

Intelligent Scheduling Systems and Healthcare Workforce Efficiency: A Survey-Based Study of 155 U.S. Healthcare Professionals



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Abstract

Background: Healthcare organizations depend on effective workforce scheduling to sustain quality care, yet conventional scheduling approaches frequently produce uneven workloads, administrative strain, and diminished staff morale. Whether intelligent, algorithm-driven scheduling systems meaningfully address these problems remains only partially understood. **Methods:** A cross-sectional online survey was administered to 155 U.S. healthcare workers, including physicians, nurses, allied health professionals, and administrative staff. A structured questionnaire using five-point Likert-scale items assessed Intelligent Scheduling Accuracy (ISA), User Satisfaction (US), Ease of Use (EOU), System Reliability (SR), and Healthcare Workforce Efficiency (HWE). Data were analyzed in SPSS (version 26) using descriptive statistics, reliability analysis, Pearson correlation, and multiple linear regression. **Results:** All constructs were rated favorably, with mean scores ranging from 4.05 to 4.21. HWE showed the strongest correlation with ISA ($r = 0.703$), followed by US ($r = 0.681$), EOU ($r = 0.642$), and SR ($r = 0.617$). Internal consistency was strong across constructs (Cronbach's $\alpha = 0.873$ – 0.915), and the regression model explained 61.0% of the variance in workforce efficiency ($R^2 = 0.610$, $F = 58.74$, $p < .001$), with ISA emerging as the strongest individual predictor ($\beta = 0.341$). **Conclusion:**

Intelligent scheduling systems appear to be positively associated with healthcare workforce efficiency, largely through the combined influence of scheduling accuracy, usability, and reliability. These findings, while preliminary, offer empirical support for continued investment in intelligent scheduling technologies within U.S. healthcare settings.

Keywords

intelligent scheduling systems; healthcare workforce efficiency; user satisfaction; system reliability; healthcare workforce management

1. Introduction

Healthcare, whether we like it or not, keeps getting more complicated to manage. Hospitals now juggle unpredictable patient volumes, tightening budgets, and workforce shortages that seem to deepen year after year — and somewhere near the center of all this sits an unglamorous but consequential function: staff scheduling. It is easy to underestimate how much scheduling shapes everything else. Get it wrong, and burnout tends to follow, along with slower response times and, frankly, worse patient outcomes (Zhai et al., 2022). Get it right, and the

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Significance | Empirical evidence linking intelligent scheduling system attributes to measurable improvements in U.S. healthcare workforce efficiency.

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whole operation seems to breathe a little easier.

Workforce efficiency has, for good reason, become something of a proxy metric for hospital performance more broadly (Ala & Chen, 2022). When clinicians are working at or near capacity — not overextended, not idle — care tends to move faster, and patients tend to fare better (Klumpp et al., 2021). That much is fairly intuitive. What is less settled in the literature is how organizations actually get there. Rising patient loads collide with limited staff availability and organizational complexity that resists easy fixes (Ala et al., 2021), and nowhere is that tension more visible than in the everyday work of building shift schedules (Oueida et al., 2018).

Traditional scheduling approaches — the manual spreadsheets, the ad hoc adjustments, the systems held together more by institutional memory than by software — were never really built for this level of complexity. They tend to produce uneven workloads, they struggle to absorb last-minute changes, and they often leave units short-staffed precisely when demand spikes (Oueida, Aloqaily, et al., 2018). The downstream effects are not subtle: stress accumulates, burnout sets in, and the broader work climate suffers as a result (Tursunbayeva, 2019). Administrators, meanwhile, end up spending a disproportionate share of their time resolving scheduling conflicts rather than attending to higher-order priorities — a quiet but persistent drain on organizational performance (Foresti et al., 2020).

Into this gap, intelligent scheduling systems have emerged — not as a silver bullet, exactly, but as a genuinely different way of approaching an old problem. These systems draw on algorithmic and data-driven methods to coordinate shift assignments and allocate resources in ways manual processes simply cannot replicate (Subrahmanya et al., 2021). Rather than applying a fixed template, they attempt to weigh staff availability, individual skill sets, and real-time departmental demand simultaneously (Devaraj et al., 2013), adjusting as conditions change rather than waiting for the next scheduling cycle to catch up (Kaluarachchi, 2020). Within the U.S. context specifically — where patient volumes and operating costs continue to climb while expectations for care quality hold steady or rise — this kind of adaptive capacity has started to look less like a luxury and more like a practical necessity (Albahri et al., 2018).

