twelve of the 26 clips contained one hazard, five clips contained two hazards, and nine clips contained zero hazards. Three videos were provided in each condition, including a video with one hazard, a video with two hazards and a video with no hazards. This resulted in an equal distribution of the different video scenarios in each condition. Over the five conditions, each participant was offered 15 potential hazards, including five videos with no hazards (see Vansteenkiste, Zeuwts, Greet, & Lenoir, 2016). In order to obtain a sufficiently large number of hazardous situations and reliable data for each condition, the videos with hazardous situations predominate overall. To avoid fatigue, within the conditions a rest interval of 1 min was provided to the participants between each video clip. The cadence and the heart rate were monitored by the experimenter on a PC (Dell Latitude 5310) connected via Bluetooth to the bike computer. The hazardous situations were identified verbally by the participants. Therefore, the individuals were instructed to respond by the word 'Yes' (German 'Ja'). By verbalizing the identified hazardous situations, we obtained information about which situations the rider reacted to in particular. According to Horswill, Hill, and Wetton (2015), this method provides additional information about what cyclists react to and has the potential to reduce measurement errors. Further, to increase the reliability of the information on what constitutes a hazard and what does not, the experimenter was trained to recognize hazardous situations in the video and to immediately note the correct and incorrect answers for each participant. The response was noted by the experimenter in a ready-made Excel sheet on a computer.

1.4. Areas of interest

The two main Areas of Interest (AoI) were the video clips with the traffic and the bike computer. The AoIs are the boundary around an element that an individual spent looking. The boundary for the AoI 'Bike Computer' was the surface of the bike computer (Garmin® Edge1030), and for the AoI 'Traffic' the whole 2 m × 2 m projection screen where the video clips were presented (see Lemonnier et al. (2015); for AoI definition). A third AoI was defined, including the remaining environment. This AoI was labeled 'Environment'. At the AoI, Environment the eye movements were not within the two primary AoIs.

1.5. Measures and data analysis

Data analysis was performed using MatLab 2022a (MathWorks, Natick, MA, USA) and a commercial software 'rainorshine.bike' to retrieve the data from the Garmin® Edge1030 bike computer.

1.5.1. Eye movement measure

Eye movement recording was started several seconds prior to each condition. To provide information about visual behavior, the time that athletes maintained their eyes on the AoIs, the dwell time in each AoI, was analyzed. The dwell time was captured as a temporal metric of eye movements (Bakhit, Osman, Guo, & Ishak, 2019). The dwell time is the sum of all fixations, saccades and blinks that hit the AoI and represents the portion of the time the cyclist looked within a certain AoI (Vansteenkiste et al., 2014). The first frame of the hazard video clip appeared as an external trigger for the eye-tracking system. The data analysis was performed by manual frame-by-frame analysis method of the video images. Therefore, the scene camera images were superimposed with the gaze position (eye cursor). When the gaze position was within the defined AoI (inside the AoI boundary) onset of the dwell time was determined. When the gaze position was outside the target boundary offset of the dwell time was determined. The dwell time was defined as the time that an individual spent looking within the onset and offset of the gaze position on the AoI (Vieluf, Massing, Blandin, Leinen, & Panzer, 2015). Then, the individual dwell time values of each AoI were summed, yielding a global estimate of dwell time on the AoI. Finally, the percentage of dwell time (%dwell time) for each condition was calculated as a ratio of the dwell time for the condition at an AoI divided by the sum of the dwell times of the three AoIs for the conditions and multiplied by 100. The %dwell time represents individuals' level of interest in the AoI.

1.5.2. Hazard detection measure

To evaluate hazard perception, the percentage of the hazard detection parameter for each video clip was computed to quantify the number of correctly detected hazard traffic situations in the video clips. The percentage correct (%correct) was calculated as the ratio of the correct identified hazard situations divided by the number of presented situations and multiplied by 100.

