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Safety equipment use and crash involvement among cyclists – Behavioral adaptation, precaution or learning?

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ABSTRACT

The present study has investigated relationships between cyclists' safety equipment use, crash involvement, and other safety relevant behavior. The main focus is on relationships that indicate either behavioral adaptation (safety equipment use leads to riskier behavior) or precautionary behavior (safety equipment is used for cycling in risky situations). Three consecutive surveys were conducted in 2015, 2016, and 2017 years among 650 Norwegian cyclists. Most items were dichotomized and analyzed with logistic regression models. In contrast to the behavioral adaptation hypothesis, regular use of safety equipment (bicycle lights, high-visibility clothing, and helmets) was found to be negatively related to some types of high-risk behavior (listening to music and taking chances while cycling). Regular use of bicycle lights and high-visibility clothing is also negatively related to collision involvement. Safety equipment use was found to be positively related to regular winter cycling and cycling in mixed traffic (not on sidewalks), and it is most likely used as a precautionary measure in such situations. Some cyclists learn from crash involvement by starting to use safety equipment after a crash, but the results do not indicate that crash involvement deters from cycling. The main conclusion from the study is that recommending, promoting or even mandating safety equipment for cyclists can be expected to improve safety and that behavioral adaptation is not likely to occur, at least not to an extent that will outweigh the positive safety effects. The results do not support reservations against the use of "sporty" (well-equipped) models in campaigns for promoting cycling.

1. Introduction

During the last 20 years, the annual number of cycled kilometers has about doubled in Norway (Bjørnskau, 2017) and public authorities have ambitious goals for further increasing the share of bicycle trips in order to avoid increasing motor vehicle volumes. The use of bicycle helmets has also increased, from 32% in 2006 to 56% in 2015 among adult cyclists (NPRA, 2015). Since cyclists are more vulnerable than motor vehicle occupants, increased cycling may be expected to be accompanied by increases in injuries and fatalities among cyclists. Bicycle helmets, high-visibility clothing, and bicycle lights are measures that may improve cyclist safety. Thus, they may at least partly counteract potential increases of the number of cyclist injuries.

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However, the use of safety equipment may be related to other types of safety-relevant behavior and some claim that behavioral adaptation may lead to less safe cycling behavior (Robinson, 2007). If this is the case, promoting or even mandating the use of safety equipment may have unintended effects such as more injured cyclists or even more other injured road users due to more reckless cyclist behavior. On the other hand, if use of safety equipment is associated with more cautious behavior, as has been found in many other studies (Esmaeilikia, Radun, Grzebieta, & Olivier, 2019), it may be worthwhile promoting, both because of its direct safety effects and because of potential effects on generally improved safety behavior. Promoting cycling as a means of transport may also have other safety effects, depending on how cyclists are presented. If safety equipment use is associated with riskier behavior, cycling should, from a safety perspective, be promoted as an everyday activity for people in everyday clothes (without helmets or other safety equipment). If, on the other hand, safety equipment use is associated with generally more safe behavior, promoting cycling may take more of a "safety gear" perspective, for example by showing fully equipped cyclists with helmets, high-visibility clothes, and lights.

On this background, the aim of the present study is to investigate relationships between cyclists' use of safety equipment, other types of safety behavior, and crash involvement and to test specific hypotheses that describe these relationships. The study is based on self-reported data that have been collected with repeated measurements over a period of three years.

2. Hypotheses

Hypotheses about different mechanisms that may affect the relationships between use of safety equipment, other safety behavior, and crash involvement, and that are tested in the present study, are described in the following. They are schematically illustrated in Fig. 1. In short, hypothesis (1) describes direct effects of safety equipment use on crash involvement. Hypothesis (2) describes positive relationships between safety equipment use and other types of safety behavior. Hypothesis (3) is opposite to hypothesis (2). It states that there are negative relationships between safety equipment use and other types of safety behavior. Negative relationships may arise from two different mechanisms: Behavioral compensation (safety equipment use leads to less safe behavior otherwise) or precautionary behavior (cycling under risky conditions increases the use of safety equipment). Hypothesis (4) describes a learning effect which means that crash involved cyclists who had not used safety equipment before the crash, will start doing so after the crash. They may also be deterred from cycling.

2.1. Safety effects hypothesis

The safety effects hypothesis (Fig. 1) describes direct effects of safety equipment use on crash involvement. The expected effects are different for different types of safety equipment.

Bicycle lights are meant to make cyclists more conspicuous in the dark and thereby reduce collisions in darkness (Kwan & Mapstone, 2006). Bicycle lights may also affect collisions in daylight (Madsen, Andersen, & Lahrmann, 2013). In the present study, bicycle light use refers only to use of bicycle lights when cycling in the dark. No direct effects are expected of bicycle lights on single bicycle crashes. Results from other studies of the effects of bicycle lights on crash involvement are highly inconsistent and partly counterintuitive. For example, a Danish experimental study found large (but non-significant) crash reducing effects of bicycle lights both in daylight (−18%) and in twilight (−51%), but not in darkness (Madsen et al., 2013). Martínez-Ruiz, Lardelli-Claret, Jiménez-Mejías, Amezcua-Prieto, Jiménez-Moleón, and Luna del Castillo (2013) found a large reduction of collisions, and a non-significant increase of single bicycle crashes among cyclists using lights. However, other studies found increased crash involvement among cyclists using lights (Hagel et al., 2014; Hollingworth, Harper, & Hamer, 2015). Thornley, Woodward, Langley, Ameratunga, and Rodgers (2008) found a crash reduction for use of rear lights, but a (non-significant) increase for front lights. Washington, Haworth, and Schramm (2012) did not find any effect of bicycle lights on collision involvement. A common explanation for such results is behavioral adaptation. However, counterintuitive or inconsistent findings can in some cases also be explained by insufficient control for exposure, endogeneity issues, or self-reporting biases.

High-visibility clothing, such as neon-colored jackets and garments with reflective devices, make cyclists more conspicuous both in daylight and in darkness. They are expected to affect collision involvement, regardless of lighting conditions.

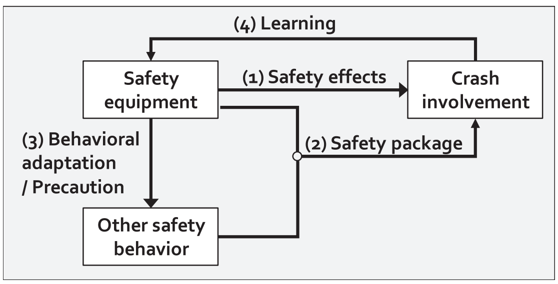

Fig. 1. Hypothesized relationships between use of safety equipment, other safety behavior, and crash involvement.

Direct effects on single bicycle crash involvement are not expected. Results from previous studies are less inconsistent than those for bicycle lights. Lahrman et al. (2014) found a large (-48%) and statistically significant effect of high-visibility clothing on collision involvement in an experimental study. A study that is based on self-reported data found reduced collision involvement as well (Tin Tin et al., 2013). For total crash involvement, some studies also found reductions (Chen & Shen, 2016; Thornley et al., 2008) while others found only small or no effects (Hollingworth et al., 2015; Washington et al., 2012).

For ***bicycle helmets***, it is well documented that they reduce injury severity (Høye, 2018). Evidence for potential effects on crash involvement is sparse. Some studies found increased crash involvement among helmeted cyclists (Fuller, Gauvin, Morency, Kestens, & Drouin, 2013; Thornley et al., 2008; Porter et al., 2016). However insufficient control for exposure may be a part of the explanation because helmeted cyclists cycle far more on average than unhelmeted cyclists (Rodgers, 2000). The main hypothesis in the present study is that helmet use does not directly affect crash involvement.