There is also a human dimension here that is easy to lose

sight of amid the technical framing. Unpredictable hours do not just affect productivity metrics; they spill into people's personal lives, their sleep, their relationships, their sense of control over their own time (Tursunbayeva, 2019). Systems that distribute workload more evenly and operate with greater transparency appear to address this directly, and available evidence suggests they can meaningfully improve how satisfied staff feel in their roles while still preserving continuity of patient care (Dogru & Keskin, 2020).

And yet, despite this promise, something of a gap persists. Much of what is known about intelligent scheduling systems remains conceptual or descriptive in nature — useful, but not quite empirical (Fragapane et al., 2020). Comparatively few studies have attempted to determine, using actual respondent data, how the individual components of these systems — their accuracy, how satisfied users feel with them, how easy they are to use, how reliably they perform — come together to shape workforce efficiency as a single, integrated outcome. That is, broadly, the space this study tries to occupy.

Accordingly, this paper investigates how four interrelated dimensions of intelligent scheduling systems — Intelligent Scheduling Accuracy, User Satisfaction, Ease of Use, and System Reliability — relate to Healthcare Workforce Efficiency among a sample of U.S. healthcare professionals, using a quantitative, survey-based design. The intent is not to advance a definitive causal claim, which a cross-sectional design cannot support, but to offer grounded empirical evidence that can inform how healthcare organizations evaluate, and invest in, the scheduling technologies they adopt.

2. Materials and Methods

2.1 Study Design and Setting

This study used a cross-sectional, quantitative survey design to examine associations between intelligent scheduling system attributes and healthcare workforce efficiency among healthcare professionals in the United States. A cross-sectional approach was selected, somewhat pragmatically, because it allowed data on several variables of interest to be captured at a single point in time and examined for association — a reasonable first step given that empirical work in this specific area remains limited, though it should be said upfront that this design cannot establish causal direction or account for changes over time.

2.2 Participants and Sampling

A total of 155 healthcare professionals participated, drawn from physicians, nurses, allied health professionals, and administrative staff working across multiple U.S. healthcare organizations. Participants were recruited via convenience sampling — that is, individuals who had direct experience with scheduling systems in their workplace and who were willing and available to participate were invited to take part. This approach was chosen primarily for feasibility, since it enabled relatively rapid access to a population that is otherwise difficult to reach in large numbers, though it does come at the cost of generalizability, a limitation discussed later in this paper. Eligibility required that respondents currently work, or had recently worked, in a healthcare setting using some form of digital or intelligent scheduling tool. No formal a priori power analysis was conducted; the achieved sample of 155 nonetheless exceeds the commonly cited minimum of 10–15 cases per predictor variable for multiple regression with four predictors (Field, 2018).

2.3 Data Collection Procedure and Instrumentation

Data were collected through a structured, self-administered online questionnaire distributed via digital platforms accessible to healthcare staff across participating organizations. The questionnaire was developed by adapting item content from established instruments used in prior healthcare technology and information-systems research (Ma et al., 2018; Fox et al., 2021), and comprised two sections: (1) demographic characteristics (gender, age, profession, years of experience) and (2) construct-specific items measuring the study's five core variables.

Five constructs were assessed: Intelligent Scheduling Accuracy (ISA), User Satisfaction (US), Ease of Use (EOU), System Reliability (SR), and Healthcare Workforce Efficiency (HWE). All items were rated on a five-point Likert scale ranging from 1 (*strongly disagree*) to 5 (*strongly agree*) (Demirkan & Spohrer, 2014). An online distribution format was chosen because it allowed the survey to reach a geographically dispersed sample of healthcare staff relatively efficiently and at low cost (Zhou et al., 2022).

For transparency and reproducibility, the following elements are reported, consistent with recommendations for survey-based research reporting: the survey was distributed over a defined data collection window [dates to

be specified by author]; participation was voluntary and anonymous; informed consent was obtained electronically prior to survey access; and the study protocol was reviewed and approved by [institutional ethics review board name and approval number to be inserted by author] prior to data collection. The complete item pool, along with response rate and any exclusion criteria applied to incomplete responses, should be made available as supplementary material to support replication.