1.5.3. Cadence measure

The data of the cadence of the individuals was read out by the 'rainorshine.bike' software. When the cadence reached the first time the target cadence onset was determined. The offset was determined at the end of the video clip. To assess the cadence accuracy within one condition the constant error (CE) of the cadence in RPM was calculated as:

$$CE = \sum (\text{cadence–target cadence}) \Big/ n,$$

where 'n' is the number of values within each video. Across the three videos within a condition, the mean CE was computed. The CE captured the average error, the amount, and the direction relative to the target cadence (see Schmidt, Lee, Winstein, Wulf, & Zelaznik, 2019).

1.5.4. Heart rate

To evaluate the heart rate the frequency of the interval within or outside 50% to 70% was calculated from HF_{max} of each athlete. The participants were informed of the interval on the second test day.

1.5.5. Statistical analysis

The statistical analysis was conducted using SPSS 25.0 software (IBM Corp., Armonk, NY, USA). Adjustments were made for violations of homogeneity and sphericity. According to Holmqvist et al. (2011), %dwell time analysis depends on the shape, distance, and size of the AoI. In the current study, the distance and the size of the AoIs differed. Therefore, between the three different AoIs (AoI Traffic, AoI Bike Computer, AoI Environment), three 5 (condition: STO, STnO, MT70, MT90, CO70) ANOVAs with repeated measures were conducted for the %dwell time. Further, the CE a 5 (Condition: STO, STnO, MT70, MT90, CO70) ANOVA with repeated measures was calculated. The %correct was analyzed by the non-parametric test by Friedman. The absolute frequency within or outside the interval of 50% to 70% from the HF_{max} was analyzed by Cochran's-Q test. The two possible outcomes were within the interval or outside the interval. Partial eta square (η_p^2) was used as the effect size for the ANOVAs, Kenndalls *w,* as the effect size for the Friedman-test, and eta square (η^2) was the effect size for Cochran's-Q (Cohen, 1988; Serlin, Carr, & Marascuilo, 1982). The significance level was set at $p < .05$. Post-hoc multiple comparisons of significant main effects were computed using Bonferroni corrections.

2. Results

2.1. Eye-movement analysis

Figure 2 displays the mean % dwell time for the three AoIs across the five conditions. Table 1 provides detailed information about the mean % dwell time of the analyzed AoIs and the standard deviation (SD) across the different conditions.

2.2. %Dwell time AoI traffic

The mean %dwell time of the AoI Traffic was with 85.87% lowest for the MT70 condition. The %dwell for all other conditions was above 90%. Further, the analysis for the %dwell time at the AoI traffic indicated a main effect condition, $F(4,76) = 4.96, p = .015, \eta_p^2 = 0.21$. Multiple post-hoc comparisons indicated that the %dwell time significantly differed between the single-task condition STnO and the dual-task condition MT90 (95% CI [STnO: 97.86%, 99.80%; MT90: 88.57%, 95.29%]). The %dwell time was significantly lower in the MT90 condition compared to the STnO condition.

2.3. %Dwell time AoI bike computer

The analysis for the %dwell time on the AoI Bike Computer indicated a main effect of condition, $F(4,76) = 4.75, p = .017, \eta_p^2 = 0.20$. Multiple post-hoc comparisons indicated that the %dwell time significantly differed between the two single-task conditions (STnO, STO), and the two multi-task conditions (MT70, MT90), and the control condition (CO70) (95% CI [STO: −2.37%, 7.46%; STnO: −0.08%, 0.61%; MT70: 4.39%, 9.71%, MT90: 4.51%, 11.31%; CO70: 2.54%, 8.05%]). The %dwell time was highest in the MT90 (mean 7.93%, SEM +/− 1.62%) followed by MT70 (mean 7.05%, SEM +/− 1.27%) and the CO70 condition (mean 5.29%, SEM +/− 1.32%). In this context, it should be noted that in the STO condition, in which the bike computer was obscured, no gaze behavior on the bike computer could occur and therefore, the resulting significant effect is not worthwhile to discuss.

