Using Ecological Momentary Assessment to Study Variations in Daily Experiences and Behaviors during the COVID-19 Pandemic

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Abstract

To stop the spread of the coronavirus disease (COVID-19), major restrictions to reduce social contacts have been introduced, which affect virtually all everyday behaviors including social relations. The main aim of the present study was to assess health as well as risk behaviors and COVID-19 related risk perception in a real-world setting, capturing daily variations and changes over time in the context of the COVID-19 pandemic, to understand how variations in risk perception relate to behaviors. Towards this end, during the first lockdown period of the COVID-19 pandemic in Germany (April to May 2020), a smartphone-based Ecological Momentary Assessment (EMA) was implemented including a final sample of *N* = 49 participants (73.5% female) recruited from the general population with a mean age of 29 years, ranging from 18 to 75 years. During the 14-day EMA period, health-related behaviors (i.e., eating and drinking behaviors, physical activity, sedentary behavior and overnight sleep), COVID-19-related risk behaviors (i.e., in-person social contacts and leaving home), as well as risk perception (i.e., likelihood of contracting COVID-19) were assessed at the end of each day for each participant. Daily assessment allows to conduct intraclass correlations and multilevel analyzes, to investigate both inter-individual (between-person) and intra-individual (within-person) variations. The data indicates that perceived likelihood of having contracted COVID-19 was significantly higher on days when participants had had more in-person social contacts and had left their homes for multiple reasons. Furthermore, there was substantial variation in health-related behaviors, including eating healthy foods, unhealthy snacking, alcohol consumption, physical activity, sedentary behavior, and overnight sleep not only between, but also within individuals. Overall, the data indicates relative accuracy in risk perception as participants acknowledged times of greater risk exposure. Moreover, although the first lockdown massively interrupted and restricted individual daily routines and habits, COVID-19-related risk as well as health-related behaviors showed marked short-time variations on a daily basis.

Introduction

The new emergence of the coronavirus disease (COVID-19) in 2019/2020 has caused a global pandemic with the death of hundreds of thousands of people and major disruptions to society and individual behaviors in daily life. To contain the spread of the virus, nationwide restrictions and lockdowns have been introduced asking people to stay at home, avoid in-person social contacts and follow strict hygiene behaviors as no medical treatment or vaccine was immediately available after the outbreak.

While nationwide restrictions and lockdowns help to reduce infection rates and to save lives (Fang et al., 2020), they have marked consequences for daily life behaviors. Fitness facilities, recreational sports and many food suppliers have been closed, hampering the engagement in physical activity and putting an additional burden on routine food-related behaviors. Early evidence suggests that widespread restrictions and changes in daily life during the COVID-19 pandemic have negatively impacted health-related behaviors, leading to lower levels of physical activity and increased sedentary behavior (Constandt et al., 2020; Fitbit, 2020), negative changes in eating behavior and dietary habits (Robinson et al., 2021), increased alcohol consumption (Ammar et al., 2020; Winstock et al., 2020), and a decrease in sleep quality (Blume et al., 2020). Thus, introducing restrictions and lockdowns to contain the spread of COVID-19 is also a challenge for general health and well-being of the population.

The course of the COVID-19 pandemic and public health policies not only affect behaviors but also our perception of the risk. Risk perceptions of adverse health outcomes have been examined as a motivational factor driving protective behaviors since the 1950s (Slovic, 1964). Since then, risk perception has become a key component of many theoretical frameworks for predicting and changing protective behaviors (Portnoy et al., 2014; Renner & Schwarzer, 2003; Weinstein, 2003). In general, these frameworks imply that perceiving a health risk for the self signals the need to take protective action (see also Finkel, 2008; Loewenstein et al., 2001; Menon et al., 2008; Renner et al., 2015; Slovic, 2000; Weber & Morris, 2010; Weinstein, 2003). Findings from prospective field studies conducted during acute epidemics (BSE, H1N1) provide empirical support for the behavior motivation hypothesis. Specifically, high perceived risk was associated with subsequent precautionary behavior (e.g., vaccination, hand sanitizer pick-up rate; Renner et al., 2007; Renner & Reuter, 2012; Reuter & Renner, 2011). Furthermore, a meta-analysis showed that heightening risk appraisals induced within experimental studies had effects of $d+ = .31$ ($k = 217$) and $d+ = .23$ ($k = 93$) on intention and behavior, respectively (Sheeran et al., 2014). A different facet of the risk perception-behavior relationship is addressed by the accuracy hypothesis, assuming that people who behave in a riskier way should also feel more at risk (Weinstein & Nicolich, 1993; Weinstein et al., 1998). Assessment of the risk perception-behavior relationship in the context of the COVID-19 pandemic is important considering the dynamic nature of pandemics (Ibuka et al., 2010; Lages et al., 2021). Ecological Momentary Assessments (EMA; Shiffman et al., 2008; Stone et al., 2007) or Ambulatory Assessments (AA; Trull & Ebner-Priemer, 2013, 2014) seem particularly well-suited to track daily variations and systematic changes over time with a high resolution. Up to date, there is a considerable gap in knowledge about the stability of risk perception and what factors drive changes in perceived risk (Lages et al., 2021; Siegrist, 2014). Investigating risk perceptions by using EMA enables research to capture possible dynamics in perceived risk on a daily basis and thus with high resolution, which will advance our understanding of the dynamics of risk perception.

