Workplace Health Promotion: mHealth as a preventive mediator between psychosocial workplace characteristics and well-being at work

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Abstract. High levels of mental work stress have significant implications for employees and employers. Epidemiological studies consistently show links between high levels of work stress and self-reported mental and physical health problems, including depression, anxiety, cardiovascular disease, and type 2 diabetes. Therefore, helping employees to cope with mental stress is becoming more and more important. The present study examines the mediating influence of mobile health (mHealth) technology use on the relationship between psychosocial workplace characteristics and employee well-being. The investigated sample consisted of 2946 employed working adults from four different countries (United Kingdom, United States, Canada and Australia) who used a mHealth application between 2019 and 2021. The results indicate a positive indirect relationship between psychosocial workplace characteristics, mHealth use, and employee well-being, suggesting that mHealth use can have a positive impact on employee well-being and help them cope with psychosocial demands at work. The results further suggest an influence of gender and age. In the long term, mHealth technologies may provide support in everyday work to help manage psychosocial demands.

Keywords: Mental stress, Psychosocial demands, Employee well-being, mHealth.

1 Introduction

Increasing digitization and the emergence of new forms of work organization has led to profound changes in our working world. Looking at the effects of these changes on our work and in particular on our work tasks, it is noticeable that mental stress is gaining in importance. The reason for this is, on the one hand, that the mental demands at work are increasing, e.g., due to work intensification, accelerated communication, dissolution of boundaries and constant reachability. On the other hand, there is a change in the actual work tasks, from formerly rather physical activities to increasingly cognitive and informational work demands [1–3].

One effect is increasing absences from work due to illness. In recent years, absenteeism, which refers to “the failure to report to work as scheduled” [4], especially due to mental illness, has increased rapidly. Mental health problems have become one of the leading causes for absenteeism from work and early retirement all over the European Region [5]. In the United Kingdom, the overall annual cost of work-related mental stress to employers is estimated to be over £26 billion, driven by increased staff turnover, performance degradation, and absenteeism [6]. In Germany, sick leave due to mental illness has more than doubled in the last 14 years. Whereas in 2006 every employed person was on sick leave for an average of 1.4 days due to a mental illness, by 2020 this number had risen to 2.99 days per employed person per year [7]. Absenteeism contributes significantly to lower productivity in the workplace and incurs substantial financial costs through health insurance claims, overtime pay, and legal claims [8]. Even though it is not only the changed working conditions and work demands that have an influence on these increased numbers of mental illnesses, there is strong evidence to believe that high mental stress in the workplace has a significant impact on the health of employees.

1.1 Psychosocial Workplace Conditions

Epidemiological studies consistently show links between high mental work demands and self-reported mental and physical health problems, including depression, anxiety, cardiovascular disease, and type 2 diabetes [9]. A poor psychosocial work environment has been found to increase the risk of sick leave and disability pensions not only due to mental disorders [10, 11] but also physical health issues [12]. Work and health are closely related, so that health and the ability to work have a bidirectional interaction and can influence each other. In addition to monetary livelihood, the positive effects of work include, for example, daily structuring, social relationships, appreciation and self-fulfilment. However, possible negative or unhealthy effects of work may result from excessive physical and psychological stress at work. [13].

A number of models have been established that are suitable for describing mental stress and strain at the workplace. The basis of the ISO standard 10075, which describes work design guidelines regarding mental workload. is the stress-strain model [14]. Here, mental stress is understood as the "totality of all assessable influences that act on a person from the outside and affect him psychologically", while mental strain is understood as the "direct effect of mental stress within the individual depending on his or her current condition". Whereas physical strain describes the effects of stress on the muscular and cardiovascular systems, mental strain is the totality of all detectable influences that have a mental, e.g. cognitive and emotional effect on the working person. The terms are value-neutral, i.e. positive and/or negative effects are possible, depending on the individual reaction of the working person to the stress.