2.4. %Dwell time AoI environment

For the %dwell time AoI environment, the analysis failed to reach significance, $F(4,76) = 2.18, p = .16, \eta_p^2 = 0.10$.

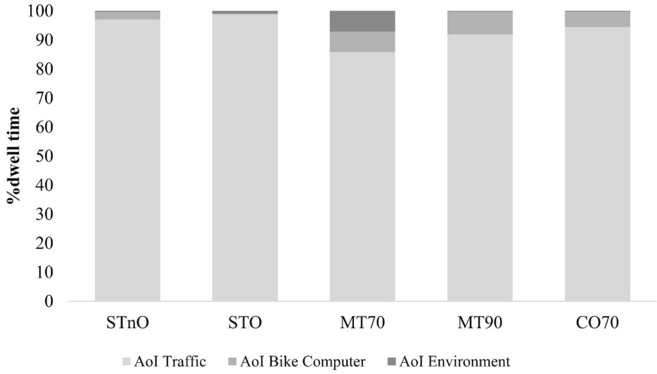

Fig. 2. Mean %dwell time of the AoIs Bike computer, Traffic, and Environment across the five conditions.

Table 1
Mean % dwell time of the analyzed AoIs and the SD across the different conditions.

	STnO	STO	MT70	MT90	CO
%dwell time traffic	98.83 ± 2.06	97.08 ± 10.43	85.87 ± 18.98	91.93 ± 7.18	94.43 ± 5.83
%dwell time bike computer	2.54 ± 10.49	0.29 ± 0.65	7.05 ± 5.67	7.92 ± 7.23	5.29 ± 5.89
%dwell time environment	0.87 ± 1.60	0.38 ± 0.54	7.07 ± 20.14	0.14 ± 0.11	0.27 ± 0.34

2.5. Hazard detection task

The median %correct are illustrated in Fig. 3. The analysis of the %correct indicated no significant difference between the condition, $\chi^2(4) = 1.89, p > .05, w = 0.02$. While the median of the MT90 condition is superior compared to the other four conditions multiple alpha adjusted Wilcoxon-Tests were conducted. The analysis indicated no significant differences.[1]

2.6. Cadence

The constant error from the target cadence is displayed in Fig. 4. The analysis of the CE indicated a significant main effect of condition, $F(4,76) = 9.62, p < .001, \eta_p^2 = 0.34$. Multiple post-hoc comparisons indicated that MT90 differed significantly from all other four conditions.

2.7. Heart rate

The absolute mean frequency within or outside the interval of 50% to 70% from the HF_{max} for each individual is illustrated in Fig. 5. The analysis of the absolute frequency indicated a significant main effect of condition, $Q(4) = 32.83$, $p < .001$, $\eta^2 = 0.41$. Between 19 and 17 individuals of the testing group showed for the STO, STnO, MT70 and CO70 conditions that they can stay within the designated interval of the heart rate. However, for the MT90 condition only 8 individuals stayed within the interval and 12 were outside the 50% to 70% interval. The heart rate for all individuals across all conditions was never under 50% from HF_{max}.

3. Discussion

The primary purpose of the present study was to determine the effect of visually monitoring parameters on a bike computer fixed on a racing bike and simultaneously detect hazardous traffic situations. One parameter was the physical output measure, the cadence, and the second the 50% to 70% interval from the HF_{max}, provided information about the physiological demand of the cyclist. According to the Expectancy-Value hypothesis (Wickens et al., 2003), we assumed that the increase in expectancy and the value evaluated by the amount of relevant and changing visual information in a perceptual field on the bike computer is accompanied by increased visual

