Operationalizing Well-Being Using Work Determinants of Well-Being: Building a Well-Being Analytics Approach

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ABSTRACT

Improving the well-being of healthcare workers (HCWs) requires embedding well-being into healthcare operations. However, limitations of current well-being metrics serve as barriers for healthcare systems to address well-being in the same manner as other operational challenges, such as patient access and safety. Identification and measurement of Work Determinants of Well-Being (WDOW), organizationally attributable characteristics that are related to HCW health and well-being, are necessary first steps for healthcare institutions to take a systems approach to well-being. By leveraging existing data within healthcare systems, we describe how we built a well-being analytics team and database to identify WDOW. We use a case example of Paid Time Off (PTO) utilization to illustrate the potential of this approach to reduce burnout and improve well-being among HCWs.

KEYWORDS: work determinants of well-being, well-being data analytics, paid time off

INTRODUCTION

The well-being movement is at a crossroads. Post-pandemic recovery brings many health systems back to a pre-pandemic state in many ways. While we celebrate this "win," we must not forget that healthcare workers (HCWs) were struggling far before the pandemic and that simply returning to pre-pandemic levels of well-being is not the transformative culture change to aspire to. The National Plan for Health Workforce Well-Being states, "the solution is to take a systems approach that recognizes that no single variable in the health system is to blame for the problem of burnout. Addressing the issue from multiple angles is necessary to redesign environments."[1] Both redesigning the work environment and optimizing the operations by which we deliver healthcare while centering workforce well-being will be needed to achieve transformative culture change.[2]

What has prevented us from embedding well-being into operations? If no single variable is to blame for the problem of burnout, how do we identify these various variables? Are these variables the same for all healthcare workers, or as is likely, are the variables unique to various job families such as physicians, nurses, pharmacists, and medical assistants? How do we support our healthcare system leaders at all levels in approaching well-being with the same rigor as they would for routine operational problems such as access, throughput, or surgery turnaround times? A central maxim in operations is, "If you can't measure it, you can't manage it." For well-being to be embedded in operations, core metrics that can be easily and continuously measured in real time (just as we do for access, for example) are needed.

Currently, there are several challenges to measuring well-being. First, organizations typically focus on well-being metrics (usually engagement and burnout related) gathered from HCWs using surveys. These surveys rely on subjective well-being metrics that are usually lagging indicators, add another task for already overburdened healthcare workers to complete leading to reports of survey fatigue, have considerable non-respondent percentages that lead to uncertainty about the general applicability of the results, and are often administered too infrequently (usually annually). This leads to subjective data that does not provide a complete picture of the entire workforce, requires active collection and burdensome analysis, is retrospective, quickly dated, and too downstream (lagging) to allow for effective intervention. We need data that are objective, complete, passively collected, updated regularly (or better yet, in real time), and upstream enough to allow for intervention.

These data, which we believe are the multiple variables the National Plan is referring to, can be found by identifying and measuring work determinants of well-being (WDOW), or organizationally attributable, employment-related conditions that contribute to group differences in health risk and status.[3] This is the first step for well-being to be addressed the same way we address other operational matters. WDOW control whether work promotes well-being or serves as a hazard to HCW well-being and can serve as powerful system-level prevention and intervention targets. Fortunately, there is a massive amount of relevant workforce data buried within healthcare organization systems that can help identify objective WDOW that impact well-being. Examples include electronic health record log data to understand after-hours work, assessment of vacation time, and staffing ratios.[4,5]

The primary challenge to use these data includes siloed sources across different institutional databases, including human resources, risk, injury, electronic health records, facilities, and financial records. Without a cohesive approach to data collection and analysis, organizational leaders struggle to identify trends, patterns, and potential areas for systems level intervention to enhance workforce well-being.[6]