Another highly influential model in research on the relationship between work and health is the Job-Demand-Control (JDC) model, also known as job strain model. The JDC model identifies two critical aspects of the work situation: job demands and job control [15]. In the 1980s, a social dimension was added to the model [16, 17] resulting in the Job-Demand-Control-Support (JDCS) model. Job demands refer to workload and have been operationalized mainly in terms of time pressure and role conflict, whereas job control refers to the person's ability to control his or her work activities. The model states that the most negative reactions in the form of psychological strain and illness are produced in a work environment with high demands and low control. On the other hand, high demands combined with high control lead to more learning, motivation, and skill development. Therefore, control over one's own work can mitigate the consequences of high demands. In addition, the extended model includes social integration as a crucial aspect in the development of workers' health. The JDCS model characterizes the most harmful work situation as having high demands, low control, and low support (or isolation).

One step further goes the Job Demands-Resources (JD-R) model [18, 19]. The JD-R model assumes that employee well-being is explained by work demands and work resources. High work demands deplete workers' mental and physical resources and therefore lead to energy depletion and health problems. In contrast, work resources promote engagement and off-the-job performance. Several studies have shown that work resources can buffer the effects of work demands on stress responses [19, 20]. Moreover, research has confirmed that work resources have a motivational potential especially when work demands are high [21]. Workplace resources are defined as "anything perceived by the individual to help attain his or her goals" [22] and enable employees to successfully accomplish their tasks and goals while enhancing their well-being and performance [19]. According to the JD-R model, resources at the workplace have the potential to increase well-being and to mitigate or even change the negative effects of work demands [18]. While psychological factors such as supportive managers and colleagues or role clarity are generally understood as such resources, the question arises as to what extent technologies exert an influence on the relationship of job demands and the employee health outcomes. This paper aims to provide a first approach to consider the use of mHealth technology in the context of psychosocial workplace characteristics and health outcomes.

1.2 Mobile Health Technology at Work

Mobile health (mHealth) technologies have rapidly gained popularity among the general population. MHealth technologies include wearable monitoring devices or trackers and smartphone applications (apps) designed to help people manage their own health and well-being. The potential value of mHealth in health promotion lies in its widespread appeal, accessibility and ability to reach large populations at a low cost. Not surprisingly, current research has focused on the potential benefits of mobile health apps for health prevention and care [23–25]. Mobile health has also become relevant from a legal and policy perspective, for example, the European Commission's e-health strategy identifies mobile health applications as playing a central role in the e-health action plan 2012-2020 [26]. Although mHealth apps have been a great success in both the private sector and professional healthcare [27], their use in professional settings presents difficulties. However, work is an important factor for health. Individual health behaviours are shaped by workplace culture and values, there is no clear dividing line between "work-related" and "non-work-related" illnesses, as our health behaviours span these environments and cannot be artificially separated [28]. More and more employers establish workplace health promotion programs responding to the (mental) health needs of their employees by developing and implementing workplace (mental) health programs that focus on providing health promotion services to improve employee productivity by optimizing employee health [29]. The most common outcomes related to mHealth technology at work are less absenteeism, higher psychological well-being and engagement as well as higher productivity. For example, research has shown that digital interventions can reduce depression, anxiety, and stress in the workplace [30]. Furthermore, there is evidence of a positive effect of mHealth use and psychological well-being at work [31], as well as a positive impact of mHealth interventions on employee productivity and engagement immediately and in the medium term after use [32]. While prior research has analysed direct effects of mHealth usage and health outcome, this paper now seeks to address the mediating influence of mHealth technologies in the context of psychosocial workplace characteristics and health outcomes.

1.3 Research Objective

Research has demonstrated the effectiveness of mHealth technology on the consequences of psychological stress in the workplace - direct relationships to absenteeism, well-being, and productivity have been observed. However, previous research has focused on the direct relationship to health outcomes. This paper focuses on the use of mHealth technologies in relation to psychosocial workplace characteristics and health outcomes, and seeks to examine the mediating influence of mHealth technologies on the relationship of psychosocial workplace characteristics and health outcomes. This is a step toward understanding the benefits of mobile health technologies in the work context and how they can mitigate or even change the negative effects of psychosocial work demands. Therefore, the direct relationship between psychosocial workplace characteristics and employee well-being, including the mediating influence of usage behaviour of a mHealth app, is analysed. Thus, the research question that was investigated was:
RQ1: Does the use of a mHealth app mediate the relationship between psychosocial workplace characteristics and employee well-being?

