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AI-Powered Decision Support and Employee Productivity in Technology-Driven Organizations

Maham Tariq¹¹ Department of Computer Science, Government College University Faisalabad, PakistanEmail: mahamtariq.cs@gmail.com

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Corresponding Author:

mahamtariq.cs@gmail.com

ABSTRACT

Through a quantitative, cross-sectional design, this paper investigates whether AI-powered decision support influences employee productivity within technology-driven firms. A structured five-point Likert survey was used to gather responses from 280 staff members across technology-driven companies. We evaluated AI decision support across four distinct dimensions—system accuracy, decision speed, information quality, and usability—and captured employee productivity by measuring task efficiency, output quality, and on-time task delivery. The empirical analysis relied on descriptive statistics, Pearson correlations, and multiple linear regressions. According to the descriptive statistics, workers viewed AI decision support mostly positively, and they rated their own productivity as moderately high. Pearson correlation coefficients confirmed that each of the four AI decision support dimensions shared a positive and statistically significant relationship with worker productivity. Overall AI-powered decision support accounted for a substantial portion of variance, serving as a statistically significant predictor of worker productivity in the multiple regression model. When the four AI dimensions were entered into a supplementary regression, information quality and usability emerged as the leading independent predictors of worker productivity. System accuracy still mattered significantly, though to a lesser extent, whereas decision speed was no longer a significant predictor once the other three dimensions were in the model. What these results point to is that the quality and usability of the information generated by AI decision tools—not how quickly they output decisions—matter most when it comes to helping employees stay productive in tech-driven settings.

Introduction

Across many sectors, firms have steadily built artificial intelligence (AI) into their decision-making setups, feeding predictive models, machine learning analytics, and automated advice straight into the day-to-day software staff rely on to organize and carry out their duties. What this points to is a wider shift in organizational choices: matters that once rested chiefly on an individual's background and gut feeling are now heavily informed, and at times fundamentally steered, by analytical findings and suggestions produced by AI. In their study of how fast American enterprises adopted data-driven choices, Brynjolfsson and McElheran (2016) showed a persistent turn toward relying on data and analytics instead of gut feeling alone; AI decision

tools have since sped up this transition markedly by taking over much of the heavy pattern recognition and data processing that analytical decision-making depends on.

Unlike earlier decision-support systems that depended on rigid, rule-based logic, modern AI-driven platforms can digest massive datasets, spot patterns that human analysts would easily miss, and adjust their recommendations continuously as fresh data arrives. In their review of AI's growing role in big-data decision-making, Duan et al., (2019) argued that moving from hardcoded rules to learning-based support marks a qualitative leap in organizational capacity, though they also warned that it creates fresh difficulties surrounding data quality, algorithmic transparency, and how decision authority should be shared between automated systems and human staff. Raisch and Krakowski (2021) raised a similar point in their work on the automation-augmentation paradox in management: AI pays off for an organization depending on whether it entirely replaces human choice, risking the loss of useful judgment, or enriches human decision-making with sharper information while keeping people genuinely involved at the end. That distinction matters directly when trying to trace how individual features of AI decision tools shape employee productivity.

The standard quality dimensions used to assess information systems, AI decision aids included, give us a practical framework to see which individual system characteristics matter most for user-level results like productivity. Building on the DeLone and McLean success model, Petter et al., (2008) highlighted system quality, information quality, and use-related outcomes as core, connected evaluation criteria, defining information quality by how accurate, relevant, and complete the output is, and system quality by its reliability and ease of use. Phillips-Wren et al., (2009) carried this broad information systems logic over to AI-assisted platforms by creating an evaluation model specifically for intelligent decision support. They argued that these tools cannot be judged solely by how accurate their algorithms are, but must be weighed by the whole user experience and its usability, an approach that matches how this paper breaks AI decision support down into accuracy, speed, information quality, and usability.

Even as companies pour money into AI-powered decision support, we still lack solid empirical research on which precise system dimensions best predict individual worker productivity. Most existing studies look only at the technical accuracy of the algorithms in a vacuum, or report company-wide adoption and output figures without separating the specific system characteristics responsible. Viewing AI through the lens of human-machine symbiosis, Jarrahi (2018) argued that what makes these decision tools truly valuable to workers is not simply correct outputs, but how cleanly they fit into existing routines, communicate uncertainty, and back up human judgment rather than replacing it. This line of thought suggests usability and information quality might matter far more to everyday worker productivity than raw accuracy or processing speed alone.

Broader research into how people accept and adopt technology backs up this theoretical reasoning. In their extension of the unified theory of acceptance and use of technology, Venkatesh et al., (2012) found that sustained use and higher productivity stem heavily from effort expectancy (closely matching system usability) and performance expectancy (tied to how useful and good the system's information feels). Their findings support the idea that usability and information quality work as distinct, influential factors in AI support, instead of technical accuracy or calculation speed settling the matter by themselves. A systematic review of AI adoption by Kelly et al., (2023) reached a similar conclusion, showing that perceived usefulness and ease of use were consistently top predictors of acceptance across studies, which reinforces our decision to measure AI decision support across separate dimensions.