2.4 Statistical Analysis

All statistical analyses were conducted using IBM SPSS Statistics, version 26. Descriptive statistics (means, standard deviations, frequencies, and percentages) were first computed to characterize the sample and summarize responses across all constructs. Internal consistency reliability was assessed using Cronbach's alpha, supplemented by Composite Reliability (CR) and Average Variance Extracted (AVE) to evaluate convergent validity (Ahmadi-Assalemi et al., 2020); values of α and CR above 0.70, and AVE above 0.50, were treated as evidence of acceptable psychometric performance, consistent with conventional thresholds (Fornell & Larcker, 1981).

Bivariate associations among constructs were examined using Pearson product-moment correlation coefficients (Persis et al., 2020), which offered a first look at the direction and strength of relationships before moving to multivariable modeling. A multiple linear regression model was then estimated to evaluate the combined and independent contributions of ISA, US, EOU, and SR to HWE, specified as:

$$\text{HWE} = \beta_0 + \beta_1 \text{ISA} + \beta_2 \text{US} + \beta_3 \text{EOU} + \beta_4 \text{SR} + \epsilon$$

where β_0 denotes the model intercept, β_1 through β_4 represent standardized regression coefficients for each predictor, and ϵ represents the residual error term (Muthuri et al., 2020). Variance Inflation Factor (VIF) values were examined to rule out problematic multicollinearity among predictors. Statistical significance was set at $\alpha = 0.05$ (two-tailed) throughout (Beheshti & Beheshti, 2010).

3. Results

3.1 Demographic Characteristics of Respondents

The final analytic sample comprised 155 healthcare professionals (Table 1). Women made up the largest share of respondents (53.5%), followed by men (43.2%), with 3.2% preferring not to disclose gender. Most

Table 1. Demographic characteristics of study respondents (N = 155). Frequencies (n) and percentages (%) are reported for gender, age group, professional role, and years of clinical or administrative experience among the 155 U.S. healthcare workers who completed the survey. Percentages may not sum to exactly 100% due to rounding.

Variable	Category	Frequency (n)	Percentage (%)
Gender	Male	67	43.2
Female	83	53.5	Prefer not to say
5	3.2	Age	20–29 years
34	21.9	30–39 years	55
35.5	40–49 years	42	27.1
50 years	24	15.5	Profession
Physician	40	25.8	Nurse
68	43.9	Allied Health Professional	31
20.0	Administrative Staff	16	10.3
Experience	<5 years	37	23.9
5–10 years	49	31.6	11–20 years
43	27.7	>20 years	26

Table 2. Descriptive statistics for the five study constructs. Mean (M), standard deviation (SD), and observed minimum–maximum values are reported for each construct, based on five-point Likert-scale responses (1 = strongly disagree, 5 = strongly agree) aggregated across items within each construct. ISA = Intelligent Scheduling Accuracy; US = User Satisfaction; EOU = Ease of Use; SR = System Reliability; HWE = Healthcare Workforce Efficiency.

Variable	Mean	SD	Min	Max
ISA	4.18	0.67	2.20	5.00
US	4.09	0.72	2.00	5.00
EOU	4.05	0.69	2.10	5.00
SR	4.11	0.65	2.30	5.00
HWE	4.21	0.61	2.40	5.00

Table 3. Internal consistency and convergent validity of measurement constructs. Cronbach's alpha, Composite Reliability (CR), and Average Variance Extracted (AVE) are reported for each of the five constructs. Cronbach's alpha and CR values above 0.70, and AVE values above 0.50, are conventionally interpreted as evidence of acceptable reliability and convergent validity, respectively (Fornell & Larcker, 1981). ISA = Intelligent Scheduling Accuracy; US = User Satisfaction; EOU = Ease of Use; SR = System Reliability; HWE = Healthcare Workforce Efficiency.

Construct	Cronbach's Alpha	CR	AVE
ISA	0.901	0.921	0.699
US	0.887	0.909	0.682
EOU	0.873	0.896	0.646
SR	0.881	0.904	0.658
HWE	0.915	0.931	0.731

participants fell within the 30–39 year age bracket (35.5%), followed by the 40–49 year group (27.1%) — suggesting, unsurprisingly perhaps, that the sample skewed toward professionals in the more established stages of their careers. By profession, nurses were the largest single group (43.9%), followed by physicians (25.8%), allied health professionals (20.0%), and administrative staff (10.3%). In terms of tenure, close to a third of respondents (31.6%) reported 5–10 years of experience, and 27.7% reported 11–20 years, indicating a reasonably experienced pool of respondents overall.