[1] An equivalence test, a two-one sided test (TOST), was conducted for the MT90 condition and the STnO condition (Lakens, 2017; Lakens, Scheel, & Isager, 2018). The TOST was performed with Jamovi 2.2.5 and the TOSTER package for paired samples. Cohen's d as a standardized effect size was calculated by using G*power 3.1 (test family: *t*-Test; statistical test: means difference between two dependent means; type of power analysis: sensitivity) with given sample size ($n = 20$), power of 80% and an alpha level of 5% (Faul, Erdfelder, Lang, & Buchner, 2007). This resulted in a Cohen's d of 0.50 and was set as the smallest effect size of interest. Equivalence testing is based on t-statistic. Therefore, the TOST procedure *t*-Test for paired samples had the equivalence bounds of $\Delta L = -0.50$ and $\Delta U = 0.50$. The resulting effect size is significantly higher than the lower bound ΔL, $t(19) = 1.93$, $p = .034$ and significantly lower than the upper bound ΔU, $t(19) = -2.53$, $p = .010$. This indicated that the %correct difference in the STnO and the MT90 condition is small to moderate, if it exists.

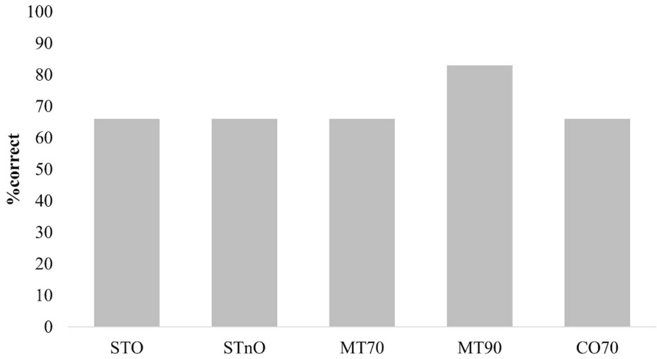

Fig. 3. Median percentage of the correctly judged hazard traffic situation across the five conditions.

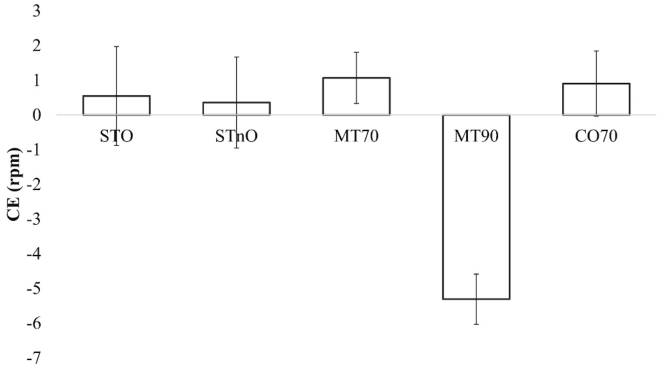

Fig. 4. Mean and the standard error of the means (SEM) of the CE of the cadence across the five conditions.

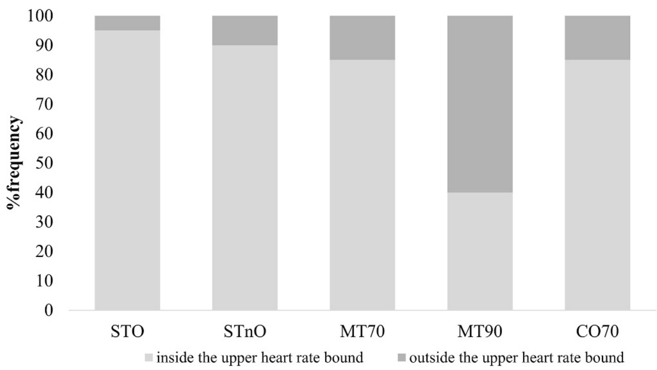

Fig. 5. Mean %frequency of the heart rate within the 50% to 70% interval and outside the upper bound.

behavior. The visual behavior on the traffic situations is reduced and the identification of hazardous traffic situations is decreased. In a virtual environment cyclists rode a racing bike with a bike computer mounted on the bicycle handlebars stem and video clips with or without hazardous traffic situations were provided. The eye movements were recorded with a mobile eye-tracking system and cyclists were instructed to perceive and name hazardous traffic situations. As the prime determiner for the level of interest the %dwell time as a temporal metric of the eye movements was analyzed. We chose that metric because dwell time reflects the time spent watching a specific AoI (Mantuano, Bernardi and Rupi, 2017) and a higher dwell time increases the likelihood of detecting and anticipating traffic safety risks for responding cyclists in advance to avoid future collision potential (Kovácsová et al., 2018). To induce a multi-tasking situation, it was emphasized to the cyclists to monitor both tasks (hazardous situations in the traffic videos & information provided on the bike computer) with equal priority.