2 Method

2.1 Procedure of data collection

The evaluated database consists of persons who used the “HeadUp” health app between 2019 and 2021 [33]. The app is used to track the user's health data to generate customized interventions and tips based on the results and is used in terms of company´s health intervention program. To do this, the app initially asks users a short questionnaire to get to know health relevant parameters covering topics like workplace and work environment, family and friends, physical and mental illnesses as well as previous illnesses in the family, nutrition habits, hobbies and leisure activities as well as demographic data such as gender and age. These questions are asked to understand and take then into account in terms of the intervention advice. The app also offers the ability to set individual goals so that the app can assist in achieving them, such as increasing activity, learning better sleep habits, or focusing on one's mental health. Furthermore, if the user agrees, it can record daily data on e.g. exercise and sleep habits and generate suitable interventions and tips, motivating and supporting the user in living a healthy life.

The app was available via App- and Google-Play Store in English. At the moment the app is still available as a white label solution companies could integrate into their health programs.

Data was retrieved from the app provider in an anonymous form as secondary data. The subjects consented to the anonymized analysis of the data. As described, the app was publicly available, which is why participants from all over the world were recorded. For the present analysis, to ensure sufficient data quality, only English-speaking countries with a sufficient sample size and western cultural background were included in the analysis in order to rule out linguistic misunderstandings and to maintain comparability of data. The procedure of data processing is explained in the following section.

2.2 Pre-processing of data set used

To ensure sufficient data quality investigated data was filtered for English-speaking countries with a sufficient sample size (> 100) and western cultural background were included in the analysis in order to rule out linguistic misunderstandings and to maintain comparability of data. Person living in an English-speaking country using the app in English language were expected to have sufficient command of the language to adequately use and understand the app. However, it needs to be mentioned that therefore not necessarily only native speakers were included in this analysis.

The app's measured data cover 110 different countries; after excluding all countries that did not recognize English as a national language, 17 countries remained for further analysis. Since this publication is particularly focused on working conditions and worker health, which vary greatly depending on the country's level of development, only developed countries were included in the analysis. The selection of developed countries was based on the Human Development Report 2020 [34]. After this step, eight countries remained in the analysis. The next step involves the analysis of the sample size per country. A threshold of at least 100 subjects per country was used to obtain an appropriate sample size for the following structural equation model [35]. In addition, at the individual level, only individuals who were employed at the time of app use were selected, as the analysis focuses on workplace characteristics. Four countries remained in the analysis: N = 1527 respondents from the United Kingdom, N = 713 from Canada, N = 550 from the United States, and N = 469 from Australia (in total: N = 3259 individuals). The final step involves the identification of outliers, using the one-dimensional box-plot method [36]. Outliers are defined as such if they lie outside the whiskers of the box plot diagram, i.e. are larger than 1.5 times the quartile distance in both directions. The present data set contains only outliers above the upper whisker. For the analysis of the outliers, the variable of usage frequency was used, which means that users who opened the app excessively more often in a short period of time than most of the users were excluded from the analysis. The sample used breaks down into N = 431 users living in Australia, further N = 482 are residents of the United States, N = 635 are living in Canada and N = 1398 of the users are residents of the United Kingdom (in total: N = 2946 individuals).

2.3 Measures

The app contains two scales that are relevant for the following analysis.
The two scales used are composed of a scale for recording psychosocial workplace characteristics with five items and the general employee well-being using the WHO-5 questionnaire with five items too. In addition, log files of the app were used to analyse usage behaviour. A detailed description follows below.