3.2 Descriptive Statistics of Study Variables

Across all five constructs, mean scores clustered in a fairly narrow, favorable range (Table 2). Healthcare Workforce Efficiency received the highest average rating ($M = 4.21$, $SD = 0.61$), followed by Intelligent Scheduling Accuracy ($M = 4.18$, $SD = 0.67$), System Reliability ($M = 4.11$, $SD = 0.65$), User Satisfaction ($M = 4.09$, $SD = 0.72$), and Ease of Use ($M = 4.05$, $SD = 0.69$). The relatively modest standard deviations across constructs point to a fair degree of agreement among respondents — participants were not, for the most part, deeply divided in their perceptions of these systems.

3.3 Perceived Benefits of Intelligent Scheduling Systems

When asked to identify the most valuable benefits of intelligent scheduling systems, respondents most frequently selected Workforce Efficiency (21.8%), followed by Scheduling Accuracy (19.6%), Staff Satisfaction (17.4%), and Resource Optimization (16.2%) (Figure 1). Patient Care Quality (13.5%) and Work–Life Balance (11.5%) were endorsed somewhat less often, though it is worth noting these still represent a meaningful proportion of responses rather than an afterthought.

3.4 Reliability and Convergent Validity

Reliability analysis indicated strong internal consistency across all constructs, with Cronbach's alpha values ranging from 0.873 to 0.915 — comfortably above the conventional 0.70 threshold (Table 3). Composite Reliability values (0.896–0.931) reinforced this pattern, and Average Variance Extracted values (0.646–0.731) exceeded the 0.50 benchmark typically used to establish convergent validity. Taken together, these figures suggest the measurement instrument performed acceptably well psychometrically, lending reasonable confidence to the correlation and regression analyses that follow.

3.5 Pearson Correlation Analysis

All bivariate correlations among the study's five constructs were positive and statistically significant (Figure 2), consistent with the general expectation that stronger scheduling-system attributes co-occur with higher perceived workforce efficiency. HWE correlated most strongly with ISA ($r = 0.703$), followed by US ($r = 0.681$), EOU ($r = 0.642$), and SR ($r = 0.617$). Correlations among the independent variables themselves ranged from 0.539 to 0.624 — moderate in magnitude, and importantly, all below the 0.80 threshold often used as an informal warning sign for multicollinearity, which supported proceeding to multivariable regression.

3.6 Multiple Regression Analysis

The regression model explaining HWE from ISA, US, EOU, and SR was statistically significant overall, $F(4, 150) = 58.74$, $p < .001$, and accounted for a substantial share of variance in workforce efficiency ($R = 0.781$, $R^2 = 0.610$, adjusted $R^2 = 0.600$) (Table 4). Intelligent Scheduling Accuracy emerged as the strongest individual predictor ($\beta = 0.341$, $p < .001$), followed by User Satisfaction ($\beta = 0.286$, $p < .001$), Ease of Use ($\beta = 0.218$, $p = .001$), and System Reliability ($\beta = 0.173$, $p = .005$) — all statistically significant and all in the expected direction. VIF values (1.31–1.54) remained well within acceptable limits, indicating multicollinearity was not a material concern for this model.

4. Discussion

Taken as a whole, these findings suggest — cautiously, and with the usual caveats attached to cross-sectional survey work — that intelligent scheduling systems are meaningfully associated with how healthcare staff perceive their own workforce efficiency. Ratings across all five constructs clustered between 4.05 and 4.21, a fairly narrow and consistently favorable band, which on its own is a modest but reassuring signal that these systems are, at minimum, not experienced as a burden by the people using them. That Healthcare Workforce Efficiency received the single highest mean score (4.21) is perhaps worth sitting with for a moment: it implies that respondents felt the improvements were tangible enough to notice in their day-to-day coordination, workload distribution, and general operational rhythm — not simply a theoretical benefit described in a policy memo somewhere.

4.1 The Central Role of Scheduling Accuracy

Of the four predictors examined, Intelligent Scheduling

Table 4. Multiple linear regression predicting Healthcare Workforce Efficiency from intelligent scheduling system attributes. Standardized regression coefficients (β), standard errors (SE), t-values, p-values, and Variance Inflation Factors (VIF) are reported for each predictor (ISA, US, EOU, SR) in a simultaneous multiple regression model with Healthcare Workforce Efficiency (HWE) as the outcome variable ($N = 155$). Model summary statistics include the multiple correlation coefficient (R), coefficient of determination (R^2), adjusted R^2 , and the overall F-test of model significance. VIF values below 5 indicate the absence of problematic multicollinearity among predictors. Note: ISA = Intelligent Scheduling Accuracy; US = User Satisfaction; EOU = Ease of Use; SR = System Reliability; HWE = Healthcare Workforce Efficiency; SE = Standard Error; VIF = Variance Inflation Factor.