2.2. Safety package hypothesis

The safety package hypothesis (Fig. 1) assumes positive relationships between safety equipment use and other safety behavior. Such relationships have been found in several empirical studies (Bambach, Mitchell, Grzebieta, & Olivier, 2013; Chataway et al., 2014; Esmaeilikia et al., 2019; Teschke et al., 2012). They are here referred to as safety package because it is assumed that use of safety equipment (at least partly) is based on a desire to reduce risk. Therefore, behaving safely in one respect, is expected to be generalized to other types of behavior.

According to this hypothesis, negative relationships to crash involvement can be expected for all types of safety equipment, including bicycle helmets, and for all types of crashes, because of the relationship between safety equipment use and other safety behavior. Moreover, negative relationships with crash involvement can be expected even without statistical control for behavior.

2.3. Behavioral adaptation / precautionary behavior hypothesis

This hypothesis refers to negative relationships between safety equipment use and other safety behavior. According to this hypothesis, one may find increased crash involvement among safety equipment users, unless other safety behavior is controlled for.

Negative relationships may arise from two different mechanisms. According to the behavioral adaptation hypothesis, cyclists adapt their behavior to the perceived reduced risk when using safety equipment, for example by riding faster or taking more chances (Fyhri & Phillips, 2013; Fyhri, Sundfør, Weber, & Phillips, 2018). If cyclists adapt to safety equipment by taking higher risks, the safety effects of using such equipment may be offset or even overcompensated, resulting in unchanged or increased crash involvement among cyclists using safety equipment (Lahrmann et al., 2014).

Especially bicycle helmet use is often assumed to lead to behavioral adaptation, such that helmeted cyclists more often are involved in crashes than other cyclists (Robinson, 2007). The assumption is mainly based on the highly controversial risk compensation theory, which states that road users change their behavior in response to safety improvements, in order to hold crash risk at a constant level (Sivak & Tsimhoni, 2008). Elvik (2004) proposes a model of behavioral adaptation that contains specific predictors of behavioral adaptation and that does not assume any homeostatic processes regarding crash risk. Amongst other things, behavioral adaptation is more likely if the road user may gain some additional utility. Empirical evidence for behavioral adaptation and bicycle helmet use is inconclusive (Olivier, Wang, Scott, & Grzebieta, 2014). A recent systematic review concludes that most studies do not support the behavioral adaptation hypothesis for helmet use (Esmaeilikia et al., 2019).

Negative relationships between safety equipment use and other safety behavior may also arise from cyclists taking precautions by using safety equipment, such as using high-visibility clothing in order to be able to cycle in mixed traffic or using a helmet when cycling fast. For example, the studies by Schleinitz, Petzoldt, and Gehlert (2018) and Fyhri et al. (2018) indicate that the positive relationships between helmet use and high speed that were found in both studies, should be interpreted as an effect of taking precautions, rather than behavioral adaptation. The studies by Aldred and Woodcock (2015) and Hollingworth et al. (2015) indicate that cyclists use safety equipment because they perceive a high risk while cycling in mixed traffic or under unfavorable conditions. In the study by Aldred and Woodcock (2015), use of safety clothing decreased in environments where cyclists felt relatively safe. Chaurand and Delhomme (2013) showed that cyclists who are regularly wearing helmets, perceive on average higher crash risk in interactions with cars than cyclists who are not usually wearing helmets.

2.4. Learning hypothesis

The learning hypothesis (Fig. 1) refers to behavior changes after crash involvement. It states that cyclists who have been involved in a crash, and who have not been using safety equipment previously, will start using safety equipment to reduce crash or injury risk in the future. This type of behavioral adaptation has been far less investigated among cyclists than other types of behavioral adaptation. Kaplan, Luria, and Prato (2019) found that incidents in traffic may lead to cyclists being less willing to ride in mixed traffic. A study among alpine skiers and snowboarders (Hasler, Benz, Benneker, Kleim, Dubler, Zimmermann, & Exadaktylos, 2011) indicates that accident involvement may increase the use of protective equipment (helmets and back protectors).

For bicycle helmets, a learning effect may be expected for any type of crash (both collisions and single bicycle crashes). Regarding light and high-visibility clothing, this effect can be expected to be strongest for collisions because lights and high-visibility clothing mainly aim at preventing collisions. Crash involved cyclists may also cycle less or they may stop cycling altogether out of fear for further crashes. Those who stop cycling are not included in the sample of the present study, but we have investigated whether those respondents who had a crash, cycled less in the following year than they did previously.

3. Method

3.1. Study design and sample

This study is designed as a prospective cohort study, with data collections in 2015, 2016, and 2017. Participants were recruited by email from a random sample of cyclists in the 12 largest Norwegian towns from a national bicycle register (previously Falck, now BikeMember). Registration is voluntary and cheap. Members get their bicycle frame numbers and their name and address registered and they can get discounts on their bicycle insurance. A large proportion of all bicycles in Norway are registered. In 2016 and 2017, invitations were sent to all those who had participated in the preceding year and who had given their consent to being contacted again.

In 2015, 6475 invitations were sent out. The response rate was 26,7% (N = 1728 completed surveys). In 2016 and 2017, new invitations were sent to all consenting respondents from 2015 and 2016 respectively. The final sample consists of 650 respondents who completed surveys in all three years which is 37,6% of the 2015-sample. The online questionnaires were identical in all three years, except for some questions that only were asked in 2015 (such as age and gender) and they were sent out at the same time of the year.

3.2. Questionnaire

The questionnaire contained questions about cycling behavior and bicycle crash involvement during the past year or years. Completing the survey took about 10–15 min. Table 1 gives an overview about the variables included in the study with

Table 1
Variables in the empirical study; all variables (except for exposure) are dummy variables; variables were measured each year unless denoted otherwise.

Variables	Questions and explanations
Crash involvement	"*Did you have at least one crash during the last year / the last five years?*" The question referred to the last five years in 2015 and to the last year in 2016 and 2017. Crashes include crashes in which the bicycle was damaged (not ridable) or the cyclist was injured (at least abrasion). Follow-up questions on the crash (crash type) were asked only for the most recent crash.
■ **Singe bicycle crash**	At least one crash and the last crash involved no other road users.
■ **Collision**	At least one crash and the last crash involved at least one other road user (motor vehicle, bicycle or pedestrian).
■ **Nighttime collision**	At least one crash and the last crash was a collision in twilight or darkness.
Exposure	Exposure was estimated based on questions about the number of months cycled per year, number of days cycled during a typical week in summer and winter, and the average number of kilometers per day when cycling. The questions refer implicitly to the current year.
■ **Kilometers per year**	Estimated number of kilometers cycled per year.
Safety equipment use and other safety behavior	Questions about behavior (except for winter cycling) were asked in one block with the same introduction for all questions: "*How often are you doing the following when cycling in traffic?*" Possible answers were always, often, sometimes, seldom, and never. Responses were dichotomized to create distributions that are as even as possible for each question.
■ **Light**	"*Use front and rear lights when cycling in the dark*" (1 = always)
■ **High-viz**	"*Wear high-visibility clothing or reflective garments*" (1 = always or often)
■ **Helmet**	"*Wear a bicycle helmet*" (1 = always)
■ **Cycle faster**	"*Try to ride faster than others*" (1 = always, often, or sometimes)
■ **Take chances**	"*Take chances when cycling in traffic*" (1 = always, often, or sometimes)
■ **Cycle on the sidewalk**	"*Cycle on the sidewalk*" (1 = always or often)
■ **Winter cycling**	Regularly cycling in winter; based on a question about the number of cycling days during a typical week in winter (1 = at least 2–3 days per week; 0 = fewer or none)
Background variables	
■ **Bicycle type**	"*What type of bicycle do you normally use when cycling in traffic?*" Answer categories were hybrid, classic, racer, mountain bike (MTB), other (one dummy variable for each type of bicycle, with hybrid as reference category)
■ **Experienced (2015 only)**	Five or more years cycling experience in 2015 (1 = yes). Based on the question "*For how many years have you been cycling more or less regularly?*"
■ **Gender (2015 only)**	Female (1 = yes)
■ **Age (2015 only)**	Young (1 = below 40), middle age (1 = 40–49), old (1 = 50 + years). One dummy variable for each age group, with middle age as reference category.
■ **Purpose (2015 only)**	Cycling for exercise, occasionally or exclusively (1 = yes; 0 = cycling for transport only): Based on the question "*For what purpose are you normally cycling?*"

explanations of how they were measured. The safety behaviors other than safety equipment variables were dichotomized because the original distributions were highly skewed for some of them. These variables are described in more detail in the following, focusing on how they can be assumed to be related to risk and risk propensity.

