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Who’s Not Talking? Nonresponse Bias in Healthcare Employee Well-Being Surveys

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SUMMARY

Goal: Employee well-being surveys are essential tools used by healthcare leaders to assess workforce functioning, such as burnout, team dynamics, and perceptions of support, but surveys frequently have low response rates, which may skew results. Research on nonresponse bias is limited because of the difficulty in sourcing data on outcomes of interest from nonrespondents. This study aimed to examine whether nonrespondents and respondents differed on key outcomes of interest to healthcare leaders to understand whether results of an employee well-being survey were valid. Specifically, we examined differences between respondents and nonrespondents in terms of demographics, turnover over one-year postsurvey, and employee functioning such as productivity and work outside of regular work hours. By using objective data as a proxy for physician functioning, our innovative approach allowed us to study nonresponse bias without relying on a follow-up survey of nonrespondents. The goal was to inform leaders about potential biases that impact survey conclusions and, therefore, better interpret the survey results in decision-making.

Methods: The longitudinal study included physicians (N = 348) and advanced practitioners (APs) (i.e., physician assistants, nurse practitioners, and certified nurse midwives; N = 143) from obstetrics and gynecology clinics in the Midwest and Northwest United States, who were invited to complete an employee well-being survey in 2021. Data on demographics, turnover, and other

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workplace environment indicators—i.e., productivity measured by relative value units (RVUs), work outside of regular work hours, duration of encounters, and appointment cancellations—were collected from electronic health records (EHRs) and human resources information systems (HRIS). Employment status was tracked for 1.25 years post-survey. The study examined demographic differences (i.e., age, gender, race/ethnicity, marital status), assessed the relative risk of turnover at each quarter over 1.25 years, and evaluated differences in productivity and workplace variables between respondents and nonrespondents. For relative risk, we observed turnover differences between retirement age and below retirement age subgroups.

Principal Findings: AP nonrespondents had a nearly 10 times higher risk in the full sample and a 12 times risk in the below-retirement age sample of turnover in the quarter after the survey was deployed. Physician nonrespondents below retirement age had a 5 times relative risk of turnover in the two quarters postsurvey. Among APs, nonrespondents were significantly older and more likely to be married; no differences existed for physicians.

Practical Applications: Results demonstrate that individuals at higher risk within an organization, as indicated by higher turnover risk and lower productivity, are less likely to fill out employee surveys. This suggests that employee survey results are skewed by nonresponse bias with respect to outcomes of interest, and that relying solely on survey data may lead to incorrect conclusions about workforce functioning, and subsequently, interventions that do not meet the needs of those most at risk within the organization. In addition to the valuable qualitative insights that surveys provide, healthcare leaders should leverage alternative data-collection methods, such as EHRs and HRIS data, to augment survey data and find out how nonrespondents differ from respondents. In this way, they can gain a comprehensive understanding of employee functioning to inform procedural and policy changes to enhance employee well-being and decrease negative outcomes, such as turnover and low productivity.

INTRODUCTION

Employee well-being surveys are commonly used to assess provider functioning. The American Medical Association (2025) recommends that healthcare systems regularly measure constructs of interest to develop targeted action plans to enhance provider well-being, reduce burnout, and improve organizational effectiveness (Nadkarni et al., 2021; Schiemann & Morgan, 2006; Wallace et al., 2009). Unfortunately, healthcare surveys are often characterized by low response rates, averaging only 35% (Cunningham et al., 2015). If survey results are to be useful in informing action plans, it is crucial that they be externally valid and generalizable, meaning that the responses collected accurately represent the entire employee population. Nonresponse bias, which occurs when survey respondents differ systematically from nonrespondents, can undermine this representativeness (Turnbull, 2017).

Nonresponse bias, if present, can profoundly impact the interpretation and application of survey findings in healthcare settings. When nonrespondents differ systematically from respondents, survey results may become skewed, leading to misinterpretations about prevalence, incidence, and relationships among key variables (Groves, 2006). For healthcare leaders, this can result in misallocated resources, ineffective interventions, and missed opportunities to address critical workforce needs, ultimately compromising physician well-being and patient care quality (Shanafelt et al., 2002, 2017). Such issues also hinder broader organizational goals, including those of the Triple Aim framework, which aims to optimize patient experience of care, improve population health, and reduce per capita cost (Berwick et al., 2008). Ineffective action plans can further exacerbate physician burnout, compromise workforce well-being, and increase turnover, which is associated with reduced continuity of care and higher costs (Shanafelt et al., 2016, 2017).

