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Brigitte Leeners *
Research Article

Utilizing Wearable Biosensor Technology for Monitoring Sleep Duration Patterns in Pregnancy – a Pilot Study

Annika Haufe [1], Tiara Ratz [1], Nina Kimmich [2,3], Brigitte Leeners [1,3]*

[1]Department of Reproductive Endocrinology, University Hospital Zurich, Frauenklinikstrasse 10, 8091 Zurich, Switzerland.

[2]Department of Obstetrics, University Hospital Zurich, Frauenklinikstrasse 10, 8091 Zurich, Switzerland.

[3]University of Zurich, Rämistrasse 71, 8006 Zurich, Switzerland.

***Corresponding Author:** Brigitte Leeners, Department of Reproductive Endocrinology, University Hospital of Zurich, Frauenklinikstrasse 10, 8091 Zurich, Switzerland.

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Abstract

Background: Sleep disturbances in pregnancy are associated with adverse outcomes. Sleep monitoring in traditional laboratory settings is inconvenient and may disrupt natural sleep patterns. Modern sensor technology wearables offer a more user-friendly alternative, enabling realistic data collection through continuous measurements in the home environment.

Aim: To evaluate the use of sensors in prenatal care, we measured sleep duration throughout a physiologic pregnancy.

Materials and Methods: A prospective longitudinal cohort study involving 23 healthy pregnant women using sensor wrist devices to document sleep patterns during pregnancy. Data on stress (Perceived Stress Scale. PSS 10) and eight factors of well-being/emotions (anxious, stressed, tired, sensitive, unmotivated, calm, energized, and happy) were collected to evaluate potential associations with sleep. In addition to descriptive statistics with frequencies, proportions, and means ± SD, associations between sleep and emotions were evaluated using linear mixed models after Bonferroni correction for multiple testing.

Results: Average duration of sleep ranged between 8.42 ± 0.91 hours (gestational week 12) and 4.65 ± 1.1 hours (gestational week 40), i.e. sleep duration decreased as the pregnancy progressed. Tiredness and stress levels were high in the first trimester (scores 3.4 and 2.8), declined during the second trimester (scores 2.74 and 2.21) and increased again as the third trimester (scores 2.92 and 2.36) approached. The use of sensor wearables was well-received, allowing for high-frequency, longitudinal monitoring of sleep throughout the entire pregnancy.

Conclusion: As lack of sleep can result in adverse pregnancy outcomes, wearables equipped with sensor technology prove highly beneficial in monitoring sleep to identify risk factors early in pregnancy.

Key words: pregnancy; sleep; wearable sensor technology

Introduction

Biosensor wearables, offering the potential for high-frequency remote monitoring, are becoming increasingly significant not only in general health but also in prenatal care - a significance underscored by the impact of the COVID-19 pandemic (Bossung & Kast, 2021). Remote monitoring, especially in rural areas, can assist in detecting general health and pregnancy-related risk situations and complications. Still, continuous monitoring of physiological data in earlier stages of pregnancy has undergone little innovation, especially in low-income settings lacking access (Ryu et al., 2021).

Sleep plays a crucial role in obstetrical health, as inadequate sleep during pregnancy is linked to adverse outcomes for both the mother and the fetus. These outcomes may include severe complications such as gestational hypertension, pre-eclampsia, gestational diabetes mellitus, or preterm birth (Lu et al., 2021; Cai et al., 2017). Therefore, it is essential to identify sleep disturbances early in pregnancy and to address this topic during prenatal counseling.

Despite the well-established connection between sleep disturbances and unfavorable pregnancy outcomes, there is currently a lack of detailed information on the longitudinal development of sleep throughout pregnancy, primarily due to limitations in previous measurement techniques that did not allow sleep to be measured every night throughout an entire pregnancy.

Wearable biosensor technology presents a solution to this limitation. Prior studies have indicated that smart wristbands are a practical tool for continuous monitoring during pregnancy (Grym et al., 2019) and women have responded positively to the integration of wearable electronics in prenatal care (Runkle et al., 2019; Bossung et al., 2023). Recognizing that sleep patterns may be influenced by pregnancy as well as daily events, it is crucial to control for influencing factors such as stress experiences in these measurements.