The present study

The aim of the present study was to assess health-related as well as risk behaviors and risk perception in a real-world setting, capturing high-resolution data with daily variations and changes over time in the context of the COVID-19 pandemic. Towards this end, a smartphone-based EMA was implemented between the beginning of April and mid of May 2020 during the first lockdown period of the COVID-19 pandemic in Germany assessing daily health-related and risk behavior as well as risk perception across 14 days. Risk perception was assessed by the perceived likelihood of having contracted COVID-19 that day. Behavior was assessed with regard to COVID-19-related risk behaviors, i.e., leaving home and in-person social contact, and health-related behaviors, i.e., eating healthy foods, unhealthy snacking, alcohol consumption, physical activity, sedentary behavior, and overnight sleep. According to the accuracy hypothesis, we predicted a positive cross-sectional relationship between risk behaviors and risk perception. To control for the specificity of the effect, the relationship between health-related behaviors and risk perception was analyzed for comparison. The behavior motivation hypothesis was examined by time-lagged multilevel analyzes using risk perception as a predictor for behaviors on the following day. Finally, change over time in risk perceptions and behaviors were examined with particular focus on intra- and interindividual variation in order to determine effects between as well as within individuals.

Methods

Sample

Participants were recruited via the department online study platform of the University of Konstanz, social media postings (e.g., Facebook, Instagram) and email lists. Due to technical requirements of the application, only people with an Android smartphone (except Huawei due to compatibility problems) were eligible for participation. Out of 137 participants who filled in the baseline assessment, 52 participants started the EMA, of whom three were excluded due to low compliance (< 50% of days), resulting in a final sample of N = 49 (73.5% female). The sample had a mean age of 29.04 years (SD = 13.50, range = 18 - 75 years) with a great majority of participants being single (81.6%) and students or in training (77.6%). Overall, self-rated health status was good with an average of 4.43 on a 7 point Likert scale (SD = 0.65) with 45 participants (91.8%) reporting a 'very good' or 'good' health status. As compensation, participants had the choice between a 10€ voucher for local shops or donating the money to the COVID-19 emergency aid by the German Red Cross.

Procedure

Data was collected as part of the "EUCLID" project (https://euclid.dbvis.de/home) funded by the German Research Foundation (DFG FOR 2374), the Federal Ministry of Education and Research (BMBF 01EL1820A), and the Centre for the Advanced Study of Collective Behaviour (EXC 2117). The study was approved by the University of Konstanz ethics committee and carried out in accordance with the Declaration of Helsinki and the guidelines of the German Psychological Society. All participants gave informed consent prior to participation.

After completing an online baseline questionnaire about risk perception, protective behavior and future expected developments in regard to the COVID-19 pandemic (see the "EUCLID" project for further details, https://euclid.dbvis.de/home), participants were asked to install the study app (movisensXS, available on Google Play for Android) on their own smartphone and were sent an individual code to start the EMA. For the following 14 days, participants were asked to fill in a questionnaire on their smartphone at the end of the day about their risk perception, experiences and behaviors during the day. Assessment was possible starting at 6 p.m. each day, facilitated by individually timed reminders in the evening. EMA data was recorded from April 9 to May 18, 2020. At the beginning of the assessment, a lockdown was imposed on Germany, which was lifted towards the end of the study period as the epidemiological situation regarding COVID-19 improved (see Fig.1). Compliance during the EMA assessment was good with an average of 12.57 sampling days (*SD* = 1.96), ranging from seven to 14 days. After the EMA, participants were asked to fill in an online questionnaire similar to the baseline questionnaire at the beginning of the study.

Material and Measures

Health-related behavior

To assess health-related behaviors, participants were asked to report on their daily eating and drinking behaviors, i.e., healthy eating (portions of fruit/vegetables), unhealthy snacking (portions), alcohol consumption (number of 0.25l drinks), and the duration of physical activity (e.g., climbing stairs, going for a walk, sports; min), sedentary behavior (h) during the day and overnight sleep (h) during the last night. For the assessment, open scales with the respective unit were used.