Examination of Nonresponse Bias in Healthcare Surveys

Research on nonresponse bias in healthcare is limited and generally falls into two categories (Fauth et al., 2013). The first investigates whether respondents differ from nonrespondents on factors unrelated to the survey topic, often demographics. Some studies show significant differences: Hendrix and colleagues (2024) found variations by age, system size, and setting; Barclay and colleagues (2002) noted higher qualifications among respondents; Bjertnaes and colleagues (2011), and Cull and colleagues (2005) found small differences in service years, practice type, and society membership. Yet other studies report minimal or no demographic differences (Menachemi et al., 2006; Ziegenfuss et al., 2011), highlighting that demographic differences are inconsistent and often minor.

The second category of nonresponse bias research investigates whether respondents and nonrespondents differ in survey outcomes, such as employee well-being (Fauth et al., 2013). This line of inquiry is less common due to the difficulty of measuring outcomes like burnout without survey data. A notable exception is Simonetti and colleagues (2020), who compared approximately 27,000 primary care employees and found no significant difference between unadjusted and propensity-adjusted burnout estimates, suggesting minimal nonresponse bias. However, relying solely on observable demographics may miss unobserved factors. Similarly, Peytcheva and Groves (2009) showed that demographic differences do not necessarily predict outcome differences, indicating that propensity scoring based on demographics may not fully capture response bias.

Theories of Survey Participation: Application to Healthcare

Several theories offer frameworks for understanding survey participation (for a review, see Albaum and Smith, 2012).

Social exchange theory (SET) posits that individuals participate in activities when perceived benefits outweigh the costs (Blau, 1964). In healthcare, SET suggests that providers who trust organizational leadership and trust that their feedback will lead to meaningful changes are more likely to participate in surveys. Such employees often feel valued and supported, correlating with higher productivity and retention.

Conversely, SET posits that nonrespondents may experience disengagement or mistrust, leading to both nonresponse and potential turnover/lack of productivity at work.

Commitment/involvement theory asserts that participation in organizational activities signals deeper emotional and psychological involvement (Kanungo, 1982; Meyer et al., 1991). For healthcare employees, survey participation may reflect strong organizational attachment and a sense of belonging, traits often linked to higher performance and lower turnover. Nonrespondents, in contrast, may indicate weaker organizational ties, potentially correlating with higher turnover intentions and reduced productivity.

Leverage-salience theory emphasizes that survey participation depends on how individuals perceive the relevance and salience of the survey's topic, the organization conducting it, and other individual factors such as time requirements and workload (Groves et al., 2000). In healthcare, heavy workloads and lack of time can make surveys feel like an additional burden, reducing participation rates. Providers overwhelmed by clinical duties, such as working outside of normal hours, may prioritize immediate patient care over long-term organizational initiatives like surveys. This nonresponse not only reflects disengagement but may also signal underlying risks of burnout and turnover, as heavy workload and time pressure are linked to decisions to leave the profession.

The Current Study

The current study examined nonresponse bias among physicians and advanced practitioners (APs) in various obstetrics and gynecology practices across the United States, who were invited to participate in an employee well-being survey. For information on survey content and results, see Blackburn and colleagues (2023). Specifically, we explored whether survey respondents and nonrespondents differed in terms of demographic characteristics and workplace indicators linked to employee well-being. To address the challenge of not having outcomes for nonrespondents, we used proxies of provider functioning recorded in electronic health records (EHRs) and human resources information systems (HRIS). These included turnover and aspects of clinical work that are theoretically and empirically linked to well-being. By leveraging EHR and HRIS data as objective measures, our study offers a novel methodological advancement, providing insights into nonresponse bias that would otherwise require follow-up surveys or imputation methods. This method builds on the recommendation by Sinsky and colleagues (2020) to use EHR data to understand the practice environment and inform leadership decisions.

Research Questions and Hypotheses

We examined whether respondents and nonrespondents differed in three domains:

Aim 1: Demographics. We examined whether respondents and nonrespondents differed by age, race/ethnicity, gender, employment status (i.e., part-time versus full-time), and marital status. Given the mixed results in previous studies, we did not make specific hypotheses about the direction of these differences.