The item ***cycling faster*** was intended to measure general competitiveness. Ambitious cyclists who have a focus on working out, may also try to ride faster than others. Speed is commonly used as an indicator of risky behavior (Fyhri et al., 2018), and it is strongly related to both crash risk and injury severity (Elvik, Vadeby, Hels, & van Schagen, 2019). Inappropriate cycling speed has been found to be associated with involvement in single bicycle crashes (versus collisions; Billot-Grasset, Amoros, & Hours, 2016). Thus, the item cycling faster is expected to be related to safety, but it is not meant to be an indicator of risk propensity.

The item ***take chances*** is meant to reflect risk-propensity or deliberate chance-taking. Negligent behavior which also may involve increase risk (such as overlooking red lights, changing lane without checking backwards) is less likely to be covered by this item. We aimed to measure chance taking while cycling in traffic and did therefore not refer to existing scales for (general) risk propensity. Poulos et al. (2015) found relationships between general risk propensity and both liking to ride fast on a bicycle and sensation seeking.

For ***listening to music*** (or radio) while cycling it is well documented that it increases crash risk (Tin Tin et al., 2013; Wilbur & Schroeder, 2014). Listening to music while cycling is also related to other types of high-risk behavior (Stelling-Konczak, van Wee, Commandeur, & Hagenzieker, 2017). It can be regarded as an indication of chance-taking because cyclists who listen to music deliberately disconnect from the environment. It distracts attention and eliminates external acoustical cues from their perception (Stelling-Konczak et al., 2017).

Sidewalk cycling may be regarded as safe behavior because cyclists usually perceive cycling in mixed traffic (among motor vehicles) as risky (Jensen et al., 2006). However, even if the intention is to increase (the feeling of) safety, the result is not necessarily reduced risk. Sidewalk cycling has in several studies been found to be positively associated with crash involvement (De Rome et al., 2013; Poulos et al., 2015), and cyclists who are frequently using cycling on sidewalks have generally higher crash risk than other cyclists (Aultman-Hall & Adams, 1998; Carlin, Taylor, & Nolan, 1998).

Cycling in winter is usually regarded as a high-risk behavior in Norway because road conditions often are adverse, and because it is dark during most of the day or even the whole day. Both snowy and icy roads and darkness are mostly regarded as high-risk conditions (Winters et al., 2011).

3.3. Analyses

Since all variables in the present study, except for exposure, are dummy variables, logistic regression has been applied for all analyses. All analyses were performed in Stata (version 14.2).

For all analyses, we report p-values. Results with p-values below 0.05 are regarded as statistically significant. Interpretations are additionally based on effect sizes (coefficients and differences). The consistency of the results over time and between similar variables is considered as well. By focusing only on statistical significance, much information would get lost (Amrhein, Greenland, & McShane, 2019; Wasserstein, 2016; Ziliak & McCloskey, 2008).

4. Results

The proposed hypotheses concern the joint magnitude and direction of associations between different sets of variables that require separate analyses. In the following, we present one type of analyses in each section, but most of the analyses are relevant for more than one hypothesis. The results are discussed with respect to the hypotheses in chapter 5.

4.1. Descriptive statistics and drop-out analysis

Descriptive statistics for crash involvement, safety equipment, behavior, and background variables are shown in Table 2. Table 3 shows descriptive statistics for exposure and average crashes per 1000 km. Both tables display results for the final sample (2015, 2016, and 2017) and for drop-outs (respondents who participated in 2015 but were lost to follow-up).

In the final sample, the apparent drop in crash involvement from 2015 to 2016 and 2017 is due to the different time frames (the last five years in 2015, the last year in 2016 and 2017). Both exposure and crash involvement decreased somewhat over time. The use of bicycle lights increased by about ten percentage points after 2015. Otherwise, there have only been minor changes over time.

A comparison between dropouts and respondents from 2015 who are included in the final sample in Table 2 and Table 3, shows several differences. Those in the final sample were less often involved in crashes, they were more often using safety equipment (the difference for helmet use is relatively small), and they have different behavior patterns: They report more often to ride faster and in winter, and they are less often listening to music or cycling on the sidewalk. More of them are male, above 50 years, and they have more experience as cyclists. The estimated number of kilometers cycled per year is greater in the final sample than among the dropouts, and the average number of crash-involved cyclists per 1000 km is lower. The latter is a typical finding; several other studies also found lower crash risk among more experienced cyclists (Heesch, Garrard, & Sahlqvist, 2011; Schepers, 2012; Thornley et al., 2008).

Table 2
Descriptive statistics for cyclists in the final sample (2015, 2016, and 2017) and dropouts (2015 and not in the final sample); proportions of cyclists in each category, all percentages refer to the total N per column.

	Dropout 2015		Final sample 2015		Final sample 2016		Final sample 2017	
	N	%	N	%	N	%	N	%
All cyclists	1728	100%	650	100%	650	100%	650	100%
Crash involvement								
■ **Any crash**	239	22%	214	33%	82	13%	62	10%
■ **Single bicycle crash**	164	15%	146	22%	59	9%	44	7%
■ **Collision**	75	7%	68	10%	23	4%	18	3%
■ **Nighttime collision**	7	1%	15	2%	7	1%	5	1%
Safety equipment use								
■ **Light**	603	56%	497	76%	557	86%	550	85%
■ **High-visibility clothing**	372	35%	309	48%	294	45%	306	47%
■ **Helmet**	757	70%	486	75%	489	75%	492	76%
Other safety behavior								
■ **Cycle faster**	386	36%	292	45%	273	42%	278	43%
■ **Take chances**	186	17%	115	18%	111	17%	112	17%
■ **Listen to music**	276	26%	124	19%	113	17%	122	19%
■ **Sidewalk cycling**	422	39%	201	31%	189	29%	194	30%
■ **Winter cycling**	326	30%	336	52%	337	52%	320	49%
Background variables								
■ **Type of bicycle: Hybrid**	410	38%	307	47%	296	46%	290	45%
■ **Type of bicycle: MTB**	263	24%	164	25%	144	22%	137	21%
■ **Type of bicycle: Classic**	188	17%	80	12%	82	13%	79	12%
■ **Type of bicycle: Racer**	78	7%	44	7%	41	6%	23	4%
■ **Type of bicycle: Other**	139	13%	55	8%	87	13%	121	19%
■ **Female**	528	49%	268	41%	268	41%	268	41%
■ **Age: Young**	326	30%	146	22%	146	22%	146	22%
■ **Age: Middle age**	323	30%	153	24%	153	24%	153	24%
■ **Age: Old**	429	40%	351	54%	351	54%	351	54%
■ **Experienced cyclist (5 years + in 2015)**	647	60%	531	82%	531	82%	531	82%
■ **Exercise**	436	40%	300	46%	300	46%	300	46%

Table 3
Exposure and crashes per year for final sample and dropouts.

		Final sample		
	Dropout 2015	2015	2016	2017
N	1078	650	650	650
Kilometers per year				
Mean	2272	4016	3924	3806
SD	3864	4132	3970	3975
Min.	1	13	31	26
Max.	54,600	33,800	33,800	33,800
Crashes				
Crash involvement[1]	239	214	82	62

[1] The results for crash involvement refer to the number of cyclists who had at least one crash during the last year (2016 and 2017) or the last five years (2015).