Predictor	β	SE	t	p	VIF
ISA	0.341	0.071	4.81	<0.001	1.54
US	0.286	0.068	4.21	<0.001	1.47
EOU	0.218	0.064	3.41	0.001	1.39
SR	0.173	0.061	2.84	0.005	1.31

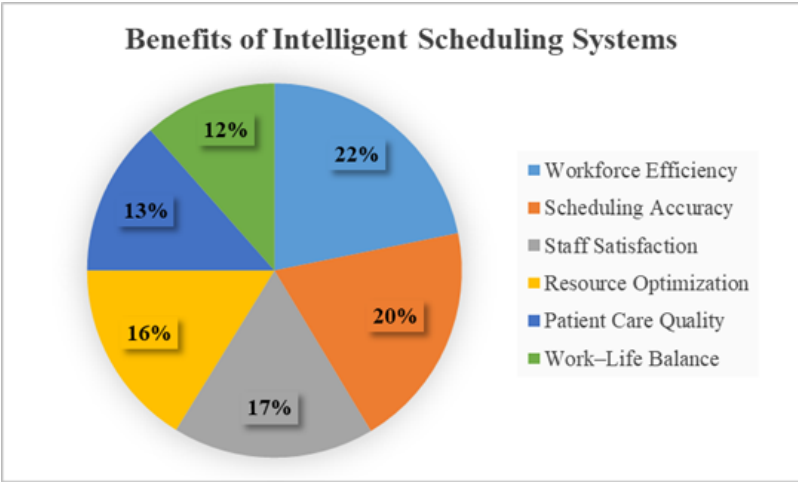


Figure 1. Respondent-perceived benefits of intelligent scheduling systems. Bar chart showing the percentage of respondents ($N = 155$) who identified each listed outcome — Workforce Efficiency, Scheduling Accuracy, Staff Satisfaction, Resource Optimization, Patient Care Quality, and Work–Life Balance — as a primary perceived benefit of intelligent scheduling system adoption. significant at $p < .001$ (two-tailed, $N = 155$).

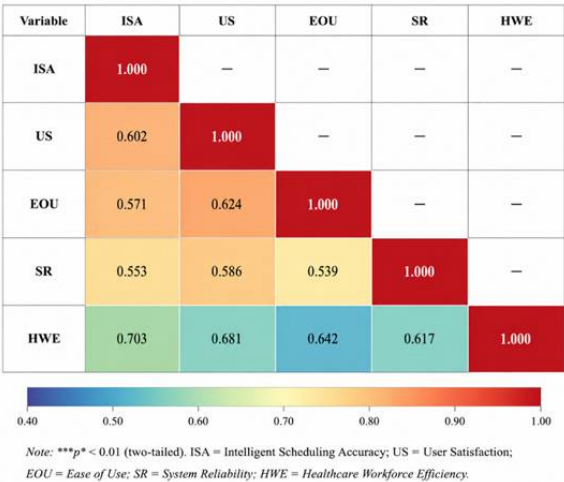


Figure 2. Pearson correlation matrix among study constructs. Heat map / matrix displaying pairwise Pearson product-moment correlation coefficients (r) among Intelligent Scheduling Accuracy (ISA), User Satisfaction (US), Ease of Use (EOU), System Reliability (SR), and Healthcare Workforce Efficiency (HWE). All correlations shown were statistically significant.

Accuracy carried the most explanatory weight ($\beta = 0.341$, $p < .001$), and this is probably the least surprising finding in the study, if also one of the more important. Accurate scheduling, almost by definition, means the right people end up in the right place at the right time — and when that breaks down, the consequences tend to cascade: understaffing, unplanned overtime, delayed care, and workloads that fall unevenly across a team (Espinosa et al., 2021). Algorithmic scheduling tools, by weighing staff availability, competency, and required coverage simultaneously rather than sequentially, appear reasonably well positioned to reduce these breakdowns (Ammendolia et al., 2016), which may in turn support more continuous, uninterrupted patient care (Holden et al., 2013). The correlation between ISA and HWE ($r = 0.703$) reinforces this — organizations that get scheduling accuracy right seem, unsurprisingly, to see that reflected in broader efficiency outcomes.