Psychosocial workplace characteristics. The initial questionnaire of the app included five items to assess aspects of the psychosocial work characteristics are used, namely work demands (“My job is more stressful than I ever imagined”), control over one´s own work (“Have freedom to decide how I do my work”), work satisfaction (“I´m satisfied with my job”), support of colleagues (“I feel comfortable asking for support”) and support of the supervisor (“My boss tries to understand me”). The dimensions were selected based on the Job Demand-Control-(Support) model [16]. Each dimension is asked with a single item, which was to be answered on a 5-point Likert scale, subjects could indicate whether they *strongly agree* (5), *agree* (4), were *neutral* (3), *disagreed* (2) or *strongly disagreed* (1) with the statement.

Well-Being. The 5-item World Health Organization Well-Being Index (WHO-5) is a short and generic global rating scale measuring subjective well-being. The WHO-5 was derived from the WHO-10 [37], which in turn was derived from a 28-item rating scale [38] used in a WHO multicentre study in 8 different European countries [39]. The WHO-5 items are: “I have felt cheerful and in good spirits”, “I have felt calm and relaxed”, “I have felt active and vigorous”, “I woke up feeling fresh and rested” and “My daily life has been filled with things that interest me”. The respondent is asked to rate how well each of the five statements applies to him or her when considering the last 14 days. Each of the five items is scored from 5 (all of the time) to 0 (none of the time). From the items a raw score can be calculated (addition of the item values), which ranges from 0 (absence of well-being) to 25 (maximal well-being).

App usage. Users' log files were analysed to determine how often the app was used. The actual opening of the app was calculated in relation to the months of use in order to be able to map both the time of use and the actual active use.

2.4 Participants

The analysed sample consisted of 2946 employed working adults. On average, the subjects were 39.69 years old (SD = 11.393 years). The sample represents an over-representation of female participants (64.8 %) and breaks down into 14.6 % participants living in Australia (N = 431), further 16.4 % are residents of the United States (N = 482), 21.6% are living in Canada (N = 635) and finally 47.5% of the participants are residents of the United Kingdom (N = 1398). The following Table 1 gives an overview of the sample demographics.

Table 1. Descriptive statistics for the sample demographics.

Female (n, %)	1910 (64.8)
Male (n, %)	1036 (35.2)
Age in years (*M*, *SD*)	39.69 (11.393)
Education level	
School graduation (n, %)	896 (30.4)
Training Courses / Diploma (n, %)	1009 (34.2)
University degree (n, %)	971 (33.0)
PhD (n, %)	29 (1.0)
Country	
Australia (n, %)	431 (14.6)
Canada (n, %)	635 (21.6)
United Kingdom (n, %)	1398 (47.5)
United States (n, %)	482 (16.4)

2.5 Procedure of calculation and evaluation of results

To answer hypotheses and research questions different methods were used. Exploratory factor analyses (principal component analyses) and reliability analyses were calculated to verify the structure and internal consistency of the scales, using IBM SPSS Statistics version 25 was used. The research question was addressed by calculating a simple mediation model using R version 4.0.5 and package lavaan, version 0.6-9. In case of non-normally distributed data, the Satorra-Bentler scaled chi-squared test was calculated as it is robust to the violation. To make the model more robust bootstrapping with 5000 samples was used. To analyse indirect effects, the product terms of latent variables are calculated [40]. The fit of the model was evaluated using $\chi 2$, Comparative Fit Index (CFI), Root Mean Square Error of Approximation (RMSEA) and Standardized Root Mean Square Residual (SRMR) [40]. CFI ≈ 0.95 describes a good model fit, a perfect fit would correspond to a value of one, RMSEA-values ≥ 0.10 are described as unacceptable for samples > 250 data points [41]. In order to quantify the correlation of the latent variables without the influence of the mediator, Pearson correlation coefficients were calculated. The effect size of the correlation is based on the following classification: $r = .10$ describes a small effect, $r = .30$ a medium effect and $r = .50$ a large effect [42]. In order to take into account any influences of demographic data, these were examined beforehand by means of correlation analyses, t-tests and ANOVAs. It was examined, on the one hand, whether age has an influence (correlation analysis), or if gender (t-test), or the country significantly affects the variables psychosocial workplace characteristics, mHealth usage and well-being.