COVID-19-related risk behavior

To assess risk behavior, the number of reasons for leaving home and in-person social contacts were

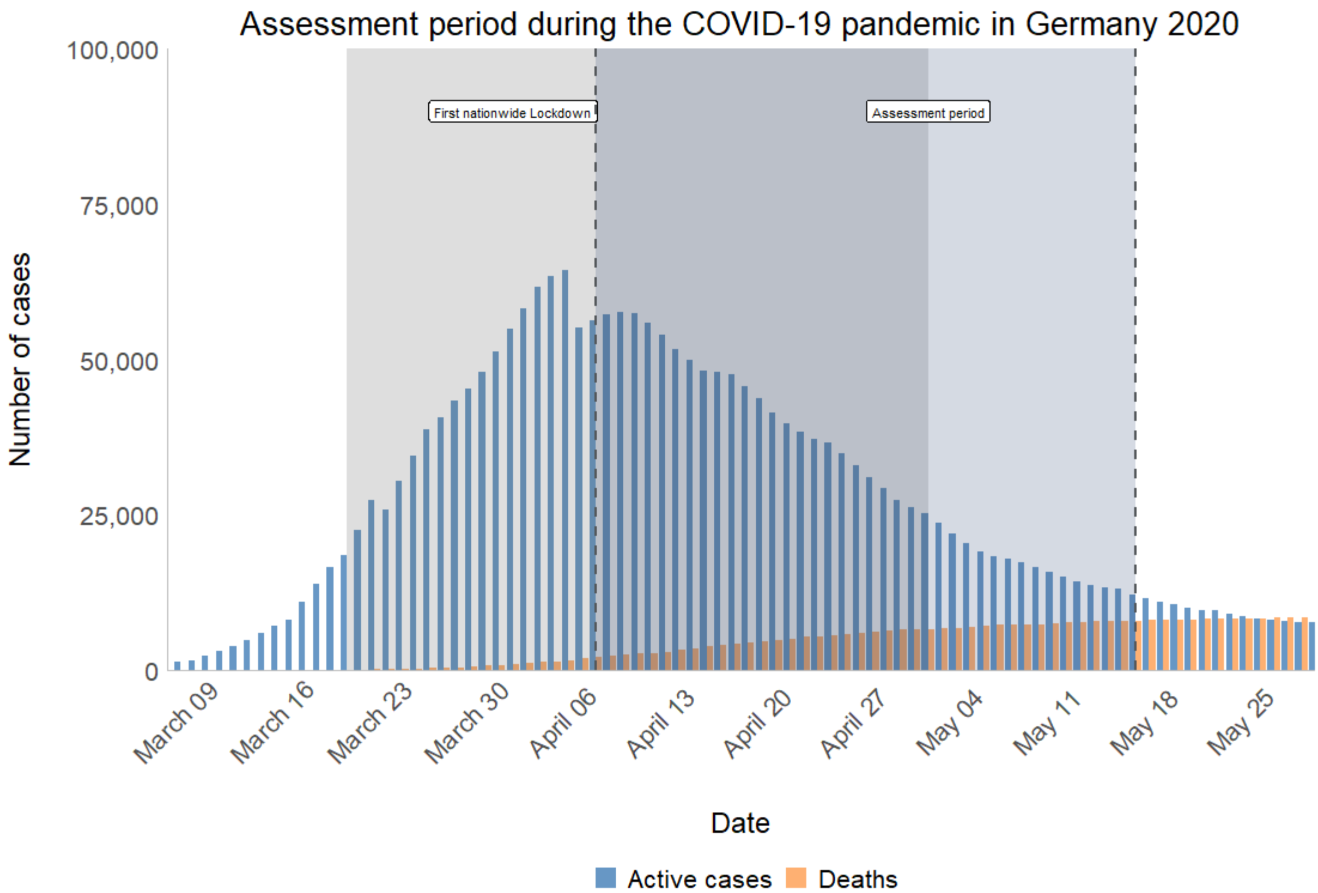


Figure 1. Epidemiological curve of COVID-19-related active cases and total deaths in spring 2020 in Germany. The grey area marks the first nationwide lockdown in Germany. The blue area between the dotted lines indicates the EMA period. Data source: Robert Koch Institute.

recorded. Participants were asked to indicate all reasons for leaving their home: (1) necessary grocery shopping or medical needs, (2) work, (3) physical activity outdoors, (4) visiting other people and/or (5) other reasons. In order to gauge the frequency of risk behaviors, the number of reasons for leaving home and in-person social contacts were recorded.

Risk perception

To assess daily risk perception, participants were asked to estimate how likely they were to have contracted COVID-19 that day on a visual slider ranging from (0) very low to (100) very high. The item was based on previous studies (see Brewer et al., 2007; Renner & Reuter, 2012; Weinstein et al., 2007).

Statistical analysis

For the statistical analysis, only data assessed during the EMA period was used, resulting in 616 assessment points that were included in the analysis. Variation between as well as within participants was analyzed using intraclass correlation coefficients (ICCs) and graphical depictions. Unrealistic values (> 24 h) in health-related behaviors and outliers in the number of in-person social contacts (> 11; n = 22), identified via boxplots (Tukey, 1977), were excluded.