4.2. Bivariate relationships between safety equipment use and behavior

The behavioral adaptation and the safety package hypotheses make conflicting predictions about relationships between safety equipment use and other safety behavior. Table 4 presents bivariate relationships of safety equipment use to other safety behavior. Since all variables were dichotomized, logistic regression models are applied. Each model contains one type of safety equipment or other safety behavior as the dependent variable, and one other type of safety equipment or other safety behavior as (the only) predictor variable.

The results show that associations between different types of safety equipment use are consistently positive, which is in line with the safety package hypothesis. Similarly, consistently negative associations between safety equipment use and listening to music and taking chances support the safety package hypothesis, and they contradict the behavioral adaptation/precaution hypothesis. In contrast, users of safety equipment are more likely to ride faster than others, they cycle more often in winter, and they cycle less on sidewalks. For these behaviors, results align more with the behavioral adaptation/precaution interpretation.

Table 4
Bivariate relationships between safety equipment use and other safety behavior, results from logistic regression (coefficients and p-values; one predictor per model; coefficients with p-values below 0.05 in bold letters).

	Faster		**Take chances**		**Music**		**Sidewalk cycling**		**Winter cycling**		**Light**		**High-visibility clothing**	
	Coef.	***p***	**Coef.**	***p***	**Coef.**	***p***	**Coef.**	***p***	**Coef.**	***p***	**Coef.**	***p***	**Coef.**	***p***
Take chances														
2015	**0.965**	*0.000*												
2016	**1.039**	*0.000*												
2017	**0.702**	*0.001*												
Music														
2015	0.132	*0.509*	**0.999**	*0.000*										
2016	0.371	*0.074*	**0.650**	*0.008*										
2017	−0.007	*0.971*	**0.573**	*0.018*										
Sidewalk cycling														
2015	−0.332	*0.054*	−0.286	*0.217*	−0.308	*0.172*								
2016	**−0.386**	*0.031*	−0.068	*0.770*	−0.152	*0.515*								
2017	−0.150	*0.389*	−0.127	*0.582*	0.216	*0.314*								
Winter cycling														
2015	**0.402**	*0.011*	**0.453**	*0.031*	−0.163	*0.413*	−0.026	*0.878*						
2016	**0.522**	*0.001*	0.327	*0.121*	−0.068	*0.743*	−0.119	*0.491*						
2017	**0.458**	*0.004*	0.210	*0.313*	−0.043	*0.831*	−0.192	*0.265*						
Light														
2015	0.025	*0.892*	−0.436	*0.056*	−0.358	*0.110*	−0.223	*0.256*	**1.181**	*0.000*				
2016	0.320	*0.170*	**−0.631**	*0.017*	**−0.740**	*0.004*	−0.117	*0.629*	**1.305**	*0.000*				
2017	**0.489**	*0.033*	−0.506	*0.053*	**−0.508**	*0.046*	−0.228	*0.324*	**1.640**	*0.000*				
High-visibility clothing														
2015	**0.354**	*0.025*	**−0.504**	*0.017*	**−0.699**	*0.001*	0.042	*0.806*	**0.529**	*0.001*	**1.421**	*0.000*		
2016	0.294	*0.066*	**−0.505**	*0.020*	**−0.540**	*0.012*	−0.257	*0.141*	**0.642**	*0.000*	**1.334**	*0.000*		
2017	0.306	*0.054*	−0.383	*0.070*	−0.346	*0.091*	−0.346	*0.091*	**0.682**	*0.000*	**1.537**	*0.000*		
Helmet														
2015	**0.743**	*0.000*	−0.421	*0.060*	**−0.848**	*0.000*	−0.272	*0.155*	0.287	*0.113*	**1.421**	*0.000*	**2.056**	*0.000*
2016	**0.773**	*0.000*	**−0.566**	*0.012*	**−0.876**	*0.000*	−0.318	*0.102*	0.214	*0.240*	**1.334**	*0.000*	**1.895**	*0.000*
2017	**0.815**	*0.000*	−0.268	*0.248*	**−0.856**	*0.000*	−0.190	*0.334*	0.228	*0.215*	**1.537**	*0.000*	**1.958**	*0.000*

Table 5
Estimated average annual cycling length for cyclists using and not using safety equipment in 2017. 2015 and 2016 omitted for brevity.

	N		**Km per year (mean)**	
	With	**Without**	**With**	**Without**
Light	550	100	4 125	2 054
High-visibility clothing	306	344	4 607	3 093
Helmet	492	158	4 064	3 004
Cycling faster	278	372	4 385	3 374
Listening to music	112	538	3 729	3 822
Taking chances	122	528	3 555	3 864
Sidewalk cycling	194	456	3 159	4 081
Winter cycling	320	330	5 853	1 821

For a more thorough investigation of the relationships between safety equipment use and behavior, Table 5 compares the average annual cycling length for cyclists using and not using each of the types of safety equipment, and between cyclists who are showing and not showing the other types of safety behavior. Those who are using safety equipment (all types), who are cycling faster, who are not cycling on sidewalks, and who are cycling in winter, are on average cycling more than other cyclists. For taking chances and listening to music, there are only small differences in average cycling length.

4.3. Relationships between past behavior and current crash involvement

The hypotheses about safety effects, safety package and behavioral adaptation/precaution all make predictions about associations between safety equipment use, other safety behavior, and crash involvement. For testing these associations, we calculated logistic regression models with crash involvement in the year of analysis (2016 or 2017) as the dependent variable. Predictor variables include safety equipment use and other safety behavior in the preceding year (2015 or 2016) to minimize any effects of crash involvement on behavior.

As an exposure variable, all models include the natural logarithm of the estimated annual number of kilometers cycled in the crash year. The natural logarithm is used because the relationship between exposure and crash involvement usually is non-linear (Elvik & Goel, 2019). In accordance with findings from other studies, the coefficients for exposure are positive and below one in most models, indicating that the absolute number of crashes increases, while the number of crashes per kilometer decreases as the number of kilometers increases. Only for collisions in darkness are all exposure coefficients well above one. This does not mean that collision risk in darkness increases as cyclists cycle more in darkness. The most likely explanation for the large exposure coefficients is that cyclists who are cycling in winter, are cycling more in total and more in darkness than others.

Because of the large number of predictor variables and to test predictions about how relationships may change with vs. without control for other variables, we present both full models, including all predictor variables, and partial models with only one predictor (or set of dummy variables) in addition to exposure. All analyses were run separately for total crash involvement (Table 6), single bicycle accidents (Table 7), collisions (Table 8), and collisions in darkness (Table 9) as outcome variables.

For all models, few predictor variables have statistically significant ($p < 0.05$) coefficients. This is at least partly due to the small numbers of crashes, especially collisions and nighttime collisions (Table 2). However, for investigating the hypotheses, we did not only focus on statistical significance, but also on effect sizes and the general consistency of the results (see Section 3.3).

For crash involvement, the safety package hypothesis predicts negative relationships between all types of safety equipment use and safety behaviors with crash involvement. In contrast, positive relationships would align with the behavioral adaptation/precaution hypothesis. The behavior that is most consistently associated with increasing crash risk, and most in line with the safety package hypothesis, is listening to music.

For the remaining variables, results are mixed: Negative associations are found for some combinations of equipment/behavior and crash types, but they vary in size and direction across time period, crash type and model version (full vs. partial). Overall, there does not seem to be a "complete" safety package involving all safety equipment and behaviors. However, most results are not in line with the adaptation / precaution hypothesis.

Results that are relevant for the safety effects hypothesis are the effects of bicycle lights and high-visibility clothing on collision involvement (Table 8) and on collision involvement in darkness (Table 9). For bicycle lights, results are consistently in the expected (negative) direction for both outcomes. Coefficients from the full models for collision involvement are around 0.5. Coefficients from logistic regression translate into odds ratio by calculating $e^{\text{Coeff.}}$. Thus, a coefficient of 0.5 corresponds to an odds ratio of 1.65 (65% increased odds of collision involvement without lights). As expected, high-visibility clothing is also negatively related to collision involvement, and the full model coefficients of 0.26 and 0.73, correspond to ORs of 1.29 and 2.07. However, results for collisions in darkness are in the expected direction for only one of the time periods analyzed.