Additionally, assessing the consequences of poor sleep is necessary to better understand its association with pregnancy complications (Balkan et al., 2024; Facco, 2011; Ding et al., 2014; Luque-Fernandez et al., 2013; Pamidi et al., 2014). To allow an early detection of risk situations, normal development of essential physiological sleep modifications during pregnancy has to be fully understood and deviations from normal patterns have to be reliably detected as early as possible. However, such associations can only be evaluated reliably when sleep patterns and disturbances can be adequately monitored. Research on the exact patterns of physiological adaptations of a woman's body has been hampered by the lack of tools allowing reliable high frequency measurements in the natural environment without interference with the conditions intended to be captured (Maugeri et al., 2023). Consequently, there is a need for maternal monitoring systems that are easy to use and accessible for physicians to better monitor the pregnancy outside of hospital or practice settings.

By using wearable biosensor technology in a home environment, we aim to (i) evaluate the development of sleep duration throughout pregnancy, (ii) to investigate the association between sleep duration and subjective tiredness, stress, and different aspects of well-being as well as (iii) to gain insight into the compliance and acceptance of pregnant women applying wearable biosensor technology.

The innovative use of such technology would enrich our understanding of normal sleep physiology during pregnancy and provide a new tool to improve research on sleep during pregnancy and its consequences on obstetrical outcomes.

Materials and Methods

Clinical data

The study was designed as a prospective observational cohort study conducted with healthy pregnant women recruited at the Department of Obstetrics of the University Hospital Zurich. Patient, fetal, and obstetrical data were routinely entered into the in house institutional obstetric database, a standardized electronic file (Perinat/Mutter pass-App, USZ, Zurich, Switzerland) serving as the expectant mother's clinical record of prenatal care. Pregnant women included in the present study received routine obstetrical care without any modification for the present study. Further details, can be found elsewhere (Bossung et al., 2023). Healthy 18- to 48-year-old pregnant women with a gestational age less than 32 weeks at inclusion and who received pregnancy care mainly or solely at our institution were included. They had to currently live in Switzerland, have sufficient German or English skills to answer questionnaires and to be willing to comply with the study protocol throughout pregnancy. Exclusion criteria were problems wearing the bracelet, difficulties in understanding the study procedures, taking medication or other substances that could affect any parameters being studied, working night shifts or frequently traveling between different time zones, or having a sleeping disorder before pregnancy.

Measurement of sleep

All women wore the Ava Fertility Tracker bracelet (version 2.0, Ava AG, Zurich, Switzerland) to measure non-invasive parameters continuously each night throughout their pregnancy (Bossung et al., 2023; Goodale et al., 2019; Shilaih et al., 2018; Shilaih et al., 2017; Zhu et al., 2021; Brun et al., 2023). Participants started their measurements from the first day of enrollment. They wore the bracelet on the dorsal side of their wrist while sleeping, always on the same arm. Every 10 seconds, physiological information was automatically saved by the bracelet.

User movements (accelerations) were used to identify sleep onset and the different sleep phases. Sleep state classification distinguished between three stages: awake, light sleep, and deep sleep. To reduce the influence of movements, the nightly recordings were filtered to include only data from light or deep sleep phases from nights with at least 4 hours of recorded data and at least 3 hours of recorded data during light or deep sleep. Time spent in light or deep sleep was counted in hours per night and the sum of both sleep phases was considered as sleep duration. Within about 2 minutes/day, data was synchronized each morning with an iPhone/ Android. Women were offered to keep the Ava bracelet as compensation for study participation.

Perceived Stress Scale (PSS 10)

To control sleep for potential confounding factors, study participants filled out an electronic version of the Perceived Stress Scale (PSS 10) in 2 to 4 weeks intervals. The PSS is an internationally validated short questionnaire with good internal validity. It is a measure of the degree to which situations in one's life are considered as stressful. Items were designed to assess how unpredictable, uncontrollable, and overloaded respondents find their lives. The scale also includes several direct queries about current levels of experienced stress. The PSS was designed for community samples with at least a junior high school education. The items are easy to understand and the response alternatives are simple. Moreover, the questions are general and therefore relatively free of content specific to any subpopulation group. The questions in the PSS ask about feelings and thoughts during the last month. Respondents are asked how often they felt a certain way (Cohen et al., 1983; Cohen, 1988).