Multilevel analyzes were performed to account for the hierarchical data structure with individual assessments (level 1) within participants (level 2). Intraclass correlations were used to assess inter- and intra-individual variation, indicating the proportion of variance, which results from differences between individuals as opposed to differences between assessments. Random intercept and random slopes models were computed and compared using a deviance test. Whereas random intercept models only include level differences between individuals, random slopes models estimate relationships for each individual, which can differ in magnitude and direction of the effect between individuals (Hox et al., 2010). Models that did not converge or indicated a singular fit were reduced as proposed by Bates et al. (2015) and Barr et al. (2013). If significant, pseudo-R-squares as proposed by Raudenbush and Bryk (2002) were computed for the preferred models. For random slope models, the proportion of negative relationships was additionally reported.

To investigate changes over time, models with a time effect, which was coded based on the dates of the EMA (range = 0 - 39), were tested. To assess the relationship between behaviors and risk perception, risk perception was used as a person-mean centered level 1 predictor (Enders & Tofighi, 2007). In order to predict behaviors on the subsequent day, a time-lagged variable for risk perception was used as a person-mean centered predictor.

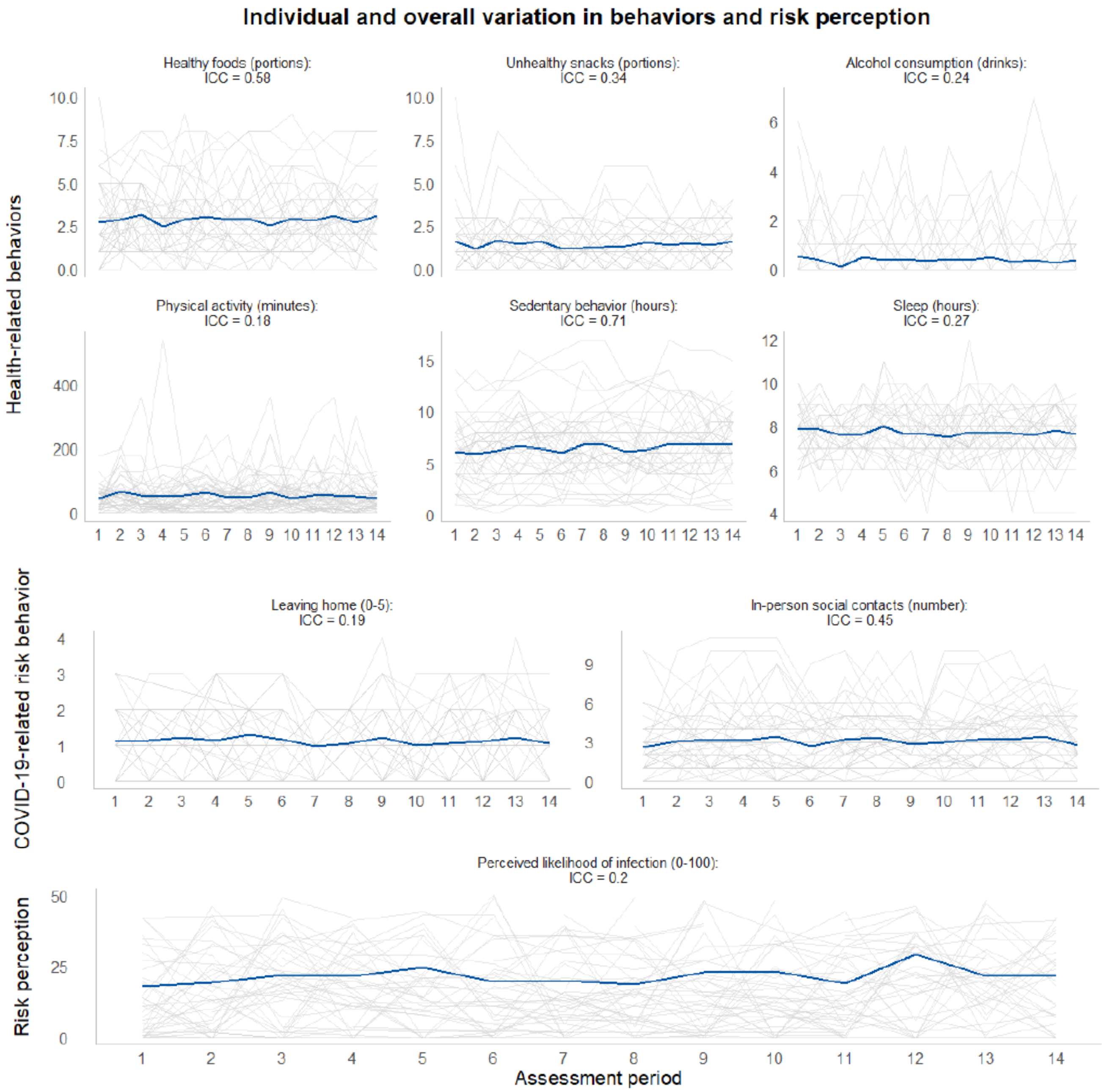
Multilevel analyzes were performed using R version 4.0.3 with the packages 'Ime4' (Bates et al., 2018), 'ImerTest' (Kuznetsova et al., 2018) and IBM SPSS statistics version 27 was used for the descriptive statistics.