Table 6
Logistic regression models for total crash involvement; partial models and full models with all predictor variables in one model (coefficients with p-values below 0.05 in bold letters).

Dependent variable:Total crash involvement	Partial models[1] (2015–2016)		Partial models[1] (2016–2017)		Full model (2015–2016)		Full model (2016–2017)	
	Coef.	*p*	Coef.	*p*	Coef.	*p*	Coef.	*p*
Lights (vs. no lights)	0.161	*0.617*	−0.679	*0.068*	0.342	*0.324*	**−0.818**	*0.050*
High-visibility clothing (vs. not)	−0.245	*0.326*	−0.228	*0.415*	−0.352	*0.204*	−0.224	*0.471*
Helmet (vs. no helmet)	0.146	*0.629*	0.530	*0.162*	−0.051	*0.884*	**0.891**	*0.038*
Cycle faster (vs. not)	0.198	*0.412*	0.041	*0.882*	0.121	*0.644*	−0.194	*0.524*
Take chances (vs. not)	−0.371	*0.282*	0.574	*0.069*	−0.465	*0.201*	0.530	*0.126*
Listen to music (vs. not)	0.248	*0.396*	0.239	*0.488*	0.300	*0.341*	0.190	*0.604*
Sidewalk cycling (vs. not)	0.008	*0.975*	0.151	*0.616*	0.124	*0.657*	0.107	*0.735*
Winter cycling (vs. not)	−0.444	*0.114*	0.250	*0.446*	−0.403	*0.172*	0.390	*0.276*
Bicycle: MTB (vs. hybrid)	0.200	*0.494*	0.527	*0.118*	0.268	*0.383*	0.494	*0.167*
Bicycle: Classic (vs. hybrid)	**−1.490**	*0.045*	0.172	*0.722*	**−1.520**	*0.044*	0.271	*0.594*
Bicycle: Racer (vs. hybrid)	0.739	*0.066*	−0.386	*0.714*	0.788	*0.080*	−0.494	*0.646*
Bicycle: Other (vs. hybrid)	−0.031	*0.936*	0.254	*0.493*	−0.073	*0.854*	0.242	*0.537*
Female (vs. male)	−0.176	*0.490*	0.345	*0.221*	−0.007	*0.981*	0.283	*0.354*
Young (vs. middle aged)	**0.923**	*0.015*	0.095	*0.792*	**1.000**	*0.011*	−0.022	*0.956*
Old (vs. middle aged)	0.588	*0.088*	−0.517	*0.117*	0.734	*0.043*	−0.388	*0.268*
Cycling as training (vs. not)	0.304	*0.208*	−0.217	*0.431*	−0.037	*0.893*	−0.153	*0.616*
Experienced cyclist (vs. not)	−0.128	*0.689*	**−0.804**	*0.013*	0.016	*0.963*	−0.570	*0.109*
Kilometers per year (log.)	**0.455**	*0.000*	**0.457**	*0.001*	**0.497**	*0.002*	**0.485**	*0.005*
Constant					**−6.496**	*0.000*	**−5.953**	*0.000*

[1] One model per predictor (type of bicycle and age are each regarded as one predictor, although each consists of more than one dummy variable); each model contains the respective variable and exposure as predictors (the results for exposure are based on an exposure only model).

Table 7
Logistic regression models for single bicycle crash involvement; partial models and full models with all predictor variables in one model (coefficients with p-values below 0.05 in bold letters).

Dependent variable:Single bicycle crash involvement	Partial models (2015–2016)		Partial models (2016–2017)		Full model (2015–2016)		Full model (2016–2017)	
	Coef.	p	Coef.	p	Coef.	p	Coef.	p
Lights (vs. no lights)	0.378	*0.327*	−0.707	*0.098*	0.656	*0.111*	−0.885	*0.064*
High-visibility clothing (vs. not)	−0.233	*0.417*	−0.093	*0.775*	−0.341	*0.284*	0.000	*0.999*
Helmet (vs. no helmet)	0.017	*0.961*	0.383	*0.373*	−0.273	*0.479*	0.699	*0.151*
Cycle faster (vs. not)	0.224	*0.420*	0.407	*0.211*	0.198	*0.509*	0.224	*0.527*
Take chances (vs. not)	−0.507	*0.225*	0.644	*0.074*	−0.584	*0.184*	0.505	*0.202*
Listen to music (vs. not)	−0.132	*0.718*	−0.019	*0.965*	−0.104	*0.789*	−0.143	*0.752*
Sidewalk cycling (vs. not)	−0.132	*0.669*	0.190	*0.587*	−0.021	*0.948*	0.245	*0.506*
Winter cycling (vs. not)	−0.591	*0.065*	0.384	*0.328*	−0.626	*0.064*	0.571	*0.176*
Bicycle: MTB (vs. hybrid)	0.197	*0.556*	0.686	*0.089*	0.248	*0.478*	0.651	*0.123*
Bicycle: Classic (vs. hybrid)	−1.212	*0.106*	0.513	*0.347*	−1.311	*0.086*	0.768	*0.183*
Bicycle: Racer (vs. hybrid)	0.742	*0.100*	0.153	*0.886*	0.747	*0.141*	0.097	*0.929*
Bicycle: Other (vs. hybrid)	−0.255	*0.588*	0.491	*0.257*	−0.280	*0.566*	0.553	*0.226*
Female (vs. male)	−0.140	*0.630*	0.230	*0.487*	0.007	*0.983*	0.275	*0.444*
Young (vs. middle aged)	0.646	*0.123*	0.095	*0.819*	0.801	*0.068*	−0.026	*0.954*
Old (vs. middle aged)	0.379	*0.316*	−0.561	*0.146*	0.464	*0.245*	−0.543	*0.184*
Cycling as training (vs. not)	0.207	*0.454*	−0.012	*0.971*	−0.168	*0.591*	0.059	*0.869*
Experienced cyclist (vs. not)	0.223	*0.577*	−0.270	*0.514*	0.332	*0.432*	0.061	*0.893*
Kilometers per year (log.)	**0.331**	*0.013*	**0.462**	*0.004*	**0.379**	*0.030*	0.358	*0.072*
Constant					−**5.771**	*0.000*	−**6.220**	*0.000*

[1]One model per predictor (type of bicycle and age are each regarded as one predictor, although each consists of more than one dummy variable); each model contains the respective variable and exposure as predictors (the results for exposure are based on an exposure only model).

Table 8
Logistic regression models for collision involvement; partial models and full models with all predictor variables in one model (coefficients with p-values below 0.05 in bold letters).