Using five-point Likert scales, eight factors of well-being/emotions (anxious, stressed, tired, sensitive, unmotivated, calm, energized, and happy) were assessed weekly ranging from never to always (Bossung et al., 2023). These measures were dichotomized as "most of the time to always" and "sometimes to never" for the statistical analyses. The feeling of anxiety was dichotomized as "sometimes to always" and "rarely to never" due to low cell counts in the responses "most of the time" and "always".

Ethics

The study was registered in the ClinicalTrials.gov database (identifier NCT03161873). It was approved by the Local Ethical Board (BASEC-No. 2016-02241) and carried out following the Declaration of Helsinki. Before any study procedures were performed, all participants gave written informed consent.

Statistical Analyses

To describe the study sample, categorical parameters were summarized as frequency and proportion (%) and continuous parameters as mean ± SD. The weekly mean hours slept per night were aggregated per gestational week. The analyses reported here were run with additional analyses of physiological parameter patterns (i.e., wearable-measured heart rate, breathing rate, heart rate variability, and wrist skin temperature) across pregnancy (Bossung et al., 2023). The associations between emotions and sleep duration throughout pregnancy, measured as gestational age in weeks, were analyzed using linear mixed models. Firstly, bivariate models were run with the eight emotions as predictors. For negative emotions, the category indicating the lower frequency was set as reference, whereas for positive emotions, the category indicating the higher frequency was chosen as reference. All models were run, testing the fit of linear versus quadratic time functions, the inclusion of a random slope, the inclusion of a time*emotion interaction term and the model with the best fit was selected using Akaike's Information Criterion. Secondly, a multivariable linear mixed model was run, including all emotions. All hypotheses were two-tailed and a Bonferroni correction was applied to account for multiple testing, leading to a p-value <.001 being considered statistically significant. All statistical analyses were performed using R (version 4.1.1) via RStudio. To support trend interpretation, line and boxplots were produced to visualize the sleep time trajectory patterns and their variability throughout pregnancy.

In addition to descriptive statistics with frequencies, proportions, and means ± SD, associations between sleep and emotions were evaluated using linear mixed models after Bonferroni correction for multiple testing.

Results

32 pregnant women were initially included in the study. Of those, eight withdrew their participation for personal reasons before the initiation of measurements. Another woman was excluded due to an implanted cardiac device. This left 23 of 32 women (72%) for analysis. The characteristics of these 23 women are presented in Table 1.

	N=23
Age (years)	34.3 ± 4.0
BMI at the beginning of pregnancy (kg/m^2)	23.3 ± 3.5
Ethnic background (N/%)	
- Caucasian	17 (73.9)
- Mediterranean	4 (17.4)
- Oriental	1 (4.3)
- Afro-Caribbean	1 (4.3)
Parity (N/%)	
- 1	17 (73.9)
- 2	5 (21.7)
- 3	1 (4.3)
Gestational age at initiation of study (days)	101 ± 36
Duration of study participation (days)	87 ± 58
Gestational age at birth (days)	272 ± 17

Table 1: Characteristics of study participants

Summary of characteristics of final study participants, results as mean ± SD, total number and %.

Measurements started at gestational week 8 and continued up until gestational week 40. Average duration of sleep ranged between 8.42 ± 0.91 hours (gestational week 12) and 4.65 ± 1.1 hours (gestational week 40). Figure 1 shows the number of sleeping hours as measured by the electronic wearable in relation to the gestational week. The boldness of the line represents the number of data synced on the respective day of the pregnancy. The figure demonstrates that sleep duration tends to decrease throughout pregnancy.