Results

Variation and changes across the assessment period

Across participants, health-related behaviors including eating and drinking behaviors, as well as physical activity and overnight sleep were stable over time with only a slight increase in sedentary behavior per day (b = 0.06, t(601.62) = 3.56, p <. 001, pseudo-$R2$ = 0.02). However, substantial inter- and intra-individual variations were observed for all health-related behaviors. For a detailed overview of the descriptives and the variation within days but also between days of assessed health-related behaviors see Fig. 2.

Similar to health-related behaviors, COVID-19-related risk behaviors were stable over time, but



	Healthy foods (portions)	Unhealthy snacks (portions)	Alcohol consumption (drinks)	Physical activity (minutes)	Sedentary behavior (hours)	Overnight sleep (hours)	Leaving home (number of reasons)*	In-person social contacts (number)*	Perceived likelihood of infection (0-100)
n	616	616	616	615	612	615	607	594	616
M	2.86	1.43	0.36	54.10	6.46	7.69	1.46	3.40	21.56
SD	1.90	1.21	0.93	55.72	3.41	1.10	0.64	2.21	19.06

Figure 2. Variation in health-related behaviors, COVID-19-related risk behavior and risk perception. Grey lines indicate the variation of each participant, bold blue lines the average change over the course of the assessment period. *n* = number of observations. **M* and *SD* include only observations when participants had left their home/had in-person contacts.

varied substantially between as well as within individuals (see Fig. 2). Participants reported having in-person social contacts on average on 86.2% of the assessment days with on average 3.40 people (SD = 2.21) and a substantial range of 1 to 11. Furthermore, participants reported to have left their home on 75.3% of the assessment days (see Fig. 2 for details).

Nevertheless, participants reported a comparably low perceived likelihood of having contracted COVID-19 (M = 21.56, SD = 19.06). Even though active COVID-19 cases in Germany decreased over the assessment period (see Fig.1), this change was not reflected in a significant decrease in perceived risk (b = 0.24, t(401.68) = 1.68, p = .095). However, the ICCs indicated substantial inter- and intra-individual variation in risk perception (see Fig. 2).

Relationship between behavior and risk perception

Multilevel analyses was used to assess the relationship of behaviors and perceived risk. The results indicate that when people perceived their likelihood of having contracted COVID-19 on a given day as higher, they had left their home for more reasons (b = 0.02, t(45.04) = 9.71, p < .001, pseudo-$R2$ = 0.31, all random slopes positive) and had more in-person social contacts that day (b = 0.05, t(548.04) = 11.66, p < .001, pseudo-R2 = 0.20). Specifically, an increase of risk perception by 10 was associated with 0.2 more reasons of having left home and 0.5 more social contacts on the specific day. Although the magnitude of the relationship regarding leaving home varied between participants, it was positive for all participants.

Results also indicated that when people experienced a higher risk perception on a given day, they were more physically active (b = 0.41, t(566.12) = 3.32, p < .001, pseudo-$R2$ = 0.02) and had more alcoholic drinks (b = 0.01, t(568.06) = 3.68, p < .001, pseudo-$R2$ = 0.02) on that same day, although the effects were rather small. Specifically, an increase of risk perception by 10 was associated with 4.1 min more physical activity and 0.1 more alcoholic drinks on the specific day.

In addition, time-lagged multilevel analyzes revealed a significant but very small predictive effect of risk perception on the consumption of alcoholic drinks (b = 0.00, t(526.34) = 1.98, p <.05, pseudo-$R2$ = -0.03), which indicates that higher risk perception on one day was associated with small increases in alcohol consumption during the following day. However, no effect on other risk- or health-related behaviors occurred, indicating that risk perception was no predictor for most behaviors on the following day.

Discussion

The present study investigated daily COVID-19 risk perception and risk behaviors, as well as health-related behaviors during the beginning of the COVID-19 pandemic in Germany using a smartphone-based EMA across 14 days. The data shows substantial variation in risk perception and behaviors between as well as within individuals. In addition, data suggests that people accurately acknowledged greater risk-related behaviors in their risk perception on a given day.

The present study taps into a considerable research gap with major implications. The current COVID-19 pandemic represents the largest threat of a respiratory virus since the Spanish flu more than 100 years ago (Ferguson et al., 2020). High adoption rates of protective behaviors remain highly important to contain the spread of the disease and risk perception is known to be an important motivator for behavior change (e.g., Renner & Schupp, 2011; Sheeran et al., 2014). However, not much is known about the stability and dynamics of risk perception (Lages et al., 2021; Siegrist, 2014). This emphasizes the great need to investigate both the stability of perceived risk and what drives changes in risk perception, with a special focus on the COVID-19 pandemic. By using an EMA design, dynamics in risk perception can be investigated with the high resolution and with a focus on intra-individual changes, allowing to relate changes in risk perception to possible changes in behavior.