Dependent variable:Collision involvement	Partial models (2015–2016)		Partial models (2016–2017)		Full model (2015–2016)		Full model (2016–2017)	
	Coef.	p	Coef.	p	Coef.	p	Coef.	p
Lights (vs. no lights)	−0.365	*0.497*	−0.482	*0.466*	−0.478	*0.428*	−0.461	0.552
High-visibility clothing (vs. not)	−0.214	*0.628*	−0.501	*0.319*	−0.260	*0.596*	−0.731	0.185
Helmet (vs. no helmet)	0.528	*0.405*	0.850	*0.264*	0.680	*0.354*	1.348	0.121
Cycle faster (vs. not)	0.098	*0.821*	−0.861	*0.112*	−0.155	*0.745*	−**1.261**	0.035
Take chances (vs. not)	0.001	*0.999*	0.294	*0.611*	−0.132	*0.826*	0.521	0.425
Listen to music (vs. not)	**0.931**	*0.042*	0.685	*0.205*	**1.156**	*0.028*	0.786	0.186
Sidewalk cycling (vs. not)	0.334	*0.461*	0.039	*0.943*	0.457	*0.361*	−0.158	0.787
Winter cycling (vs. not)	0.036	*0.946*	−0.071	*0.900*	0.292	*0.590*	−0.145	0.822
Bicycle: MTB (vs. hybrid)	0.154	*0.772*	0.132	*0.817*	0.303	*0.589*	0.091	0.886
Bicycle: Classic (vs. hybrid)	(omitted)		−0.740	*0.489*	(omitted)		−0.997	0.369
Bicycle: Racer (vs. hybrid)	0.452	*0.519*	(omitted)		0.661	*0.404*	0.000	
Bicycle: Other (vs. hybrid)	0.394	*0.518*	−0.299	*0.659*	0.203	*0.760*	−0.561	0.446
Female (vs. male)	−0.207	*0.663*	0.551	*0.264*	−0.122	*0.813*	0.184	0.735
Young (vs. middle aged)	1.562	*0.053*	0.085	*0.896*	1.534	*0.077*	0.084	0.909
Old (vs. middle aged)	1.165	*0.131*	−0.332	*0.567*	1.539	*0.063*	−0.044	0.946
Cycling as training (vs. not)	0.461	*0.296*	−0.676	*0.187*	0.281	*0.574*	−0.617	0.277
Experienced cyclist (vs. not)	−0.780	*0.117*	−**1.593**	*0.001*	−0.616	*0.286*	−**1.598**	0.005
Kilometers per year (log.)	**0.713**	*0.003*	0.384	*0.102*	**0.753**	*0.014*	**0.694**	0.028
Constant					−**11.041**	*0.000*	−**7.690**	0.003

[1]One model per predictor (type of bicycle and age are each regarded as one predictor, although each consists of more than one dummy variable); each model contains the respective variable and exposure as predictors (the results for exposure are based on an exposure only model).

4.4. Learning hypothesis test

The learning hypothesis predicts that crash involvement increases the chances of starting to use safety equipment or of showing other types of safety behavior among those who have not previously been doing so. For each type of safety equipment, a logistic regression analysis was run on the subset of respondents who did not use that equipment in 2016. Use of safety equipment in 2017 were outcome variables, and crash involvement in the previous year (2016) was the (only) predictor. The same procedure was followed for other safety behaviors, and the results are shown in Table 10. Since the items concerning crash involvement in 2015 referred to the last five years, this analysis was only conducted for the years 2016–2017, where these items referred to the last year only.

Table 9
Logistic regression models for collisions in darkness involvement; partial models and full models with all predictor variables in one model (coefficients with p-values below 0.05 in bold letters).

Dependent variable:Collision in darkness involvement	Partial models (2015–2016)		Partial models (2016–2017)		Full model (2015–2016)		Full model (2016–2017)	
	Coef.	*p*	Coef.	*p*	Coef.	*p*	Coef.	*p*
Lights (vs. no lights)	−0.032	*0.977*	−0.964	*0.401*	−2.041	*0.223*	−7.005	*0.078*
High-visibility clothing (vs. not)	−0.202	*0.797*	1.187	*0.293*	−0.137	*0.894*	3.644	*0.126*
Helmet (vs. no helmet)	(omitted)		(omitted)		(omitted)		0.000	
Cycle faster (vs. not)	0.882	*0.302*	−1.479	*0.191*	−0.228	*0.832*	−7.154	*0.085*
Take chances (vs. not)	(omitted)		0.115	*0.919*	(omitted)		−0.348	*0.871*
Listen to music (vs. not)	0.531	*0.546*	1.332	*0.152*	2.270	*0.083*	4.763	*0.071*
Sidewalk cycling (vs. not)	−0.734	*0.503*	0.833	*0.375*	0.432	*0.750*	2.891	*0.196*
Winter cycling (vs. not)	(omitted)		0.354	*0.765*	0.000		2.000	*0.418*
Bicycle: MTB (vs. hybrid)	0.550	*0.589*	0.164	*0.862*	1.204	*0.343*	1.741	*0.374*
Bicycle: Classic (vs. hybrid)	(omitted)		(omitted)		(omitted)		(omitted)	
Bicycle: Racer (vs. hybrid)	1.196	*0.265*	(omitted)		1.214	*0.423*	(omitted)	
Bicycle: Other (vs. hybrid)	0.519	*0.677*	(omitted)		−1.141	*0.500*	(omitted)	
Female (vs. male)	−0.817	*0.460*	1.375	*0.155*	−0.141	*0.918*	1.527	*0.339*
Young (vs. middle aged)	2.197	*0.061*	−0.463	*0.711*	2.224	*0.127*	−2.180	*0.457*
Old (vs. middle aged)	−0.449	*0.757*	−0.669	*0.512*	−0.639	*0.679*	−3.827	*0.151*
Cycling as training (vs. not)	0.665	*0.443*	0.000		0.429	*0.722*	0.000	
Experienced cyclist (vs. not)	−1.003	*0.250*	−1.506	*0.107*	−0.701	*0.532*	−3.484	*0.141*
Kilometers per year	**1.716**	*0.002*	1.087	*0.051*	**2.134**	*0.032*	2.143	*0.132*
Constant					**−21.605**	*0.016*	−17.673	*0.083*

[1]One model per predictor (type of bicycle and age are each regarded as one predictor, although each consists of more than one dummy variable); each model contains the respective variable and exposure as predictors (the results for exposure are based on an exposure only model).

Table 10
Logistic regression models with safety equipment use or behavior as dependent variable and the preceding years' crash involvement as predictor; each row represents one model and each model is based only on those cyclists having shown "unsafe behavior" in 2017 (coefficients with p-values below 0.05 in bold letters).

Dependent variable (2017)	Selection: "Unsafe behavior" (2016)		Predictor: Crash involvement (2016)			Result consistent with learning hypothesis
		N	Crash type	Coeff.	*p*	
Light	**Non-use of lights**	93	**Collision**	0.916	0.523	Yes
Light	**Non-use of lights**	93	**Any crash**	0.422	0.583	Yes
High-visibility clothing	**Non-use of high-visibility clothes**	356	**Collision**	1.068	0.060	Yes
High-visibility clothing	**Non-use of high-visibility clothes**	356	**Any crash**	**0.888**	0.015	Yes
Helmet	**Non-use of helmet**	161	**Any crash**	**1.595**	0.003	Yes
Faster	**Cycling faster**	273	**Any crash**	0.616	0.160	No
Take chances	**Taking chances**	111	**Any crash**	−0.118	0.846	Yes
Music	**Listening to music**	113	**Any crash**	−0.413	0.517	Yes
Sidewalk cycling	**Not cycling on the sidewalk**	461	**Any crash**	−0.418	0.356	No
Winter cycling	**Cycling in winter**	337	**Any crash**	−0.305	0.452	Yes

In terms of direction, most results are in accordance with the learning hypothesis, but only the results for high-visibility clothing (any crash) and helmet use (any crash) are statistically significant. For example, among those who did not use helmets in 2016, those who had a crash between the surveys in 2016 and 2017, more often started to wear a helmet than those who had not been involved in a crash. For cycling faster and sidewalk cycling, the results are contrary to the learning hypothesis, i.e. crash involvement is related to an *increase* in cycling faster and the non-use of sidewalks.

To investigate the effect of previous crash involvement on annual cycling length, we focused on crash involvement in 2016 and cycling length in 2016 and 2017. Those who were involved in a crash in 2016, cycled on average far more than those who were not. Therefore, if all respondents were included in the analysis, a reduction in annual cycling length among crash-involved cyclist could be expected because of the regression-to-the-mean effect (Twisk & Proper, 2004). To avoid this, we based the analysis on all crash involved cyclists and a matched comparison group consisting of one non-crash involved cyclist in 2016 for each crash-involved cyclist. The comparison group was matched on annual cycle length in 2016, which had to be as close as possible to the cycle length of one of the crash-involved cyclists. Thus, both groups are of equal size and they had similar average cycle lengths in 2016.