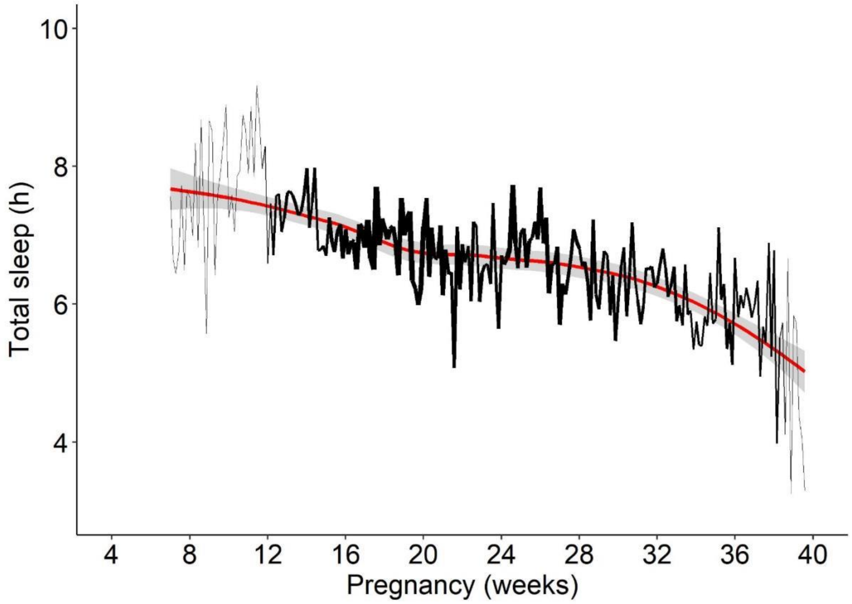

Figure 1: Sleep duration throughout of pregnancy

Tiredness decreased until gestational week 26 and then slightly increased again during the third trimester (Figure 2).

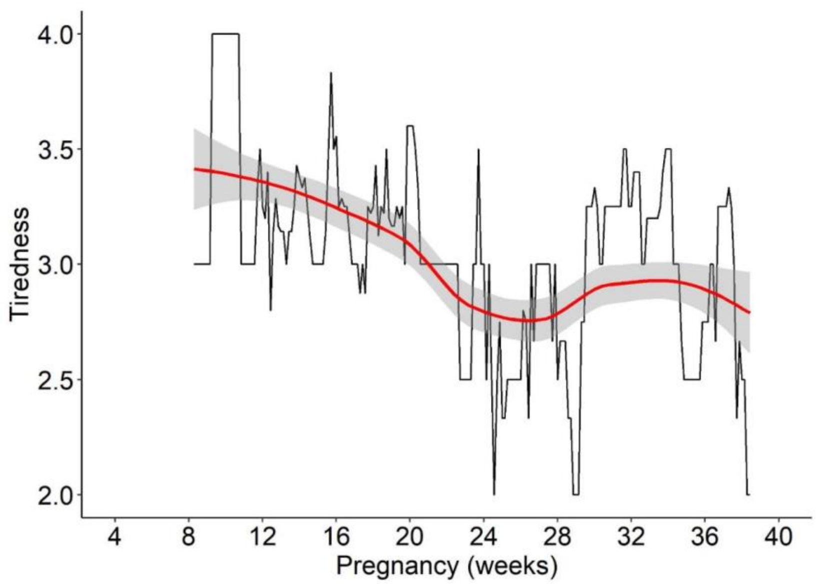

Figure 2: Tiredness over the course of pregnancy

Like tiredness, stress increased during the first trimester (Figure 3).