Accordingly, a main aim of the study was to understand how variations in risk perception relate to risk behaviors. The results of the present study suggest that participants draw on their own risk behaviors when gauging their personal risk. Specifically, the likelihood of having contracted COVID-19 was perceived to be higher on days when participants had more in-person social contacts or left their homes for multiple reasons. Although not directly related to risk, reasons for leaving home may be associated with a higher number of in-person social contacts (r = .32), thus being an indirect indicator of the risk of transmission. In addition, data showed that the positive risk perception-behavior relation was specific to those behaviors potentially increasing the risk of an infection and not a general effect across all behaviors. This finding resonates with previous research showing a positive association between risk behavior and risk perception, i.e., relative accuracy (Weinstein et al., 1998) across different risks (Brewer et al., 2004; Hay et al., 2007; Renner et al., 2008). However, the relation between perceived risk and risk behavior is complex as they influence each other continuously from day to day resulting in a dynamic interplay (Gerrard et al., 1996; Weinstein & Nicolich, 1993). Accordingly, repeated assessments are needed to investigate also the temporal dynamic and interplay of risk perception and risk behavior and describe changes and adaptive processes within individuals (i.e., adaptive accuracy; Renner et al., 2008; see also ‘risk reappraisal’; Brewer et al., 2004). The present findings suggest that, during the COVID-19 pandemic, higher risk behavior was associated with increased risk perception, in the sense of relative accuracy. However, given that the current study did not track a full cycle of the pandemic, future studies should examine adaptive accuracy, focusing on the relationship between risk perception and risk behavior in the COVID-19 pandemic across an extended period of time to further assess the notion that risk perception measures relate to risk behavior and show relative accuracy.

The strict regulation of public life due to the COVID-19 pandemic has not only a large impact on social life; it also affects routine health-related behaviors. Evidence is emerging that restrictions on daily living such as social distancing and home confinement can have compromising effects on health-related behaviors such as physical activity and eating (Ammar et al., 2020). Using EMA across 14 days, the present study provides first insights into inter- and intra-individual variation of health-related behaviors. For instance, with the implementation of the lockdown in Germany, one may assume that one day is like the other, resulting in uniform appearance of health-related behaviors across time. To the contrary, as shown in Figure 2, there was substantial intra-individual variation across all behaviors assessed in the current study including eating healthy foods, unhealthy snacking, alcohol consumption, physical activity, sedentary behavior, and overnight sleep. Accordingly, at least for the present sample consisting of young adults and 77.6% of college students, health-related behaviors show considerable variability even during governmental regulation of social life. Future studies should expand EMA to reveal triggers for protective health-related behaviors, i.e., healthy eating and increased physical activity.

The present study revealed no significant deterioration in health-related behaviors over time. However, the study period may have been too short to reveal dynamic changes in health-related behaviors. The one exception was sedentary behavior which showed a slight increase over the assessment period. Even slight increases in sedentary behavior over an extended period may have significant health impacts (e.g., Ahmadi-

Abhari et al., 2017). Furthermore, while the overall effect for sedentary behavior was small, the ICC indicated that there are substantial differences between people. Thus, to further analyze compromising effects of the regulation of public life during pandemics, future studies may capitalize on the advantages of EMA to assess intra- and interindividual differences in health-related behaviors.

Using EMA allows to assess thoughts, feelings, behaviors, and environments in daily life to investigate how individuals feel, think, and behave in-the-moment (Geukes & Back, 2018), removing the problem of recall or memory biases (Garbinsky et al., 2014; Redelmeier & Kahneman, 1996; Robinson, 2014; Robinson et al., 2011) since the assessment takes place in the 'hot' moment of behavior or experience (Fahrenberg et al., 2007; Jezior et al., 1990). However, using EMA for health psychology research is also accompanied by some problematic issues that go beyond ethical concerns and privacy issues (Albrecht, 2016; Harari et al., 2016; Short et al., 2018). On the one hand, intensive assessment can be challenging for participants and might result in low compliance rates that can impede the accuracy of the measurement. However, recent data assessing in-the-moment eating behavior, a particularly complex and challenging behavior to assess (see e.g., Boushey et al., 2017; Rozin, 2007; Wahl et al., 2020), show that high adherence rates are possible, especially when using technical assistance such as reminder or addendum features (Ziesemer et al., 2020). On the other hand, intensive assessment can also challenge research to find new, elaborated methods of analyzing these high-dimensional data (Hamaker & Wichers, 2017; Short et al., 2018). An important achievement is therefore to develop methods that facilitate data analyzes beyond aggregated mean values and to consider the between- and within-person levels as illustrated in the present paper (for a promising approach, see Blumenschein et al., 2018, 2020; Debbeler et al., 2018; Wahl et al., 2020).