Aim 2: Turnover. We investigated whether respondents and nonrespondents differed in their relative risk of turnover

over the five quarters following survey deployment. We hypothesized that nonrespondents would be more likely to turn over. Because the implications of turnover vary by retirement age, we also separately examined differences for employees 65 years and older and considered this an exploratory analysis with no a priori hypotheses.

Aim 3: Workplace Environment. We assessed whether respondents and nonrespondents differed on objective indicators of the work environment, including work outside of scheduled hours, encounter duration, relative value unit (RVU), and canceled appointments. These factors are routinely recorded in HRIS and EHR systems, and previous research suggests their relevance to provider well-being. Given the novel nature of this comparison and conflicting theoretical expectations—e.g., higher productivity might indicate greater commitment and a higher response likelihood, or time constraints and a lower response likelihood—we made no specific predictions about the direction of these differences.

METHODS

Participants and Procedures

Participants were physicians and APs working at obstetrics and gynecology clinics in the Midwest and Northwest regions of the United States, who were invited to participate in an employee well-being survey (N = 491) deployed in the third quarter (Q3) of 2021. Participants received weekly reminder e-mails for eight weeks to complete the survey. All data were anonymized using a unique identifier, and participants were informed that the data would be presented in aggregate to leadership and used for research to promote provider well-being. No incentives were offered for survey completion.

Physicians. Physicians (N = 348) included senior (N = 242) and associate (N = 106) physicians. The majority were female (66%). The racial/ethnic composition was 77% non-Latine White, 13% Asian, 4% Latine, 3% Black/African American, < 1% Native Hawaiian or Pacific Islander, and <1% multiracial. The average age was 49 years (SD = 12.1). Most were married (70%), followed by single (26%), divorced (3%), and widowed (<1%). Approximately 96% (N = 334) of physicians were full-time employees.

Advanced Practitioners. APs (N = 143) included nurse practitioners (N = 95), certified nurse midwives (N = 34), and physician assistants (N = 14). All APs were female. The racial/ethnic composition was 92% non-Latine White, 2% Latine, 1% Asian, 1% Black/African American, and 1% multiracial (1% did not to answer). Marital status was 52% married, 13% single, 3% divorced, and <1% widowed (>30% were missing data). The average age was 45.6 years (SD = 11.43). Approximately 78% (N = 112) of APs were full-time employees.

Measures

Response Status

Participants were coded as "respondents" if they completed enough survey questions (approximately 60%) to allow for the calculation of a burnout score. This threshold was chosen because it aligned with the operational definition used by the healthcare system's administrators, who considered individuals meeting this criterion as "respondents" in their presentations to leadership and summary statistics. By mirroring this approach, the study maintained ecological validity, ensuring that our analysis reflected the organization's real-world practices. Those who did not begin the survey or did not complete enough questions to meet this threshold were coded as "nonrespondents."

Demographics

Age, gender, race/ethnicity, role type (e.g., nurse practitioner, senior physician), full versus part-time status, and marital status were collected from existing EHR and HRIS systems.

Turnover

Employment status (active or terminated) was recorded quarterly for 1.25 years following the survey invitation, from Q4 2021 to Q4 2022.

Workplace Environment Indicators

For all workplace indicators, variables were calculated as monthly averages over the six months prior to survey deployment. We chose this time frame based on research linking job demands to physician well-being and burnout six months later (Demerouti et al., 2001).

Productivity. Provider productivity was measured by average monthly RVUs. The RVUs are a measure of the worth of medical services and procedures performed by a provider, derived from several factors, including level of effort, resources utilized, and professional expertise necessary to provide the service. An RVU is associated with job satisfaction, patient care, and provider well-being (Pérez-Francisco et al., 2020).

Canceled appointments. Canceled appointments were the monthly average number of appointments canceled by the clinic (either by the office or the provider). Research has reported recent increases in appointment cancellations by healthcare organizations. Office-canceled appointments have been posited to relate to the inability of a system to handle demand (Fry, 2022) and may reflect staffing shortages or other workplace dysfunction.