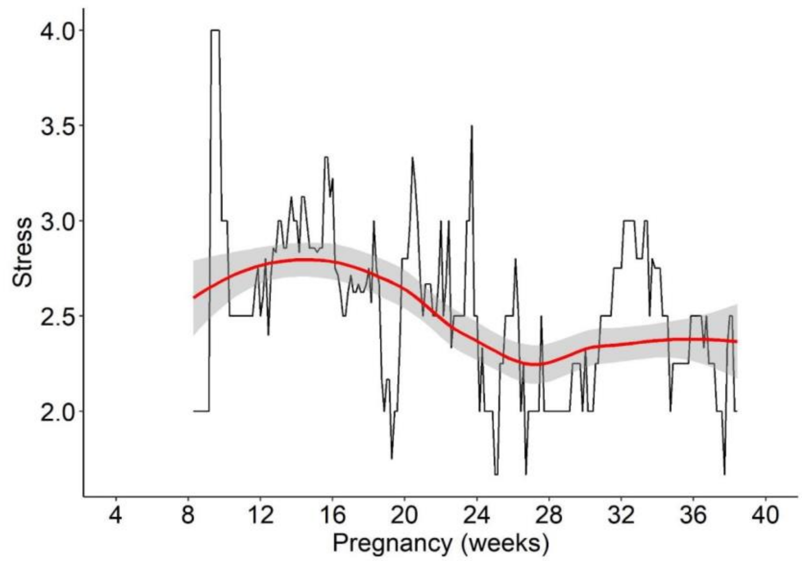

Figure 3: Stress over the course of pregnancy

During the second trimester, stress decreased and only started to increase again in the third trimester and when approaching the due date. However, the stress level was not as high as during the first trimester.

The effect of subjective emotions on the trajectory of nightly sleep time is presented in Table 2.

	Regression coefficient [95% Confidence Interval]	p-value
Model 1: anxiety		
Intercept	*7.68 [7.24, 8.29]*	-
Gestational age (weeks)	-0.04 -0.06, -0.01]	0.015
Anxious (sometimes to always)	-0.12 [-0.33, 0.14]	0.349
Gestational age * anxious	-	-
Model 2: stress		
Intercept	*7.61 [7.19, 8.21]*	-
Gestational age (weeks)	-0.04 [-0.06, -0.01]	0.015
Stressed (most of the time to always)	0.17 [-0.15, 0.48]	0.297
Gestational age * stressed	-	-
Model 3: tiredness[a]		
Intercept	*7.60 [7.10, 8.18]*	-
Gestational age (weeks)	-0.03 [-0.06, -0.01]	0.035
Tired (most of the time to always)	0.07 [0.22, 0.28]	0.579
Gestational age * tired	-	-
Model 4: sensitivity		
Intercept	*7.73 [7.22, 8.45]*	-
Gestational age (weeks)	-0.04 [-0.07, -0.02]	0.009
Sensitive (most of the time to always)	-0.66 [-1.72, 0.31]	0.217
Gestational age * sensitive	0.05 [-0.01, 0.20]	0.107
Model 5: unmotivated[a]		
Intercept	*7.90 [7.31, 8.58]*	-
Gestational age (weeks)	-0.04 [-0.07, -0.01]	0.016

Unmotivated (most of the time to always)	-1.33 [-2.82, 0.03]	0.083
Gestational age * unmotivated	0.06 [0.00, 0.13]	0.072
Model 6: calm[a]		
Intercept	*7.61 [7.04, 8.18]*	-
Gestational age (weeks)	-0.03 [-0.06, 0.00]	0.042
Calm (sometimes to never)	0.15 [-0.41, 0.49]	0.532
Gestational age * calm	-	-
Model 7: energized		
Intercept	*8.37 [7.83, 8.96]*	-
Gestational age (weeks)	-0.04 [-0.06, -0.01]	0.022
Energized (sometimes to never)	-0.34 [-0.68, -0.05]	0.947
Gestational age * energized	-	-
Model 8: happiness[a]		
Intercept	*7.64 [7.07, 8.16]*	-
Gestational age (weeks)	-0.04 [-0.06, 0.00]	0.027
Happy (sometimes to never)	-0.03 [-0.69, 0.91]	0.937
Gestational age * happy	0.01 [-0.04, 0.04]	0.692
Model 9: multivariate model[a]		
Intercept	*8.07 [7.41, 8.81]*	-
Gestational age (weeks)	-0.05 [-0.09, -0.02]	0.006
Anxious (sometimes to always)	-0.31 [-0.58, -0.02]	0.045
Stressed (most of the time to always)	0.20 [-0.16, 0.59]	0.314
Tired (most of the time to always)	-0.01 [-0.30, 0.26]	0.956
Sensitive (most of the time to always)	-0.83 [-1.88, 0.27]	0.148
Unmotivated (most of the time to always)	-1.60 [-3.29, -0.27]	0.052
Calm (sometimes to never)	0.11 [-0.40, 0.50]	0.622
Happy (sometimes to never)	0.20 [-0.56, 1.25]	0.667
Gestational age * anxious	-	-
Gestational age * stressed	-	-
Gestational age * tired	-	-
Gestational age * sensitive	0.05 [-0.01, 0.10]	0.095
Gestational age * unmotivated	0.08 [0.02, 0.15]	0.039
Gestational age * calm	-	-
Gestational age * happy	-0.01 [-0.05, 0.03]	0.812

Note. The model with the best fit was selected, respectively. All models included a linear function for time (gestational age in weeks). The models were tested for multicollinearity (based on correlation and variance inflation factor). The emotion "energized" was excluded from the multivariate model because its inclusion reduces the sample size from n=19 to n=8. Bonferroni correction was applied to account for multiple testing, resulting in a required significance level of p<0.001. Statistically significant coefficients are highlighted in bold.