Furthermore, limitations of the present research need to be acknowledged. The present convenience sample is on average substantially younger (29.04 vs. 44.3 years of age, respectively) and includes more female participants (74% vs. 51%, respectively) than the German population. Furthermore, behaviors were self-reported, potentially including a social desirability bias (see e.g., Kristiansen & Harding, 1984) and the data assessment occurring on average around 8.39 pm and may have missed some behaviors, in particular with regard to nighttime drinking or snacking. Overall, the present findings on the dynamic of risk perception and health-related behaviors await replication based on representative samples and covering longer time periods.

Conclusion

The present findings provide first insights into risk perception, risk behaviors as well as health-related behaviors during the first wave of the COVID-19 pandemic in Germany. EMA allows to examine changes over time but also the interplay between risk perception and behaviors. This will advance our understanding of both the stability of risk perception and what drives changes in perceived risk, which will in turn reveal information that may be capitalized on by public health campaigns to increase protective behaviors. Specifically, the findings indicate that people accurately relate their risk perception to social behaviors potentially increasing the risk of an infection, but not to health-related behaviors in general. Furthermore, although the first lockdown massively interrupted and restricted daily routines and habits, COVID-19-related risk as well as health-related behaviors showed considerable intra- and inter-individual variability across the 14 days of recording. Overall, EMA is promising to determine the effects of a pandemic on risk perception and behaviors.

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Declaration of Conflicting Interests

The authors declare no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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Additional Information

Table A1. Temporal dynamics of risk perception, COVID-19-related risk behavior and health-related behaviors

Predictor	Random intercept model (fixed effects)					Random slopes model (fixed effects)					
	b	*SE*	*t*	*df*	*p*	*b*	*SE*	*t*	*df*	*p*	*Pseudo-R^2*
Model 1: Perceived likelihood of infection											
Intercept	17.26	2.86	6.04	215.57	< .001	17.14	2.83	6.06	159.89	< .001	-
Time	0.24	0.15	1.68	401.68	.095	0.25	0.15	1.69	115.20	.093	
Model 2: Leaving home											
Intercept	1.17	0.13	9.21	210.87	< .001	NA	NA	NA	NA	NA	-
Time	-0.00	0.01	-0.47	396.18	.642	NA	NA	NA	NA	NA	
Model 3: In-person social contacts											
Intercept	2.90	0.37	7.76	191.60	< .001	NA	NA	NA	NA	NA	-
Time	0.01	0.02	0.69	580.44	.488	NA	NA	NA	NA	NA	
Model 4: Healthy foods											
Intercept	2.84	0.29	9.71	150.78	< .001	2.85	0.28	10.09	50.73	< .001	-
Time	-0.00	0.01	-0.05	615.90	.960	-0.00	0.01	-0.09	48.91	.929	
Model 5: Unhealthy snacks											
Intercept	1.46	0.19	7.78	221.21	< .001	NA	NA	NA	NA	NA	-
Time	-0.00	0.01	-0.31	555.86	.760	NA	NA	NA	NA	NA	
Model 6: Alcohol consumption											
Intercept	0.48	0.14	3.36	228.63	< .001	0.48	0.14	3.36	178.43	< .001	-
Time	-0.01	0.01	-1.02	470.27	.310	-0.01	0.01	-1.00	107.76	.320	
Model 7: Physical activity											
Intercept	59.66	8.33	7.16	214.73	< .001	NA	NA	NA	NA	NA	-
Time	-0.31	0.43	-0.72	388.44	.471	NA	NA	NA	NA	NA	
Model 8: Sedentary behavior											
Intercept	5.36	0.53	10.19	107.99	< .001	5.40	0.51	10.65	87.87	< .001	0.02[1]
Time	0.06	0.02	3.56	601.62	< .001	0.06	0.02	3.23	84.01	< .01	
Model 9: Overnight sleep											
Intercept	7.80	0.17	46.11	226.55	< .001	7.80	0.17	46.32	165.44	< .001	-
Time	-0.01	0.01	-0.77	494.16	.440	-0.01	0.01	-0.78	86.38	.438	

Notes. Models are not included if they did not converge or a singular fit was indicated. Pseudo-R-squares are reported for the preferred model if significant. The preferred model is indicated by 1 for the Random intercept and 2 for the Random slopes model.

Table A2. Relationship between behavior and risk perception.