The results of the current study indicated that the level of interest within the five different conditions for the AoI traffic differed with statistical significance. The %dwell time at the AoI traffic was 91.93% in the MT90 condition and significantly lower compared to the STnO condition with a %dwell time of 98.83%. At the AoI bike computer, the %dwell time was significantly higher in the MT70 and

MT90 conditions where individuals were instructed to monitor the bike computer and to observe the video clips with the hazardous traffic situations compared to the STnO condition where individuals only were required to observe the video clips and the bike computer was not occluded. This can be cautiously interpreted as an indication that cyclists followed the required instructions to visually monitor the bike computer.

On the empirical-theoretical level, this finding is partially consistent with the initial proposed Expectancy-Value hypothesis (Wickens et al., 2003) that monitoring the cadence of 70 RPM, and 90 RPM, as well as the heart rate interval increased the visual behavior on the bike computer to maintain the parameters. The amount of provided information on the bike computer and the continuous change of the provided information as a result of the pedaling demands increased the information density, and the visual inspection dedicated to this information increased, too (see also Lemonnier et al., 2015). However, the %dwell time at the AoI Bike computer represented only a small proportion compared to the %dwell time at the AoI Traffic. The low proportion of the %dwell time at the AoI Bike computer was sufficient to maintain the aimed cadence and heart rate interval across the conditions except for the target cadence of 90 RPM. Significantly more cyclists in the MT90 condition were not able to maintain the heart rate within the interval of 50% and 70% of HF_{max}. In this context, it has to be mentioned that cyclists were allowed to shift the gear to reduce the force requirements at the same cadence and to control the physical demands. Although cyclists %dwell time on the bike computer was highest in the MT90 the riders were less accurate in maintaining the cadence of 90 RPM and constantly below the target cadence. Furthermore, significantly more cyclists were not able to maintain their heart rate within the interval compared to the MT70 and the two single-tasks conditions. It seems reasonable that the performance decrements at the cadence of 90 RPM may be dependent on transfer processes and the individual experience cyclists had with the cadence of 90 RPM. In four out of five conditions individuals had to maintain the cadence of 70 RPM and then to transfer in one condition to a cadence of 90 RPM. Individuals have to adapt to the new cadence which requires a recalibration process of the muscle system (Pfeifer et al., 2023) and a change in a muscle fiber recruitment (Brisswalter, Hausswirth, Smith, Vercruyssen, & Vallier, 1999) which may explain the greater deviation from the target cadence. Furthermore, there are isolated empirical findings that especially recreational cyclists benefit from adopting to a low cadence (Graham, Zoeller, Jacobs & Whitehurst, 2018). Although sports students who use bicycles participated in the study, the sample can be categorized as recreational riders based on the mean time of use per week, which would explain the decrease in performance at a cadence of 90 RPM and the higher heart rate above the upper bound of 70%. For the participants, the cadence of 90 RPM seems to be physically more demanding. However, it is worth mentioning when the heart rate was outside the interval of 50% to 70%, it was for individuals in all conditions every time above the upper bound of 70% of Hf_{max}. This indicated that cycling under single-task and multi-task conditions on a racing bike with the option to shift the gears induced an exercise intensity above recovery for the participating individuals (Neumayr, Pfister, Mitterbauer, Maurer, & Hoertnagl, 2004).