[a] Model included a random slope.

Table 2: Results from bivariate and multivariate linear mixed models regarding the effect of subjective emotions on the trajectory of nightly sleep time in hours during pregnancy

For all measured emotions (i.e., anxiety, stress, tiredness, sensitivity, motivation, calmness, energy, and happiness), there was no statistically significant effect on nightly sleep time after applying the Bonferroni correction. Neither the univariate analysis nor the multivariate analysis demonstrated any significant interaction between gestational age in weeks and one of the emotions. The multivariate analysis indicated that anxious women (sometimes to always on the perceived stress scale) may sleep less compared to less anxious women. Unmotivated women may sleep more in advanced gestational weeks (as opposed to earlier weeks of pregnancy) compared to women who are less frequently unmotivated. However, the results of this study cannot sufficiently support the hypothesis of an association between emotions and sleep duration throughout pregnancy.

Discussion

The current study demonstrates that wearable sensors may serve as a valuable tool for continuous sleep monitoring in prenatal care. Wearable sensors are increasingly used to track physical fitness, physiology, and health metrics (Goodale et al., 2019; Sen-Gupta et al., 2019). They have applications not only in sleep monitoring but also in medical domains such as cardiovascular regulation (Conraads et al., 2014; P. Renevey et al., 2018; Schäfer & Vagedes, 2013), intensive care medicine (Michard et al., 2017), neurodegenerative diseases (Moon et al., 2017), and oncology (Gresham et al., 2018). By enabling frequent or continuous measurements of physiological parameters, this technology aids in the early detection of health risk situations and may register clinical deterioration earlier than standard vital sign monitoring allows (Gresham et al., 2018; Garbern et al., 2019; Weenk et al., 2020). The ease of integrating these measurements into home routines facilitates user-friendly data collection under real-life conditions. In light of these advancements, wearable sensor technology plays an increasingly crucial role in women's health, contributing to heightened awareness of chronic diseases and supporting mental and reproductive health (Runkle et al., 2019; Goodale et al., 2019; Derbyshire & Dancey, 2013; Shilaih et al., 2018; Shilaih et al., 2017; Zhu et al., 2021).

Other findings support that wearable sensors are a promising tool in maternity care (Grym et al., 2019; Bossung et al., 2023; Atzmon et al., 2021; Brun et al., 2023) and that monitoring physiological parameters may allow early detection of pregnancy complications in a more advanced way than ever before (Runkle et al., 2019; Bossung et al., 2023). In addition to previous findings, the present study demonstrates that such wearables can also be used to monitor sleep during pregnancy.

In our study, women slept less as pregnancy progressed and the emotions assessed did not correlate with changes in sleep during pregnancy. It is more likely that pregnancy-related physiological changes in the cardiovascular, hematological, renal, respiratory, gastrointestinal, metabolic, and endocrine systems, or anatomical changes due to the growing fetus, induce changes in sleep patterns (Haufe & Leeners, 2023; Haufe et al., 2022; Costantine, 2014; Pengo et al., 2018). As estrogen and progesterone are greatly increased in pregnancy and receptors for both hormones are localized in sleep/wake regulatory nuclei in the hypothalamus, where they influence sleep's circadian and homeostatic regulation (Mong et al., 2011; Deurveilher et al., 2011), they may also affect sleep architecture. The synergistic effect of all these factors can be captured by wearable sensors and made available for prenatal care, so that sleep disturbance, a known risk factor for adverse obstetric outcomes (Balkan et al., 2024; Facco, 2011; Ding et al., 2014; Luque-Fernandez et al., 2013; Pamidi et al., 2014) can be detected early. As women during pregnancy are particularly motivated to support a positive outcome, and as pregnancy is a limited time period, the conditions for reliable longitudinal data collection every night are ideal for the use of wearable sensors, as confirmed by the results of our study.