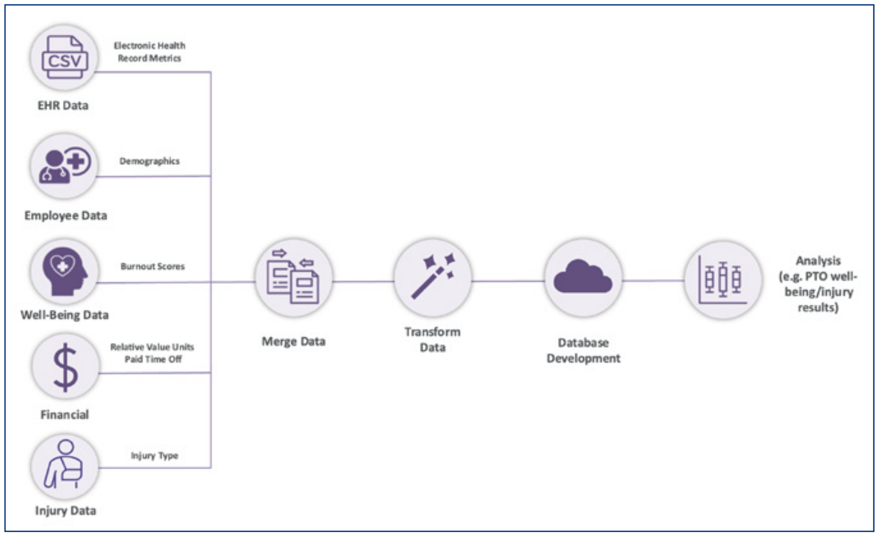
Below, we describe how our organization has taken the first step of fulfilling the promise of providing a superior work environment for our HCWs by bringing together multiple available data sources to allow for identification of WDOW that can serve as potential targets for intervention.[7] To do so, we created a well-being analytics team to build a central well-being database architecture. This approach can be replicated by health systems to create the foundation needed to achieve our ultimate vision of leaders using this data to transform well-being culture.

DEVELOPMENT

The Office of Well-Being began by cultivating partnerships with key members of the organization that owned various data sources. We began collecting various data that previous literature suggested may be particularly relevant to well-being and could help us identify WDOW. Data includes, but is not limited to, deidentified electronic health record metrics, employee demographics, subjective well-being responses, financial costs and productivity, employee injuries and leave of absences, reporting structures, and several other data sources. Our analytics team collects and makes sense of these data by looking for patterns and establishing their veracity. To accomplish this task with large amounts of data and complex hypotheses, we created a central database that merges the data above and stores data in an organized fashion allowing us to use code to retrieve exactly what variables we need to answer the question asked. We gather the data, organize it carefully, and "ingest" it into the database. Lastly, we store the database in the "cloud" which is a large space big enough for us to allow machine-learning and artificial intelligence to assess the data for patterns we cannot identify on our own.[8,9]

Our well-being analytics team is currently made up of three core members with additional access to multiple institutional experts and information systems teams. The three core members include a lead analyst, data architect, and data analyst. The lead analyst is responsible for designing the overall data architecture, ensuring all the necessary data elements (available objective variables) are known and accessible, and defining the outcomes to be measured. The data architect is responsible for building the database in the available environment, on premises or in the cloud, and ensuring the vetted elements are accurately captured, labeled, and maintained. Additionally, the data architect is often called on to creatively manage complex data requests for internal and external analysts working with our larger well-being team. The data analyst has the role of curating and transforming the data for specific projects, questions, or hypotheses. Data pulled from a large database can often have missing elements, multiple results for the same elements within the time period being analyzed, or other nuances that make the data difficult to consume and test. (**Figure 1**).

Figure 1.



WDOW PAID TIME OFF (PTO) CASE EXAMPLE

Our flagship program for the Office of Well-Being is called the Scholars of Wellness (SOW). Additional details about this program can be found here (https://edhub.ama-assn.org/steps-forward/module/2782425). One objective of this program is to allow us to explore hypotheses that can help us identify WDOW. Three separate SOW leaders identified rest and recovery opportunities as important employment-related conditions that contribute to group differences in health risk and status (i.e., WDOW).[3,10] For example, one project showed that 32% of physicians took ≤2 weeks of paid time off (PTO) per year, and those who had taken their PTO >6 months ago had a 32% increase in burnout compared to those who had taken PTO more recently. While PTO is often conceptualized as an individual choice, the interventions used in all three Scholars of Wellness projects included system-level changes such as dividing physicians into pods of coverage partners, team-based care workflows to limit the increase in work upon return from PTO and creating schedules with vacation weeks prepopulated one year in advance. These interventions were effective, including 91% physician utilization of the prepopulated weeklong vacations in their calendars across the year. These projects demonstrate that using PTO impacts physician well-being and we can redesign the process of PTO to increase healthy PTO usage at the system level.