Table 11 shows the average annual cycle lengths in 2016 and 2017 for those who have and have not been involved in a crash in 2016, and results from t-tests comparing the average cycle length between crash-involved and non-crash involved cyclists. There are only small differences in the average cycle lengths between crash-involved and non-crash involved

Table 11
Average annual cycle lengths and results from t-tests comparing the average cycle length between crash-involved and non-crash involved cyclists.

	Crash involvement (2016)	N	Km mean	SD	T-test: Crash-involved vs. not crash-involved *t*	*p*
2016	**Non-crash involved**	214	5,411	4,079	*−0.0437*	*0.9652*
	Crash involved	214	5,439	4,162		
2017	**Non-crash involved**	214	5,115	4,157	*0.0495*	*0.9606*
	Crash involved	214	5,083	4,157		

cyclists in both years. In 2017, all cyclists cycled somewhat less than in 2016, but both groups had still about equal cycling lengths, which is not consistent with the hypothesis that crash involved cyclists cycle less in later years.

5. Discussion

5.1. Safety effects

In accordance with the safety effects hypothesis, the results show that using bicycle lights and high-visibility clothing are negatively related to collision involvement. Although the results are not statistically significant, they are consistent across time periods, and specific to the expected types of equipment and crash. For instance, lights and high-visibility clothing were not consistently associated with single bicycle accidents, and helmet use was not negatively related to crash involvement. Moreover, the use of bicycle lights is, as predicted, consistently and negatively related to collision involvement in darkness.

The results for high-visibility clothing are in line with previous cross-sectional research, which generally find negative associations, albeit sometimes small (see Section 2.1). For collisions in darkness, two of four results are inconsistent with the hypothesis. However, these are based on relatively few crashes.

Regarding the association between use of bicycle lights and collision involvement, previous studies showed mixed findings. Differences in research methodology might account for discrepancies between the current study and those who found positive or no associations. For instance, the reference group used by Hagel et al. (2014) were cyclists admitted to the emergency unit reasons other than being involved in a multi vehicle crash. In contrast, the current study included many cyclists that were not involved in any accidents. Similarly, in cross-sectional surveys of accident involvement (Hollingworth et al., 2015; Washington et al., 2012), it is not possible to distinguish the effects of lights on accidents from the effects of accidents on light use.

5.2. Safety package, behavioral adaptation or precautionary behavior

The safety package hypothesis predicts negative relationships between all types of safety equipment and crash involvement, both with and without control for potential confounding variables. It also predicts that those who use safety equipment show other types of safe behavior as well. In contrast, the behavioral adaptation / precautionary behavior hypothesis predicted that cyclists using safety equipment behave less safely otherwise.

For the relationships between use of safety equipment and other safety behavior, the following are consistent with the safety package hypothesis: The use of one type of safety equipment is associated with a higher likelihood of using other types of safety equipment, and using safety equipment is negatively related to listening to music and to taking chances.

Listening to music is the only type of behavior in this study that has been found to be related to crash involvement, both in the present and in other studies (Tin Tin et al., 2013; Wilbur & Schroeder, 2014), in addition to being theoretically related to high crash risk. For example, Chataway et al. (2014) found a negative relationship between the use of safety gear and distracted cycling (listening to music can be regarded as a type of distracted cycling), which also is in accordance with the safety package hypothesis. Although chance-taking was not related to crash involvement, non-taking of chances may still be a part of a (subjective) safety package.

On the other hand, safety equipment use was positively related to riding faster, winter cycling and (weakly) to not cycling on the sidewalk. Hence, these behaviors were in accordance with the adaptation/precaution hypothesis in terms of how they relate to use of safety gear. They may be associated with a (subjective) perception of being risky (Chataway et al., 2014; Kummeneje, Ryeng & Rundmo, 2019), but they were not directly related to crash involvement in the present study. The potential directions of these relationships are discussed in the next section.

5.2.1. Equipment use and behavior: Adaptation or precaution?

For the combinations of safety equipment use and other safety behaviors that may indicate behavioral adaptation/precaution, the strongest relationships were found between helmet use and riding faster (competitiveness), and between using bicycle lights (followed by high-visibility clothing) and winter cycling. Helmet use is typical in Norway among competitive cyclists: Among cyclists in exercise clothes on well-equipped racing bicycles, practically none are unhelmeted (Høye &

Hesjevoll, 2016). In winter it is often dark and therefore it is reasonable that especially those cycling in winter, are using bicycle lights. Those who are cycling fast and in winter, may be more aware of the importance of being seen by motor vehicle drivers, especially in darkness, and thus be more motivated to use lights and high-visibility clothing. Competitive cyclists may also use safety equipment as a part of their standard equipment which often consists of well-equipped bicycles, professional cycling clothing, and helmets (Høye & Hesjevoll, 2016).

Previous studies found that the use of safety equipment is often motivated by perceived unsafety (Aldred & Woodcock, 2015), that cyclists more often use helmets when going on long (vs. short) trips (Schleinitz et al., 2018), and that helmet use is not associated with increased speed (Fyhri et al., 2018; Schleinitz et al., 2018). Cyclists using safety equipment were also found to be more compliant with traffic rules (Lawson, Pakrashi, Ghosh, & Szeto, 2013).

While the associations between equipment use, competitiveness and use of lights and high-visibility clothing are correlational in nature, these results are most reasonably interpreted in terms of precautionary behavior, not as behavioral adaptation. It appears implausible that someone who owns helmet becomes competitive or starts to cycle in winter because of the helmet, or that someone who happens to have bicycle lights and high-visibility clothing start to cycle in winter and because of this equipment.

Additionally, using safety equipment, cycling in winter, and competitiveness are strongly related to a higher average annual cycling length (Table 5). Cycling more may by itself contribute to the use of safety equipment: Firstly, as a precautionary measure (other studies show that safety equipment use is related to trip length); secondly because of experience (in line with the learning hypothesis; the same mechanism may also apply to learning from conflicts and other incidents); thirdly because it may seem more worthwhile to purchase equipment when it will be used often. It appears unlikely that someone cycles a lot just because they happen to be in possession of safety equipment. Thus, the relationship between safety equipment use and amount of cycling can also reasonably be interpreted as precautionary behavior.

5.2.2. Safety behaviors and crash involvement

Overall, the associations between safety equipment use, safety behaviors and crash involvement are mixed. Among the safety-related behaviors investigated in this study, only listening to music is positively and consistently related to crash involvement. This association between listening to music and crash involvement is also found in other studies (Tin Tin et al., 2013; Wilbur & Schroeder, 2014).

The weak and inconsistent associations between the remaining behaviors (taking chances, cycling faster than others, sidewalk cycling and winter cycling) and accident involvement prompts the questions of the degree to which these behaviors are actually related to safety. Other studies have found associations between frequent cycling on sidewalks and crash involvement (De Rome et al., 2013; Poulos et al., 2015), but its associations with crash involvement in the present study could be related to unmeasured factors such as local infrastructure availability and traffic conditions.

While conditions are often adverse for cycling in winter, cyclists who regularly cycle in winter are often far more safety-conscious than others. Amongst other things, they use more safety equipment on average and they show less high-risk behavior (Høye & Hesjevoll, 2016). A Belgian study found no large or statistically significant differences in crash incidence (with control for exposure) between winter and other seasons (de Geus et al., 2012).

More generally, the weak and inconsistent relationships may be partly due to small numbers of crashes. However, the results of the present study suggest that there are several mechanisms that affect crash involvement in opposing directions. On the one hand, safety equipment use is related to other types of safe behavior, such as not listening to music. On the other hand, it is also related to types of behavior typically associated with higher risk, i.e. competitiveness. Moreover, there may also be learning effects from past crash involvement. Thornley et al. (2008) suggest learning effects as explanations for a lack of relationships found between safety equipment use and crash involvement ("reverse causation").

Thus, among the safety behaviors investigated in this study, only listening to music can be regarded as high-risk behavior. Taking chances, cycling in winter, and cycling in mixed traffic might be subjectively experienced as risky, but are unrelated to accident involvement.