Our study examined sleep duration and is, to our knowledge, the first to provide longitudinal high-frequency information on the development of sleep patterns during pregnancy. In line with our findings, other studies have reported more nocturnal sleep disturbances in pregnant women, which increased during pregnancy (Moline et al., 2003; Mindell & Jacobson, 2000). In addition, deep sleep and REM sleep decreased and sleep quality worsened as pregnancy progressed (Izci-Balserak et al., 2018; Sedov et al., 2018). As poor sleep quality has been reported to be associated with adverse obstetric outcomes (Lu et al., 2021; Cai et al., 2017), longitudinal sleep monitoring using a convenient wearable sensor is a valuable resource for safe prenatal care. Specific primary sleep disorders, such as obstructive sleep apnea or restless legs syndrome, also increase during pregnancy (Silvestri & Aricò, 2019) and may be additional factors that could be detected and monitored by wearable sensors.

In addition to sleep disturbances, other potential causes of fatigue in pregnancy include back, hip and pelvic pain related to the extra weight to be carried, or increased nocturnal micturition (Parboosingh & Doig, 1973). Increased progesterone levels, reaching up to 300 ng/ml in the third trimester, can cause fatigue because progesterone has sedative effects (Lancel et al., 1996; Abbassi-Ghanavati et al., 2009). The higher level of stress in the first trimester is probably due to the high percentage of miscarriages in the first trimester and the resulting uncertainty about the pregnancy (Cohain et al., 2017). Hormonal changes during the first trimester also correlate with increased cortisol levels (Fan et al., 2009).

This is, to our knowledge, the only study reliably investigating sleep duration in the context of different influencing factors throughout pregnancy. Methodological bias may result from the small sample size and the fact that in this first pilot study we only included healthy women. A future study investigating a larger sample size should also include factors influencing sleep, such as age, and control for sleep quality before pregnancy. Besides emotions, exercise, food intake, or sexual intercourse could have influenced sleep. Despite the study's prospective design, our data did not permit any conclusion on how far tiredness and stress were a cause or a consequence for sleep duration. In addition to sleep duration, it would have been interesting to evaluate other sleep characteristics such as specific sleep phases or sleep quality. To investigate the effect of factors such as hospitalization, specific pregnancy complications, fever, or inflammation etc., a larger sample is needed.

Conclusion

Sleep duration, as an indicator of pregnancy complications, changed throughout pregnancy and was robust to various emotional factors. Fatigue and stress levels fluctuated during pregnancy, which should be included in medical counselling.

This prospective proof-of-principle study demonstrated that wearable sensors are a valuable tool for collecting continuous, longitudinal, high-quality data in everyday conditions. Wearable sensors help to better understand normal physiology during pregnancy and further evaluate changes in these patterns, thereby helping to detect and prevent pregnancy complications.

Ethical approval: Ethic committee Canton Zurich, Switzerland, BASEC -Nr 2016-02241

Author contribution: Conceptualization, A.H. and B.L.; formal analysis, T.R., A.H., B.L.; investigation, N.K.; writing—original draft preparation, A.H. and B.L.; writing—review and editing, A.H., N.K., B.L. and T.R. All authors have read and agreed to the final version of the manuscript.

Data availability statement: Data will be available upon reasonable request.

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Conflict of Interest disclosure: The Department of Reproductive Endocrinology employed Tiara Ratz with the support of an Innosuisse Grant. The Innosuisse grant was dedicated to support clinical studies to develop the wearable device in cooperation with Ava AG. Brigitte Leeners was affiliated with Ava AG as a member of the advisory board.

Ethics approval statement: It was approved by the Local Ethical Board (BASEC-No. 2016-02241) and carried out in accordance with the Declaration of Helsinki.

Patient consent statement: Before any study procedures were performed, all participants gave written informed consent.

Permission to reproduce material from other sources: not applicable

Clinical trial registration: The study was registered in the ClinicalTrials.gov database (identifier NCT03161873).

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