3 Results

3.1 Scale verification and descriptive statistics

Principal Component Analysis. As described, psychosocial workplace characteristics were measured using five items. To verify the structure and internal consistency a Principal Component Analysis (PCA) was calculated to extract the most important independent factors. The Kaiser–Meyer–Olkin measure of sampling adequacy is .764, representing a relatively good factor analysis, and Bartlett's test of Sphericity is significant ($p < .001$), indicating that correlations between items were sufficiently large for performing a PCA. Only factors with eigenvalues ≥ 1 were considered following the Kaiser-Guttman criterion [43, 44]. Examination of Kaiser's criteria and the scree-plot yielded empirical justification for retaining one factor with eigenvalues exceeding one, which accounts for 48.396 of the total variance.

Reliability analysis. For reliability analysis, Cronbach's alpha was calculated to assess the internal consistency of the psychosocial workplace characteristics. The internal consistency of the scale is satisfying, with Cronbach's $\alpha = .721$, and above the threshold following Schmitt (1996). The scale used to assess well-being was the WHO-5 questionnaire, which has already been scientifically studied in numerous cases. A factor analysis was therefore not calculated, but a reliability analysis was performed. The internal consistency of the scale is satisfactory with Cronbach's $\alpha = .881$ [45]. Both scales are not normally distributed according to Kolmogorov-Smirnov test ($p < .05$). Therefore, in the following analysis correction procedures such as Satorra-Bentler's scaled chi-squared test are used, as it is robust to non-normally distributed data [46].

Descriptive statistics. The descriptive statistics show that general well-being is evaluated rather positively ($M = 14.23$, $SD = 5.00$); the same applies to the psychosocial workplace characteristics ($M = 3.574$, $SD = 0.691$). Users have used the app for 390 days on average ($SD = 219.207$ days) and opened the app on average every two days. A more detailed overview of the descriptive statistics can be found in the following Table 2. The number of responses per item/scale varies because the subjects were not forced to answer all items.

Table 2. Scale verification and descriptive statistics.

	α	M	SD	Min.	Max.
Well-being	.881	14.23	5.000	0	25
Psychosocial Workplace Characteristics	.721	3.574	0.691	1	5
App - Days of Usage [days]	-	390.080	219.207	1.000	787.000
App – Foregrounded [number of times]	-	109.970	182.095	0	2500.000
App - Usage per Day [number of times/days]	-	0.40	0.39	0.00	1.71

Note. α =Cronbach's Alpha, M=Mean value; SD=Standard Deviation, "Days of Usage" represents the number of days the app was installed on the smartphone, "Foregrounded" represents the number of times the app was opened by the user, "Usage per Days" represents Foregrounded/Days of Usage.

3.2 Pre-Analysis for model development

Correlation Analyses. In a first step, in order to quantify the correlation of the latent variables without the influence of the mediators, Pearson correlation coefficients were calculated. Employee well-being and usage behaviour are significantly positively correlated ($r = .158$, $p < .001$, $n = 2941$), as well as well-being is also significantly positively correlated with psychosocial workplace characteristics ($r = .296$, $p < .001$, $n = 2915$). Both correlations show small effects [47].

To determine whether age needs to be included in the model as a control variable, a correlation analysis was used to examine the extent to which correlations exist between age and the factors under study. Age correlates significantly with all variables studied ($p < .05$). While the effects are small in all cases, well-being is most strongly affected by age, with the other two variables only slightly affected. A more detailed overview of the correlation analyses can be found in the following Table 3.

Table 3. Pearson´s correlations coefficients.

	Age	Well-being	Usage Behaviour	Work Characteristics
Age	1			
Well-being	.189**	1		
Usage Behaviour	.093**	.158**	1	
Psychosocial workplace Characteristics	.088**	.296**	0.036	1

Note. **. Correlation is significant at the 0.01 level (2-tailed).