Work outside of regular work hours. Work outside of regular work hours was calculated as the monthly average number of hours worked outside a 7 a.m.–7 p.m. schedule. This definition was based on standard scheduling practices within the healthcare system, where all providers were scheduled on regular day shifts that fell entirely within this time frame and aligns with prior research using EHR data to evaluate after-hours work (Caruso, 2014). In their recent paper calling for examinations of provider well-being using EHR data, Sinsky and colleagues (2020) recommended examining work outside regular hours as an indicator of employee functioning, hypothesizing that such work relates to decreased physician well-being.

Encounter duration. Encounter duration was the monthly average number of minutes per encounter. Providers have indicated that pressure to decrease encounter duration is related to increased burnout (Patel et al., 2018).

Data Analytic Approach

All analyses were conducted separately for physicians and APs using IBM Statistical

Package for Social Sciences Statistics version 29.

For Aim 1 (demographics), chi-square tests were performed to examine whether survey respondents and nonrespondents differed in categorical demographic variables, while *t*-tests were used to examine differences in age. Groups with fewer than five cases were excluded from analyses due to insufficient statistical power to detect effects. Gender analyses were not conducted for APs, as the entire sample identified as female.

For Aim 2 (turnover), relative risk ratios (see explanation in Monaghan et al., 2021) were used to examine differences in the risk of turnover between survey respondents and nonrespondents over 1.25 years following survey deployment. At each quarter, individuals who left their job during the preceding quarter were removed from the analyses, ensuring that risk ratios represented the risk of new turnover, excluding those who had previously quit. We then separately replicated analyses for at or above retirement age and below retirement age subgroups within each role type. Providers missing data for age were not included in retirement subgroup analyses.

For Aim 3 (workplace environment), workplace environment indicators were tested for normality and homogeneity of variance using Shapiro–Wilk tests, which evaluate whether a variable's distribution deviates significantly from a normal distribution. All tests were significant ($p < .05$), indicating nonnormality for all variables. Consequently, Mann–Whitney U tests, which are nonparametric tests used to compare whether two independent groups differ in their distributions, were used to compare differences in workplace environment indicators between respondents and nonrespondents.

RESULTS

Preliminary Analyses

The survey had a relatively high response rate, with 59.5% ($N = 207$) of physicians responding and 40.5% ($N = 141$) not responding to the survey. Similarly, 58% ($N = 83$) of APs responded and 42% ($N = 60$) did not respond to the survey. There were no significant differences in response rates between physicians and APs ($\chi^2 = 0.087$, $p = .77$).

Aim 1: Demographic Differences between Respondents and Nonrespondents

Physicians

For physicians, response status was not significantly related to any demographic variable (i.e., age, marital status, race/ethnicity, full-time versus part-time status, and gender).

Advanced Practitioners

Age was related to response status, such that nonrespondents ($M = 47.24$, $SD = 11.99$) were significantly older than respondents ($M = 42.47$, $SD = 9.66$; $t(107) = 2.452$, $p = .016$). For marital status, single APs were more likely to respond to the survey compared to married APs ($\chi^2(1) = 3.9$, $p = .048$). Race/ethnicity and working full-time versus part-time were not related to response status.

Aim 2: Relative Risk of Turnover

See Table 1 and Figure 1 for results of relative risk analyses.

TABLE 1

Relative Risk of Turnover Among Nonrespondents for Physicians and Advanced Practitioners

	Physicians			Advanced Practitioners		
Time Period	Relative Risk	Lower CI (95%)	Upper CI (95%)	Relative Risk	Lower CI (95%)	Upper CI (95%)
Full Sample						
Q4 2021	2.94	0.55	15.82	**9.68**	**1.22**	**76.65**
Q1 2022	2.69	0.92	7.87	1.55	0.10	24.21
Q2 2022	—	—	—	3.12	0.59	16.41
Q3 2022	1.41	0.62	3.23	0.99	0.25	3.95
Q4 2022	1.06	0.31	3.69	—	—	—
Below Retirement Age						
Q4 2021	5.64	0.59	53.48	**11.67**	**1.48**	**91.76**
Q1 2022	**5.14**	**1.40**	**18.93**	1.95	0.13	30.28
Q2 2022	—	—	—	7.89	0.91	68.11
Q3 2022	1.81	0.68	4.83	0.87	0.18	4.27
Q4 2022	2.15	0.44	10.41	—	—	—
At or Above Retirement Age						
Q4 2021	1.62	0.11	23.66	—	—	—
Q1 2022	—	—	—	—	—	—
Q2 2022	—	—	—	—	—	—
Q3 2022	0.94	0.19	4.82	—	—	—
Q4 2022	0.47	0.06	3.86	—	—	—

Note. Statistically significant results are indicated in bold. Relative risk ratios that could not be calculated are indicated by dashes. Due to a lack of turnover events in one of the response status groups, relative risk could not be calculated in Q2 2022 for physicians or in Q4 2022 for advanced practitioners below retirement age, Q1 2022 and Q2 2022 for physicians at or above retirement age, or at any time point for advanced practitioners above retirement age. CI = confidence interval.