Next, we chose to further explore PTO utilization as a WDOW in nursing and pharmacy HCWs because these job families had the highest burnout rates in our system, mirroring national trends.[11] First, we integrated siloed data sources about nurses (n = 2,967) and pharmacists (n = 280) employed by Northwestern Medicine's (NM) into our central well-being database. We excluded new hires who did not yet have the opportunity to accrue PTO, as well as HCWs who did not respond to NM's annual well-being surveys. Second, using the Orange Data Mining application (an open-access data visualization, machine-learning, and data-mining toolkit), we explored the data using a sieve (also known as parquet) diagram.[12] This is a graphical method to visualize frequencies in a two-way contingency table by comparing them to expected frequencies. Specifically, we plotted PTO accrual by those healthcare workers screening positive for burnout for each job family. We defined PTO as 'accrual of PTO hours,' which describes the number of hours accumulated. Higher number of hours accumulated generally means the HCW is not using as much PTO and, therefore, may have fewer opportunities for rest and recovery. We were able to produce two cohorts based upon this data visualization: those below and above the expected frequencies of burnout. The odds of burnout, as measured by scoring a 5 (experiencing burnout once a week or more), in nurses in the high PTO accrual group (>26 hours; 26% of nurses) were 1.4 times (CI 1.09–1.8) greater than those in the lower PTO hours accrual group (<26 hours); the odds of burnout in pharmacists with >65 hours of PTO (30%) were 2.12 times (CI 1.02–4.41) greater than those in the lower accumulated PTO hours group. This data provided evidence for the hypothesis that PTO is a WDOW, as fewer opportunities to rest and recover were contributing to higher rates of burnout. However, because of our central well-being database, we could further run analyses for the PTO WDOW against other previously siloed data sources. We evaluated injuries in the staff nurse population, non-managerial or tenured roles, who used PTO in the prior year but still had accrued PTO available in their PTO bank. By associating our hospital system's injury data with our available HR and well-being data, we were able to identify 882 nurses in our database that met the criteria for analysis. We found that average PTO accrual for nurses who did not sustain an injury in fiscal year (FY) 2023 was 60 hours, while the average for nurses who did sustain an injury in the same period was 66.5 hours, p= 0.026. This outcome added support to the association between accrued PTO and workforce well-being. This data can be used to make an additional compelling argument to our organization that finding systems level solutions to facilitate the healthy utilization of PTO needs to be an organizational priority.

CONCLUSION

Future directions for our team include continuing to identify additional WDOW across various job families in our healthcare system. Post-pandemic, we cannot focus well-being efforts solely on physicians and nurses. These efforts will need to be inclusive and at scale. We believe the approach above is a necessary first step for well-being leaders to shape organizational strategy. We then will move to the next step to realize our vision as we learn how to best ensure that new data can result in behavior and operational changes to improve well-being. More recently, our team has partnered with faculty in the medical school with expertise in intervention and implementation science to help focus our approach on elements with potential for dashboard development and intervention. Finally, we are optimizing our team's processes of large-scale data cleaning and database design so we can run more robust predicative efforts in the future, building on work that has already shown how even using one main data source (the EHR) can begin to predict burnout.[13]

We believe the future is bright for well-being 2.0 as we seek to create the work environments that support workforce thriving and will center well-being as an operational priority. When this happens, we believe the responsibility for well-being will be shared and distributed across the healthcare organization and large-scale transformative culture change can truly be achieved.

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Disclosures

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