Country-specific differences. In the following, differences with regard to countries have been examined in order to be able to include corresponding influences in the mediation analysis. A single factor analysis of variance was calculated, which is robust against the already described violation of the normal distribution [48, 49]. Homogeneity of variances was asserted using Levene's Test, which showed that equal variances could be assumed in all cases ($p > .05$). For both general well-being and app usage behaviour, no significant differences can be identified in relation to the different countries. In contrast, however, significant differences emerge with respect to psychosocial workplace characteristics: $F(3, 2913) = 2.654$; $p = .047$; $\eta^2 = .003$. Bonferroni post-hoc analysis revealed a significant difference ($p < .001$) only between psychosocial workplace characteristics of the United States and United Kingdom. Employees from the United States evaluated their psychosocial workplace characteristics significantly worse than users from the United Kingdom ($p = .034$). However, the effect size is very low ($\eta^2 = .003$), which is why country-specific differences are not further considered in the mediation model.

Gender specific differences. Finally, gender specific differences are examined using an unpaired t-test. The t-test is robust to violation of the normal distribution [50, 51]. Homogeneity of variances was asserted using Levene's Test, which shows that variances are equal ($p > .05$). Significant differences are found for all variables studied. Male employees' rate their psychosocial working conditions significantly worse than female employees' rate, but rate their general well-being significantly better. Male users used the app significantly less often than female user. The effect sizes are associated with moderate to high effects, which is why gender differences are further analysed in the mediation model. A more detailed overview of the unpaired t-Test is given in the following Table 4.

Table 4. Unpaired t-Test

	M (SD)	Statistics	p-value	Cohen´s d
Well-being	Female: 13.76 (4.998) Male: 15.10 (4.890)	t(2912) = -3.247	< .001	0.690
Usage Behaviour [times/days]	Female: 0.378 (0.378) Male: 0.451 (0.416)	t(2938) = -4.827	< .001	0.392
Psychosocial workplace Characteristics	Female: 3.544 (0.692) Male: 3.682 (0.416)	t(2943) = -7.007	< .001	4.960

Note. M=Mean value; SD=Standard deviation.

3.3 Mediation Model

Finally, the mediating influence of mHealth use on the relationship between psychosocial workplace characteristics and well-being was examined. Responses from 2910 subjects were included in the analysis. Following the findings on differences between female and male employees, group differences were included in the analysis. Furthermore, employee age was included as a control variable. First, the entire simple mediation model shows with CFI(r) = .937, RMSEA(r) = .075 and SRMR = .034 a reasonable fit to the data, even if the CFI is somewhat low. The Chi² Test, on the other hand, showed a significant result, $\chi 2(13) = 200.267$, $p < .001$, indicating, that the predicted model and observed data differ significantly. However, since this may be attributable to the large sample size and by the size of the correlations in the model [52]. It was decided to proceed with the mediation analysis based on the other indicators pointing to a good fit

In the following, the standardized coefficients (β) are reported to be able to ensure comparability of the groups. For both groups, female (f) and male (m) employees, an effect of psychosocial workplace characteristics on employee well-being was observed, with the effect being stronger for male employees ($\beta_m = .402$, $\beta_f = .306$; $p < .001$). In contrast, psychosocial workplace characteristics do not significantly predict the mediator ($\beta_m = .027$ $\beta_f = .022$; $p > .05$). Nonetheless, in both groups, mHealth app usage behaviour is in turn significantly related to subjective well-being, whereby differences between male and female employees are observed. While the effect size is negligible for male employees, a clear relationship is evident for female employees ($\beta_m = .097$, $\beta_f = .306$; $p < .001$). As described, age was used as a control variable. There are significant relationships for both groups with regard to psychological workplace characteristics and well-being, as well as a significant relationship of usage behaviour of the mHealth app and age for female employees. However, age leads to meaningful effect sizes, especially for female employees. The older the female employees are, the more frequently they use the mHealth app ($\beta_f = .101$; $p < .001$), furthermore the older the employees are, the better they rate their well-being ($\beta_m = .087$, $p < .005$, $\beta_f = .148$; $p < .001$) (Fig. 1).