Physicians

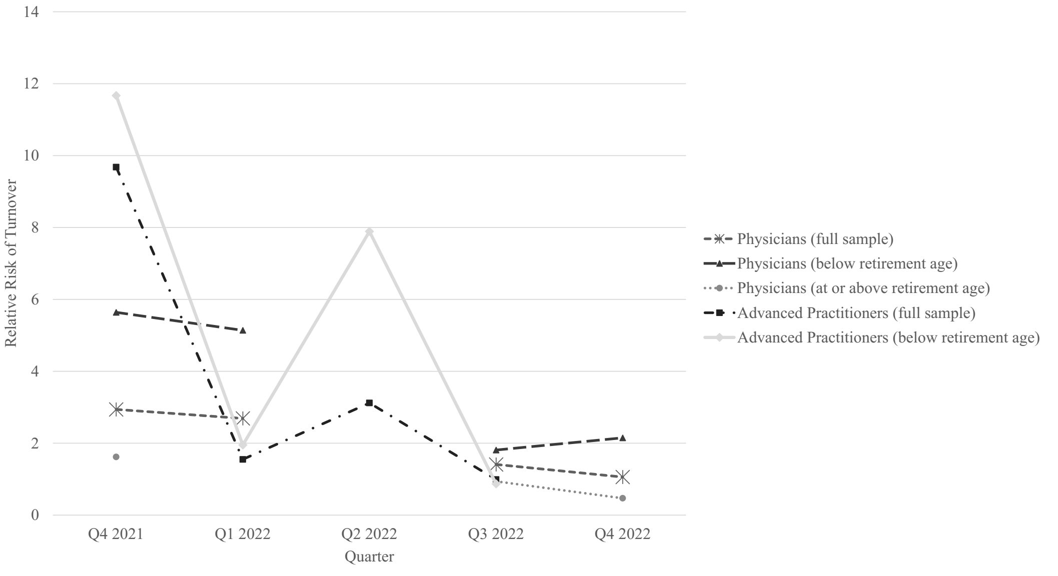
Full Sample. The risk of turnover among nonrespondents compared to respondents was 2.94 times higher in Q4 2021, 2.69 times higher in Q1 2022, 1.41 times higher in Q3 2022, and 1.06 times higher in Q4 2022, none of which were statistically significant. No turnover events occurred among nonrespondents in Q2 2022.

Below Retirement Age Subgroup. For physicians below retirement age (≤64, N = 285), the risk of turnover among nonrespondents compared to respondents was 5.64 times higher in Q4 2021, which was not statistically significant. In Q1 2022, nonrespondents were 5.14 times more likely to leave, which was statistically significant compared to respondents. No turnover events occurred among nonrespondents in Q2 2022. In Q3 2022, the risk was 1.81 times higher, and in Q4 2022, it was 2.15 times higher, with neither being statistically significant.

Retirement Age Subgroup. For physicians at or above retirement age (≥65,

FIGURE 1

Relative Risk of Turnover Among Physician and Advanced Practitioner Nonrespondents



Note. Relative risks were statistically significantly different at 11.67 (Q4 2021) for advanced practitioners (below retirement age), at 9.68 (Q4 2021) for advanced practitioners (full sample), and at 5.14 (Q1 2022) for physicians (below retirement age). Due to a lack of turnover events in one of the response-status groups, relative risk could not be calculated in Q2 2022 for physicians or in Q4 2022 for advanced practitioners.

N = 34), the risk of turnover among nonrespondents compared to respondents was 1.62 times higher in Q4 2021, 0.94 times in Q3 2022, and 0.47 times in Q4 2022, with no significant differences. No turnover events occurred among nonrespondents in Q1 or Q2 2022.