Predictor	Random intercept model (fixed effects)					Random slopes model (fixed effects)					
	b	*SE*	*t*	*df*	*p*	*b*	*SE*	*t*	*df*	*p*	*Pseudo-R^2*
Model 10: Leaving home											
Intercept	1.12	0.06	18.26	47.71	< .001	1.12	0.06	18.26	47.80	< .001	0.31[2]
Perceived likelihood of infection	0.02	0.00	13.66	557.23	< .001	0.02	0.00	9.71	45.04	< .001	
Model 11: In-person social contacts											
Intercept	3.14	0.25	12.69	48.27	< .001	NA	NA	NA	NA	NA	0.20[1]
Perceived likelihood of infection	0.05	0.00	11.66	548.04	< .001	NA	NA	NA	NA	NA	
Model 12: Healthy foods											
Intercept	2.83	0.21	13.43	49.16	< .001	NA	NA	NA	NA	NA	-
Perceived likelihood of infection	-0.00	0.00	-0.66	567.17	.509	NA	NA	NA	NA	NA	
Model 13: Unhealthy snacks											
Intercept	1.42	0.11	13.13	49.47	< .001	NA	NA	NA	NA	NA	-
Perceived likelihood of infection	0.00	0.00	0.65	567.54	.517	NA	NA	NA	NA	NA	
Model 14: Alcohol consumption											
Intercept	0.35	0.07	4.82	49.94	< .001	NA	NA	NA	NA	NA	0.02[1]
Perceived likelihood of infection	0.01	0.00	3.68	568.06	< .001	NA	NA	NA	NA	NA	
Model 15: Physical activity											
Intercept	54.37	3.97	13.71	48.88	< .001	NA	NA	NA	NA	NA	0.02[1]
Perceived likelihood of infection	0.41	0.12	3.32	566.12	< .001	NA	NA	NA	NA	NA	
Model 16: Sedentary behavior											
Intercept	6.47	0.42	15.42	48.86	< .001	6.47	0.42	15.42	48.87	< .001	-
Perceived likelihood of infection	-0.01	0.00	-1.87	562.90	.063	-0.01	0.01	-1.19	36.38	.242	
Model 17: Overnight sleep											
Intercept	7.69	0.09	85.93	49.08	< .001	NA	NA	NA	NA	NA	-
Perceived likelihood of infection	-0.00	0.00	-1.18	566.20	.238	NA	NA	NA	NA	NA	

Notes. Models are not included if they did not converge or a singular fit was indicated. Predictors were centered on the person-mean. Pseudo-R-squares are reported for the preferred model if significant. The preferred model is indicated by 1 for the Random intercept and 2 for the Random slopes model.

Table A3. Influence of perceived likelihood of infection on behaviors on the following day.

Predictor	Random intercept model (fixed effects)					Random slopes model (fixed effects)					
	b	*SE*	*t*	*df*	*p*	*b*	*SE*	*t*	*df*	*p*	*Pseudo-R²*
Model 18: Leaving home											
Intercept	1.11	0.06	18.69	46.88	< .001	NA	NA	NA	NA	NA	-
Perceived likelihood of infection	-0.00	0.00	-1.36	515.71	.175	NA	NA	NA	NA	NA	
Model 19: In-person social contacts											
Intercept	3.09	0.23	13.24	48.13	< .001	NA	NA	NA	NA	NA	-
Perceived likelihood of infection	-0.00	0.00	-0.84	502.97	.401	NA	NA	NA	NA	NA	
Model 20: Healthy foods											
Intercept	2.85	0.21	13.38	49.26	< .001	NA	NA	NA	NA	NA	-
Perceived likelihood of infection	0.00	0.00	0.71	521.89	.480	NA	NA	NA	NA	NA	
Model 21: Unhealthy snacks											
Intercept	1.42	0.11	13.32	50.25	< .001	NA	NA	NA	NA	NA	-
Perceived likelihood of infection	-0.00	0.00	-0.16	525.01	.871	NA	NA	NA	NA	NA	
Model 22: Alcohol consumption											
Intercept	0.35	0.07	4.82	50.23	< .001	NA	NA	NA	NA	NA	-0.03[1]
Perceived likelihood of infection	0.00	0.00	1.98	526.34	< .05	NA	NA	NA	NA	NA	
Model 23: Physical activity											
Intercept	54.19	4.09	13.27	48.67	< .001	NA	NA	NA	NA	NA	-
Perceived likelihood of infection	-0.06	0.12	-0.51	524.59	.612	NA	NA	NA	NA	NA	
Model 24: Sedentary behavior											
Intercept	6.51	0.42	15.38	48.81	< .001	NA	NA	NA	NA	NA	-
Perceived likelihood of infection	-0.00	0.00	-0.59	516.67	.556	NA	NA	NA	NA	NA	
Model 25: Overnight sleep											
Intercept	7.69	0.09	85.03	49.26	< .001	NA	NA	NA	NA	NA	-
Perceived likelihood of infection	0.00	0.00	1.87	523.75	.063	NA	NA	NA	NA	NA	

Notes. Models are not included if they did not converge or a singular fit was indicated. Predictors were centered on the person-mean. Pseudo-R-squares are reported for the preferred model if significant. The preferred model is indicated by 1 for the Random intercept and 2 for the Random slopes model.

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