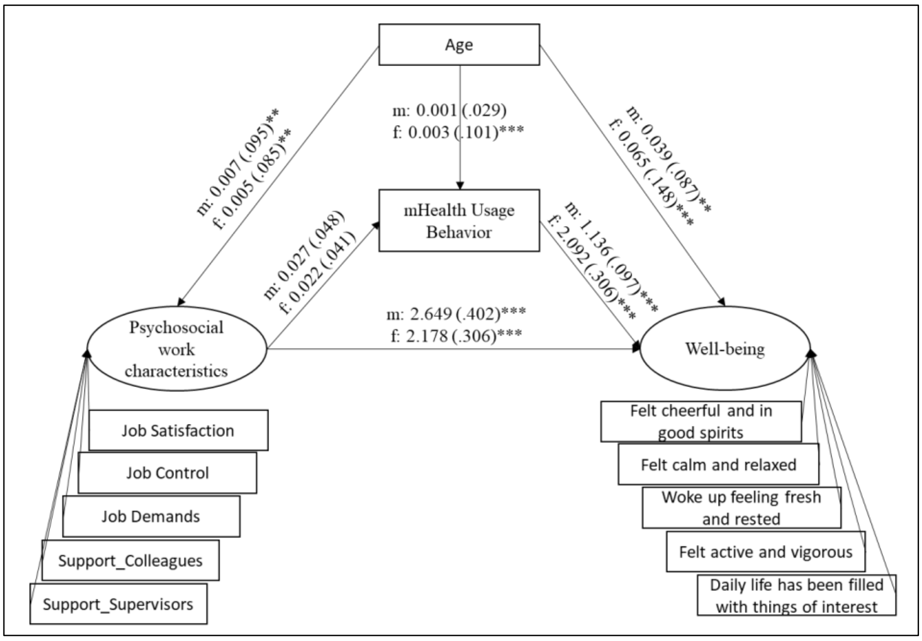

Fig. 1. Tested mediation model; unstandardized coefficients (B) and standardized coefficients in parenthesis (β) for male (m) and female (f) employees; ***: $p < .001$, **: $p < .01$, *: $p < .05$.

In a next step, for the whole sample the indirect effect was calculated. The indirect effect was calculated using the product of *a*b*. For the total effect, the indirect and the direct effect were added: *c*+(*a*b*). Both the indirect effect and the total effect show a significant result for the whole sample (Table 5).

Table 5. Simple mediation analysis

	b	β	p	c´
*a*b*	0.048	.007	*	
c	2.380	.343	***	.296**
*c+(a*b)*	2.428	.350	***	

Note. Indirect effect: a*b, direct effect: c, total effect: c+(a*b), correlation coefficient: c´, b: estimate, β : standardized estimate, ***: $p < .001$, **: $p < .01$, *: $p < .05$.

4 Discussion

The present study aims to investigate the question of whether the use of a mHealth app mediates the relationship between psychosocial workplace characteristics and employee well-being. The goal was to investigate to what extent the usage behaviour of a mHealth app can influence the (negative) outcomes of psychosocial workplace characteristics. For this purpose, the subjective well-being of employees was investigated. The app usage behaviour was operationalized via the frequency of app usage analysing the log files of the app.

The results show that psychosocial workplace characteristics have an influence on well-being. The better the psychosocial workplace characteristics are, the higher the subjective well-being, with the effect being stronger for male than for female employees. In contrast to correlation analysis, the mediation model is unable to identify a significant relationship between psychosocial workplace characteristics and mHealth app use. Nonetheless, app use is significantly related to well-being and here again a much stronger effect can be determined for female employees, while the effect size of the relationship is very weak for male employees.