Advanced Practitioners

Full Sample. The risk of turnover among nonrespondents compared to respondents was 9.68 times higher in Q4 2021, which was statistically significant. For the subsequent quarters, the risk ratios were 1.55 in Q1 2022, 3.12 in Q2 2022, and 0.99 in Q3 2022, with no significant differences. No turnover events occurred among nonrespondents in Q4 2022.

Below Retirement Age Subgroup. For APs below retirement age (*N* = 120), the risk of turnover among nonrespondents compared to respondents was significantly higher at 11.67 times in Q4 2021. In subsequent quarters, the risk was 1.95 times higher in Q1 2022, 7.89 times higher in Q2 2022, and 0.87 times higher in Q3 2022, with no significant differences. No turnover events occurred among nonrespondents in Q4 2022.

Retirement Age Subgroup. Relative risk could not be calculated for APs at or above

TABLE 2

Differences in Workplace Environment Indicators Among Nonrespondents for Physicians and Advanced Practitioners

	Physicians				Advanced Practitioners			
	z	*p*		*M* Rank	*z*	*p*		*M* Rank
Canceled appointments	−0.1	.93	Nonrespondents	71.39	−0.59	.55	Nonrespondents	168
			Respondents	70.73			Respondents	161.59
Encounter duration	−0.59	.55	Nonrespondents	68.02	−0.51	.61	Nonrespondents	163.09
			Respondents	72.15			Respondents	168.61
Work outside of work hours	−0.44	.66	Nonrespondents	72.6	−0.44	.66	Nonrespondents	167.8
			Respondents	69.92			Respondents	163.28
Relative value units (RVUs)	**−2.51**	**.01**	**Nonrespondents**	**54.85**	**−2.11**	**.04**	**Nonrespondents**	**145.85**
			Respondents	**72.24**			**Respondents**	**168.61**

Note. Statistically significant results are indicated in bold.

retirement age due to a 100% survey response among this group ($N = 8$).

Aim 3: Workplace Environment Indicators

Physicians

Results (see Table 2) indicated a significant difference in RVU between respondents and nonrespondents. Respondents ($M = 168.61$) had significantly higher RVUs compared to nonrespondents ($M = 145.85$; $z =$ —2.11 $p = .04$). Other workplace indicators, including work outside of regular work hours, number of canceled appointments, and encounter duration, were not significantly different between respondents and nonrespondents.

Advanced Practitioners

Results (see Table 2) indicated a significant difference in RVUs, such that respondents ($M = 72.24$) had significantly higher RVUs compared to nonrespondents ($M = 54.85$; $z = -2.51$, $p = .012$). Other workplace indicators, including work outside of regular work hours, number of canceled appointments, and encounter duration, were not significantly different between respondents and nonrespondents.

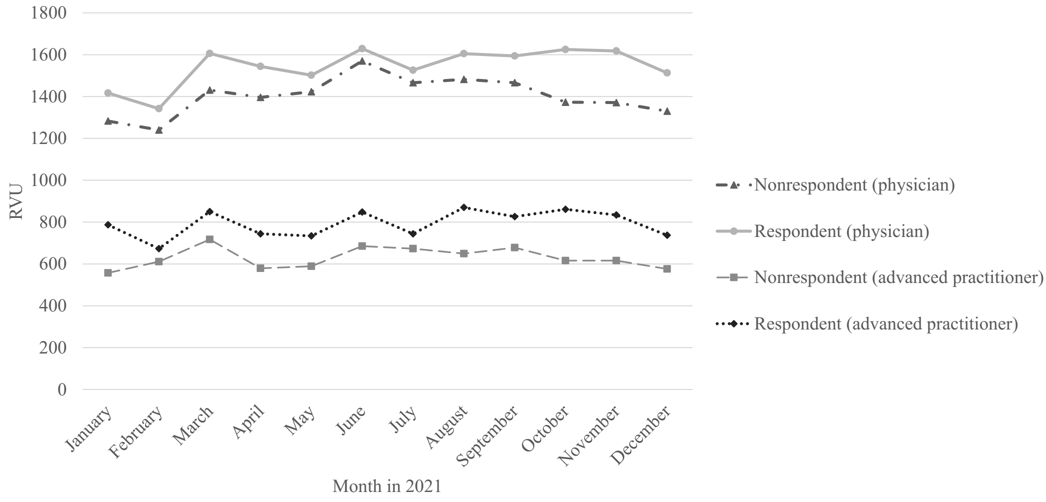
To determine if the difference in RVUs was related to survey timing, we conducted post-hoc analyses comparing RVUs over time between respondents and nonrespondents. For physicians, nonrespondents had significantly lower RVUs at all monthly timepoints from January 2021 to December 2021. For APs, RVUs were significantly lower for nonrespondents in all months except February, March, June, and July, with no consistent pattern over time (see Figure 2).