The present findings corroborate to a great extent previous results reported by Pfeifer et al., (2023) even though the amount to monitor continuously changing visual information on a bike computer was doubled. It should be mentioned that in the Pfeifer et al., (2023) study only the cadence was presented on the bike computer. Further, the present findings extend the range of explanation from dual-tasking (traffic and cadence on the bike computer) to multi-tasking (traffic, cadence on the bike computer and heart rate on the bike computer). On the one side, the results favor in some instances the Expectancy-Value hypothesis proposed by Wickens et al. (2003). Especially the pattern of results from the MT90 condition indicated that maintaining the cadence and the heart rate within the interval suffered. In addition, visual processing at the traffic situation was lower and increased for the bike computer. On the other side, the naming of the hazardous traffic situations was not negatively affected compared to the other conditions. This finding is against our initial expectation and the Expectancy-Value hypothesis that the amount of relevant and constantly changing visual information on the bicycle computer is accompanied by less hazard perception. The findings cautiously suggest that the multi-tasking costs do not arise at the visual level. However, it seems equally conceivable that the %dwell time of 91.93% for MT90 condition at the AOI traffic is sufficient to recognize the hazardous traffic situations for cyclists on a racing bike. Further, the data from the MT70 condition can be used as further support for the assumption that a critical threshold of visual behavior to control the traffic should be somewhere below 85.87%.

4. Conclusions and limitations

The present findings allow a cautious conclusion that visually monitoring a bike computer providing a performance output parameter and a physiological load parameter does not significantly distract the visual behavior of hazardous traffic situations. According to the Expectancy-Value hypothesis that scenes with higher values and more continuously changing visual information are allocated with increased visual behavior it can be argued that (a) monitoring two changing parameters on a bike computer increased the processing of visual information, but (b) it did not distract the visual behavior of traffic situations in a way that hazard perception suffered. Traffic has a high priority for the cyclist on a racing bike. This is consistent with the findings from driving in a fixed-based car driving simulator and the priority task hypothesis proposed by Lemonnier et al. (2015) that visual processing is allocated to tasks in a graded manner associated with their priority. It must also be mentioned that individuals cycled in a virtual environment, on a fixed racing bike where they do not have to keep balance and serious accidents can be excluded.

Even though, there is a lack of interference in naming hazardous traffic situations in the current study, it will be interesting to know if a further increase in the density of visual information on a bike computer or other distracting information might induce an interference effect in hazard perception. In addition, it may also be important for our understanding of visual behavior in biking, how much distracting information and the modality of the information is necessary to induce interference effects. While the factors 'density' and modality of distracting visual information were not systematically varied in the current experiment the present results lay the ground work for additional investigations into the role of distracting information and interference in cycling. Further, from the perspective of sport, an interesting question for future research would be if visual behavior between the bike computer and the traffic situations changed when the visual information of the bike computer is more dynamic and competitive cyclists participated (Rupi & Krizek, 2019). More dynamic and competing activities arise when cyclists are required to visually monitor the bike computer to maintain different parameters when the cadence changes within a condition. This situation occurs in typical practice schedules in cycling to increase athletes' performance. However, the current study took place in a controlled indoor environment and resorted to videos recorded in a real environment. This is a limitation. Even though, individuals were physically active locomotion was not considered. Taking into account that human locomotion is controlled by visual information for planning and anticipating specific events (Vansteenkiste et al., 2014) an 'in sito' field study may induce a different pattern of results (see also Acerra, Shoman, Brasile, Lantieri, & Vignali, 2023; von Stülpnagel, 2020).

Ethics and consent

All procedures performed in the current experiment were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards. All participants gave written informed consent.

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CRediT authorship contribution statement

Stefan Panzer: Writing – review & editing, Writing – original draft, Visualization, Supervision, Project administration, Methodology, Funding acquisition, Formal analysis, Conceptualization. **Christina Pfeifer:** Writing – review & editing, Visualization, Formal analysis, Conceptualization. **Peter Leinen:** Writing – review & editing, Software. **Johannes Puhl:** Writing – review & editing, Data curation.

Declaration of competing interest

The authors declare that they have no conflict of interest.

Data availability

Data will be made available on request.

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