4.2 User Satisfaction as a Contributing Factor

User Satisfaction also contributed meaningfully to the model ($\beta = 0.286$, $p < .001$), and this points to something that is easy to overlook in discussions that focus heavily on system architecture: technology, however well designed, does not do much good if the people expected to use it do not actually accept it. Scheduling platforms perceived as fair and reasonably aligned with staff preferences appear to enjoy greater buy-in (Schepens et al., 2018), and higher satisfaction seems, plausibly, to smooth communication between administrators and frontline staff, reducing friction and conflict over assignments (Rafiq et al., 2020). The moderately strong correlation between US and HWE ($r = 0.681$) is broadly consistent with the wider literature on technology acceptance, even though this study did not formally test a technology-acceptance model.

4.3 Usability and Reliability as System-Level Enablers

Ease of Use and System Reliability, while somewhat smaller in magnitude than the first two predictors, were both statistically significant contributors ($\beta = 0.218$ and $\beta = 0.173$, respectively). This pairing makes intuitive sense: an interface that reduces cognitive burden frees staff to spend more of their limited time on patient care rather than on administrative wrangling (Van Leeuwen et al., 2021), while a dependable system — one that does not crash, glitch, or lose data at inconvenient moments — allows staff to respond quickly when last-minute changes

inevitably arise (Mourtzis et al., 2022). Together, these results suggest that the “soft” usability dimensions of intelligent scheduling systems are not incidental design features but meaningful drivers of the outcomes healthcare organizations actually care about (Oueida et al., 2018).

4.4 Model Fit and What Remains Unexplained

The regression model accounted for 61.0% of the variance in Healthcare Workforce Efficiency — a respectable figure for a model built on perception-based, cross-sectional survey data, though it inevitably leaves a substantial 39% of variance unaccounted for. That residual share is a useful reminder that scheduling technology, however well implemented, operates within a much larger organizational ecosystem — one shaped by leadership style, institutional policy, staffing ratios, workplace culture, and individual motivation, none of which were directly measured here. Future research would do well to build more integrative models that combine these organizational and behavioral dimensions with technology-specific predictors, ideally using longitudinal or multi-source designs that can speak more confidently to causal direction and reduce reliance on single-source, self-reported data.

4.5 Limitations

Several limitations should temper how these findings are interpreted. First, the cross-sectional design captures associations at a single point in time and cannot establish causal direction — it remains equally plausible, for instance, that more efficient units simply adopt scheduling technology more readily, rather than the technology driving the efficiency gain. Second, participants were recruited through convenience sampling from a self-selected pool of respondents, which limits generalizability to the broader U.S. healthcare workforce and may have introduced a degree of selection bias toward staff already favorably disposed toward digital scheduling tools. Third, all constructs — both predictors and outcome — were measured through the same self-report instrument administered at the same time, which raises the possibility of common-method variance inflating the observed associations; no marker-variable test or Harman’s single-factor check was conducted to formally rule this out, and future studies would benefit from doing so or from pairing self-report data with objective operational indicators (e.g., staffing ratios, overtime hours, patient wait times). Fourth, the study relied exclusively on perceptual, subjective

measures of efficiency rather than objective performance metrics, which may not fully capture actual operational outcomes. Finally, the regression model, while explaining a substantial 61.0% of variance in workforce efficiency, leaves a meaningful share unaccounted for, suggesting that organizational, cultural, and leadership factors not measured here likely play a non-trivial role and warrant inclusion in future, more comprehensive models.

5. Conclusion

This study offers empirical, survey-based evidence that intelligent scheduling systems are positively associated with healthcare workforce efficiency, largely through the combined contributions of scheduling accuracy, user satisfaction, ease of use, and system reliability. Among these, scheduling accuracy appeared to matter most, though all four dimensions contributed meaningfully to the overall model, together explaining roughly six-tenths of the variance in perceived efficiency. These findings, while necessarily preliminary given the cross-sectional, single-source design, offer a reasonably grounded starting point for healthcare organizations weighing further investment in intelligent scheduling technology. Future work using longitudinal, multi-source, or mixed-methods designs would help clarify causal direction and capture the organizational factors this study could not directly measure.

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Author Contribution

M.R.H.: conceptualization, methodology, data collection, formal analysis, writing – original draft, writing – review and editing, and final approval of the manuscript.

Competing Financial Interests

The author M.R.H. et al., declares no competing financial interests related to this work.

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