Looking at the research question and thus the influence of app use on the relationship of psychosocial workplace characteristics on the outcome variables, we can confirm an indirect effect here. Whether mediation occurs depends on several factors. Following Baron and Kenny [53] it is necessary to first demonstrate a "zero-order effect" of the independent variable X on the depend variable Y (path c). When mediation occurs, the c´ path is smaller than the c path. This requirement is not met in the conducted mediation analysis. If we follow the requirements of Zhao et al. [54], there is only one requirement to establish mediation, that the indirect effect $a*b$ is significant. This requirement is met in the conducted mediation analysis. However, the authors go on to describe the strength of mediation in terms of the measured effect size, which is very low in the model studied. In summary, it is possible to speak of mediation, but only with a very low effect size. Accordingly, there is a mediating influence of mHealth app use on the relationship between psychosocial workplace characteristics and well-being. However, further research is needed to determine whether the effectiveness is sufficient to classify mHealth technologies as a useful resource in the work context.

The studied model, however, gives some other interesting results apart from the mediation analysis. In particular, the influence of age and gender on the variables analysed should be mentioned here. The older the employees are, the more frequently they use the mHealth app. This effect, however, is only seen for female employees. Currently, there are only a few studies that focus specifically on the characteristics of users of mHealth apps, but existing literature analysed especially younger individuals as user of mHealth apps [55]. The present study would contradict this, at least to some extent, as the analysis demonstrates that older users are more frequently using the app at least in the female population. One explanation could lie in gender differences, because it is already known that usage behaviour is gender-specific, at least for mobile fitness apps. Female users are more motivated than male users to use apps where they can set individual goals and receive support in achieving them. Male users, on the other hand, tend to prefer apps that allow live tracking and sharing of these results [56]. The mHealth app studied focuses on individual support for health related goals and motivation. Based on the results for fitness apps, this concept might appeal to female users' more than male users. Another explanation could be that mHealth apps are generally more likely to be used by younger individuals, while older individuals use them more frequently when they have decided to use them. As no analyses were performed in this regard in the present study, it is not possible to answer this question conclusively. Another interesting result is the relationship between app usage and well-being. A significant correlation with moderate effect size is observed in the female sample. This means that users who use the app more frequently also have a higher subjective well-being. The results correspond to previous research [31].

Conclusively, the present study suggests that mHealth applications can provide useful support in increasing well-being, especially for older employees. This is particularly relevant in the sense that the number of older people and thus older employees is rapidly increasing worldwide [57]. The present study confirms that mHealth applications can make a meaningful contribution to the maintenance of well-being and therefore of the health of employee, thus offering a simple way to continuously support active and healthy aging at work, since access is possible anytime and anywhere and employees can be individually supported according to their individual abilities and skills. Therefore, it is of particular importance to find out which factors have an effect and what this effect looks like in order to offer the best possible support and give the opportunity to be able to work and live healthily in the long term. The present study is able to contribute to this, but more in-depth research is necessary to identify and explain the relationships.

4.1 Limitations

The findings of this study should be interpreted in light of certain limitations. Although the large data set and multi-national recruiting by the investigated app it needs to be mentioned that a proper control setting was not implemented as real world data was used for this analysis. Thus, the data set might have influences and dependencies, which were not identified due to a limited number of control variables. These include, for example, individual factors that have already been studied in connection with app usage behaviour (e.g. technical affinity) but also, for example, country-specific differences (e.g. cultural background). Participants of four different countries were involved and the sample was compiled to be as comparable as possible. However, this also means that the results are not globally valid, as they are restricted to the analysed culture. Nevertheless just industrialized western countries were investigated which might be representative in terms of their work ethos and work concepts, but further research with regard to work culture is necessary.

A further limitation is that the sample was collected with one mHealth app, limiting the generalizability of the results in terms of other mHealth apps addressing for example resilience. Furthermore, the sampling procedure was nonprobabilistic, and respondents were self-selected based on their voluntary willingness to install the app. No specific advertisement was performed. Thus, persons with the interest in their health and aim to manage their work related stress might be overrepresented within this sample. Limitation to technical requirements might also be mentioned as a limitation although the app published was within the both most frequently used operating systems. Finally, the sample is composed of employees who have used a mHealth app at least to a small extent. No control group is included, with employees who do not use an app at all.

Despite these limitations, the results presented in this article may contribute towards a better understanding of the potential of modern technologies in supporting everyday work to help manage psychosocial demands and improve mental and physical health of workers around the globe.

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