DISCUSSION

The current study, which investigated the presence of nonresponse bias using objective measures in a sample of physicians and advanced practitioners in obstetrics and

FIGURE 2

Respondent and Nonrespondent Relative Value Units (RVUs) over Time



Note. Physicians, nonrespondents had significantly lower RVUs at all monthly time points from January to December 2021. Among advanced practitioners, RVUs were significantly lower for nonrespondents in all months except February, March, June, and July, with no consistent pattern over time.

gynecology clinics in the United States, identified distinct indicators of nonresponse using objective measures in three domains: provider demographics, turnover, and workplace indicators measured by HRIS and EHR data. We found evidence of nonresponse bias in all three domains. For APs, the risk of turnover among nonrespondents was almost 10 times higher and 12 times higher for below retirement age nonrespondents compared to respondents in the quarter after survey deployment. For physicians, below retirement age nonrespondents had a 5 times increased risk of turnover two quarters after survey deployment. Both physicians and APs showed significantly lower RVUs for nonrespondents: 27% lower for APs and 14% lower for physicians. Additionally, AP nonrespondents were significantly older and more likely to be married compared to respondents.

Review and Interpretations of Key Findings

Our findings on demographic differences align with the broader literature suggesting that demographic indicators of nonresponse bias vary by sample and context (Barclay et al., 2002; Bjertnaes et al., 2011; Menachemi et al., 2006; Simonetti et al., 2020; Ziegenfuss et al., 2011). For healthcare leaders, this inconsistency underscores the need to examine demographic differences in response rates in their own systems to determine if and how nonresponse bias affects their surveys.

We observed distinct patterns among different subgroups. For physicians, increased turnover risk appeared only among below retirement age nonrespondents, while for APs, below retirement age nonrespondents faced an even greater risk (12 times) than the full sample (10 times). These patterns suggest that nonresponse bias skews results, especially for below retirement age subgroups. The differences in strength of the effect between APs (12 times) and physicians (5 times) aligns with research indicating that APs generally have greater intentions to leave (Sinsky et al., 2021). The differences in timing of the effects, specifically, immediate turnover risk for APs and delayed risk for physicians may reflect differences in leave policies, which were at least 90 days for physicians, but not for APs, at the healthcare organization we studied. This highlights the need to consider role-specific barriers and facilitators of survey participation and turnover. Leaders should recognize that nonresponse bias impacts survey result interpretations differently across roles, necessitating tailored approaches. Both physicians and APs showed higher RVUs among respondents compared to nonrespondents, indicating that nonrespondents may be more disengaged.

These results can be interpreted through theories on motivations for survey participation (Albaum & Smith, 2012). According to social exchange theory, individuals participate in surveys when they perceive the benefits outweigh the costs. Employees who trust leadership to improve well-being based on survey responses may see participation as a way to drive change. Provider control over their work is crucial in predicting turnover and early retirement in healthcare professions (Elovainio et al., 2005; Heponiemi et al., 2008). Those who feel valued are more motivated to engage in surveys, be productive, and remain employed. Commitment/involvement theory suggests that survey participation reflects depth of involvement in an organization. Productive employees may feel a sense of belonging and, therefore, be more likely to contribute to growth through surveys and decide to remain employed (Salles et al., 2019; Schaechter et al., 2023). Finally, leverage-salience theory explains that an individual's perception of a survey's relevance influences participation (Groves et al., 2000). Providers planning to leave may find workplace improvement surveys irrelevant, leading to lower response rates.

Implications for Leaders

Given workforce shortages and the increasingly high levels of provider turnover and dissatisfaction, systems strive to adopt strategic approaches to human resource management by using employee well-being surveys to inform approaches to institutional changes (Hsiung et al., 2021). The results of the current study indicate that survey-only approaches may systematically underestimate negative aspects of functioning (such as burnout, team culture, or intention to leave) and overestimate positive aspects of functioning. In other words, the providers whom leaders most need to understand and engage through surveys may be the least likely to respond to surveys and, subsequently, be represented by their results.