5.3. The learning hypothesis

The learning hypothesis predicts that crash-involvement leads to increased use of safety equipment among those cyclists who had not previously been using safety equipment. The results are for the most part consistent with this hypothesis, and statistically significant for high-visibility clothing and helmet use. For bicycle lights, the results are in the expected direction with relatively large effect sizes.

For each type of safety equipment, the results show that non-users in 2016 were more likely to use the respective type of equipment in 2017 when they reported a crash in 2016 than when they did not. For example, among those who did not use lights in 2016, those who had a crash were more often using lights in 2017 than those who did not have a crash in 2016. For lights and high-visibility clothing, the relationships to collision involvement are stronger than the relationships to total crash involvement. This is in accordance with an assumption of specific adaptation; lights and high-visibility clothing would not help in a single bicycle crash.

For riding faster and sidewalk cycling the results are in the opposite direction to the predictions form the learning hypotheses. This might indicate that these behaviors are not subject to learning. On the other hand, as noted previously, these behaviors may in fact not be high-risk behaviors for all cyclists.

Similar studies of the relationships between past crash involvement and current behavior among cyclists have not been found. However, a study among car drivers showed that previous crash involvement does not deter car drivers from drunk driving (Purssell et al., 2010). Another study among car drivers has not found any effect of past crash involvement on speed choice (Ahie, Charlton, & Starkey, 2015).

The results do not indicate that crash-involvement leads to less cycling. When crash- and non-crash involved cyclists with about the same annual cycling length are compared, crash involvement is practically unrelated to annual cycling length in the subsequent year. It should be noted that none of the respondents quit cycling after being involved in a crash, and that crash involved cyclists generally cycled longer distances than those not involved in crashes. Therefore, these results may not generalize to less experienced crash-involved cyclists.

5.4. Limitations

A main limitation of the present study is that it is based on self-reported data. Respondents may have interpreted the questions differently. For example, they may have different thresholds for defining an incident as a crash (despite the definition given in the questionnaire), or they may have different interpretations of taking chances. Such differences will most likely introduce random variation (and weaken the observed associations), but not necessarily systematic differences.

Systematic bias may be introduced by general response styles such as social desirability. For example, some respondents may have over reported favorable behaviors such as using safety equipment, and underreported unfavorable behaviors such as taking chances. Crash involved cyclists may also have been reluctant to admit that they are not always using safety equipment. These types of bias would be expected to lead to general positive relationships between "desirable" or "safe" types of behavior. Since far from all "safe" types of behavior are positively related to each other, it is unlikely that this kind of bias has had any (large) effect on the results. However, relationships to crash involvement may be underestimated. For instance, if bicycle light use is over reported among crash involved cyclists, the relationship between bicycle light use and crash involvement will be weaker than if bicycle light use were reported correctly. The use of the prior year's safety equipment use to predict the later year's crash involvement may have somewhat limited the influence of such biases in most analyses.

To limit the length of the questionnaires, we asked only about one crash involvement per cyclist. While this may have introduced more uncertainty into the results, we believe that asking about more than one crash could have increased respondent fatigue and non-response.

Safety equipment use and other safety behavior were assessed generally, not at the time of the crash (among those who had a crash). Moreover, it was only asked about crash involvement (at least one crash), not about the number of crashes. This makes the estimated relationships between these variables and crash involvement somewhat uncertain, and the relationships may be underestimated. Additionally, the numbers of crash-involved cyclists are relatively small, especially for night-time collisions, which makes all relationships to crash involvement uncertain, and which can explain that many of the results are non-significant.

Both in the current study and in previous publications, exposure is one of the most important factors influencing crash involvement. By asking relatively detailed questions about cycling length, including differences between summer and winter, we have relatively precise estimates of exposure. However, annual average cycling lengths are still self-reported estimates, and thus uncertain.

The safety behaviors should be validated, which has not been practically possible in the present study. Especially the interpretation of safety behaviors such as "inherently unsafe" is speculative and should be investigated by research more targeted at this specific question.

Another potential source of bias is the selection of cyclists who participated throughout the whole study period. Compared to drop-outs, the cyclists in the final sample were more experienced and they used more safety equipment. It is unclear how relationships between the different variables may be affected, but as a general precaution, the findings might not generalize to less active cyclists.

A related concern is the relatively limited number of cyclists on which this study is based, and the relatively low number of accidents they reported. This makes significance testing largely uninformative. However, the longitudinal aspect of these data allows us to evaluate results based on their consistency in size and direction over time, in addition to consistency across model specifications.

Finally, the large numbers of predictor variables and relationships imply that it is relatively unlikely that a replication study will end up with exactly the same results. However, the large number of variables gives an opportunity to investigate the big picture, and a potential replication study may still draw the same or similar general conclusions. This would be worthy of investigating.

6. Summary and implications

The results are for the most part consistent with the ***safety effects*** hypothesis: Past use of bicycle lights and high-visibility clothing were found to be negatively related to collision involvement. Past use of bicycle lights is also negatively related to collision involvement in darkness.

The safety package hypothesis and the behavioral adaptation / precautionary behavior hypothesis make contradicting predictions. The results are in accordance with the ***safety package hypothesis*** (and contrary to the behavioral adaptation hypothesis) with regard to safety equipment, listening to music and taking chances: Using safety equipment, not listening to music and not taking chances are related to each other and may be regarded as a safety package. Among those who are using high-visibility clothes and who are not listening to music, there are also fewer who had a crash than among other cyclists. For lights and helmets, no consistent relationships to total crash involvement were found. Other types of potentially unsafe behavior are not included in the «safety package» (riding faster, not cycling on sidewalks, and winter cycling).

Riding faster, not cycling on sidewalks, and winter cycling are positively related to safety equipment use which is in accordance with the behavioral adaptation / precautionary behavior hypothesis. The ***precautionary behavior*** hypothesis is a more plausible explanation for these relationships than behavioral adaptation. The results from the present and other studies indicate that safety equipment use most likely is a means to reduce the perceived risk, rather than a precursor of these behaviors.

The results are partly in accordance with the ***learning hypothesis*** according to which crash involvement among non-users of safety equipment increases the use of safety equipment. In other words, cyclists tend to learn from their experience and take precautions to avoid crashes in the future. However, similar learning effects were only partly found for other safety behavior (taking chances, listening to music, and winter cycling, but not cycling faster and on the sidewalk). In our sample of generally active cyclists, the results do not indicate that crash involvement reduces average annual cycling lengths.

Based on the results for the safety effects hypothesis, the use of bicycle lights and high-visibility clothing can be recommended because both were found to reduce collision involvement. The results are more consistent with the hypothesis that cyclists use safety equipment as a precaution against increased risk in certain situations, rather than showing more risky behavior in order to compensate for reduced risk from safety equipment use. Some inherently risk types of behavior, listening to music and taking chances while cycling, are in accordance with the safety package hypothesis less common among users of safety equipment. Trying to cycle faster than others, and other presumed risk related behaviors that were more frequent among users of safety equipment, were not associated with crash involvement. Thus, when the use of safety equipment is recommended, promoted, or even mandated, the results from the present study do not indicate that one needs to take precautions against behavioral adaptation. Neither do the results support reservations against the use of "sporty" (well-equipped) models in campaigns for promoting cycling.

The results indicate that accident involvement can prompt cyclists to start using safety equipment if they did not already do so. This implies that cross-sectional self-reported studies should take precautions to avoid confounding learning effects with the safety effects of using the equipment.

In this study, respondents were relatively active and experienced cyclists, and the use of safety equipment was high. Future studies might assess the degree to which the results generalize to less active cyclists.

CRediT authorship contribution statement

Alena Katharina Høye: Conceptualization, Methodology, Formal analysis, Writing - original draft, Project administration, Funding acquisition. **Ole Johansson:** Investigation, Data curation, Writing - review & editing. **Ingeborg Storesund Hesjevoll:** Investigation, Resources, Data curation, Writing - review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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