Despite findings of nonresponse bias in surveys in multiple domains, collecting data on provider functioning through surveys remains essential for establishing systems to improve employee well-being (Sinsky et al., 2020). Healthcare leaders should therefore emphasize follow-up actions based on survey results. This is crucial for building trust and demonstrating the value of participation, showing providers that their feedback leads to tangible improvements (Cho et al., 2013). Additionally, leaders should leverage HRIS systems to complement survey findings and gain a more comprehensive understanding of the workplace environment.

The innovative use of objective data in this study offers healthcare leaders a valuable tool for addressing nonresponse bias in their own systems. Leaders can incorporate this methodology into their presentations of survey data, using it to validate results and provide a clearer understanding of workforce dynamics. For example, this approach enables leaders to detect whether nonresponse bias has impacted their estimation of critical workforce outcomes, such as retention or productivity, by comparing those outcomes between respondents and nonrespondents within their own system. Further, they can apply this methodology to retrospectively analyze prior surveys, assessing how nonrespondents might differ on key outcomes such as turnover, while also leveraging concurrent EHR/HRIS data (e.g., productivity, paid time off usage, or work outside of normal hours) to evaluate the representativeness of ongoing surveys.

Presenting real-time representation data on outcomes of interest can provide actionable insights into who is not completing surveys and why, equipping leadership to implement targeted solutions. For example, if a healthcare system identifies that nonrespondents consistently work significantly more hours outside their scheduled shifts, this could suggest that nonresponse is linked to feeling overwhelmed or work-life interference. Recognizing this pattern would allow leaders to prioritize interventions aimed at workload management or flexible scheduling, even if these issues are underreported in survey responses. By integrating this methodology, leaders can more accurately interpret survey results, identify hidden areas of need, and drive organizational improvements that directly address workforce well-being.

Study Strengths

A key strength of this research lies in its innovative approach to understanding nonresponse bias using an objective, low base rate measure (turnover) that is critical for healthcare leaders, individuals, patients, and teams. Traditionally, the impact of nonresponse on outcomes of interest has been examined using techniques like imputation or contrasting early versus late respondents to infer potential biases. This study, however, uses objective data points from EHR and HRIS systems as proxies for workplace functioning, providing an innovative alternative to self-reported data. The workplace environment indicators used in this study have been established in the literature as related to provider well-being, offering insights that may be missed by traditional self-report measures. The use of objective measures enhances the credibility of the findings and provides more direct insights into the implications of nonresponse on critical organizational outcomes.

Study Limitations

These findings should be interpreted with several limitations in mind. First, generalizability is constrained by the study's focus on obstetrics and gynecology clinics and a predominantly White, all-female AP sample, underscoring the need for diverse replication. Second, because no clear cutoff exists to classify respondents and nonrespondents, some individuals may have been misclassified, and we lacked the statistical power to examine "partial respondents." Third, the rarity of turnover events reduced the stability and reliability of some estimates, as small changes in event counts had an outsized effect. Fourth, defining after-hours work simply as any work outside 7 a.m.–7 p.m. may lead to a poorer estimation of the extent of after-hours work compared to more nuanced metrics, such as those incorporating scheduled versus regular work hours (Arndt et al., 2023; Sinsky et al., 2020). Finally, reliance on EHR data, which can be inconsistent, may skew interpretations.

Directions for Future Research

Although we found evidence of nonresponse bias, we did not examine its effect on survey conclusions. Future research should quantify how outcomes are misestimated and explore how nonrespondents' perspectives might alter action plans. Such work could uncover overlooked issues and improve the effective use of survey data despite nonresponse bias.

CONCLUSION

Our research evaluated nonresponse bias in employee well-being surveys using objective HRIS and EHR measures in obstetrics and gynecology healthcare settings. Findings demonstrated clear biases differentiated by retirement age and provider role, with notably higher turnover risk and lower productivity among nonrespondents, especially for below retirement age advanced practitioners and below retirement age physicians. The objective data-driven method developed here offers a practical and replicable strategy for healthcare leaders to assess the validity of survey conclusions within their own organizations, enhancing their ability to address hidden workforce needs and effectively promote employee well-being.

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