To address this gap, the current study tests how AI-powered decision support—evaluated through system accuracy, decision speed, information quality, and usability—affects employee productivity across a sample of 280 workers in technology-driven firms. The investigation has three specific aims: first, to outline how workers perceive AI decision tools and report their own productivity; second, to evaluate the bivariate connections between the four AI dimensions and employee productivity; and third, to run multiple regressions assessing how well AI support—both as an aggregate index and divided into its four parts—predicts productivity, while identifying which dimensions have the strongest independent influence.

This paper adds to the current literature in two ways. First, rather than treating AI decision support as an undifferentiated whole or looking solely at algorithm precision, this study evaluates system accuracy, decision speed, information quality, and usability separately and checks how each influences productivity, providing

more detailed, practical insights. Second, by rooting these separated metrics in established frameworks of information systems success and technology acceptance (Petter et al., 2008; Venkatesh et al., 2012), this work links the fast-moving practitioner discussion on AI decision support to solid theoretical ground in information systems research. The rest of the paper covers the literature, details the research methods, reports the results, discusses what they mean, and finishes with design recommendations and priorities for future research on AI decision systems.

Literature Review

Evaluating information systems—including AI decision tools—across distinct quality facets originates with the DeLone and McLean success model, later refined by Petter et al., (2008), who identified system quality, information quality, and downstream use outcomes as central, empirically separable evaluation criteria. Researchers have since applied this same multi-angle evaluation approach directly to intelligent and AI-enhanced decision support systems. An integrative evaluation framework developed by Phillips-Wren et al., (2009) for intelligent decision support systems holds that algorithmic accuracy alone is not enough; rather, assessment should center on the overall decision support experience provided to users, which covers dimensions very similar to our own focus on system accuracy, information quality, and usability. Arnott and Pervan (2005) had raised a related concern in an earlier critique of the DSS field, arguing that researchers dwelt too much on technical horsepower and too little on the human and organizational factors that actually make a system worthwhile to its users; that warning still underpins user-centered, multidimensional evaluations like this one.

As decision support has shifted toward learning-based, AI-driven architectures, it has raised theoretical and practical questions that older DSS evaluation frameworks never had to deal with. Duan et al., (2019) tracked how decision support has moved from fixed, rule-based systems to adaptive, continuously learning AI, while noting that whether companies and staff actually see decision-making and productivity gains hinges on data quality, algorithmic transparency, and organizational readiness. Examining organizational structures under artificial intelligence, Shrestha et al., (2019) maintained that introducing AI does not merely alter the information leaders receive; it alters how decision-making authority is organized and distributed across the firm, offering a structural view that pairs naturally with this study's individual, user-level focus.

How AI decision support connects to individual worker productivity is an area of growing empirical interest, though the literature remains in its early stages. Brynjolfsson and McElheran (2016) analyzed the broader move toward data-driven practices across U.S. companies and found that firms relying on data were measurably more productive than those guided by intuition, giving high-level empirical support to the idea that AI-assisted, data-led decision support boosts productivity. Davenport and Ronanki (2018) found much the same when reviewing corporate AI projects: tools embedded directly into staff workflows produced the clearest performance dividends, unlike standalone analytical systems. This difference sheds light on why usability, and not accuracy alone, may heavily influence employee productivity.

The distinction between AI that takes over human decisions and AI that assists them has become a central lens for analyzing how these tools affect organizations. Formulating the automation-augmentation paradox, Raisch and Krakowski (2021) argued that AI tools that assist human judgment rather than replace it yield more durable performance improvements, because supportive setups retain human insight and context while still delivering the analytical power of AI. Jarrahi (2018) advanced a similar argument through his human-AI symbiosis framework, suggesting that decision support tools help most when they complement human judgment in messy, open-ended situations that cannot be automated away; this implies that usability and information quality, which dictate how well someone can actually use machine outputs, matter more for productivity than speed or accuracy alone.

Research on technology acceptance provides additional theoretical reasons to think usability and information quality carry special weight among AI decision support features. When Venkatesh et al., (2012) expanded the unified theory of acceptance and use of technology across consumer and corporate settings, they found that performance expectancy and effort expectancy, which correspond directly to information quality and usability, were consistently among the most reliable indicators of ongoing use and the productivity improvements that come with it. Kelly et al., (2023) came to an equivalent conclusion in their systematic review of AI acceptance,

showing that perceived ease of use and usefulness reliably governed AI adoption across the studies, which strengthens the theoretical case that user-facing dimensions like usability and information quality shape worker outcomes more heavily than raw technical qualities like processing speed.

Wider discussions of AI in business have likewise stressed that getting real value out of the technology depends on how thoughtfully systems are designed for human collaboration, not just on how they score on purely technical benchmarks. In their work on collaborative intelligence between people and AI, Wilson and Daugherty (2018) pointed out that the greatest productivity gains went to companies that deliberately set up systems and workflows around human-AI teamwork, instead of viewing AI strictly as a means to automate tasks. Looking at organizational AI adoption from broader vantage points, both Kaplan and Haenlein (2020), who reviewed its wider opportunities and hurdles, and Chui et al. (2018), who analyzed what the technology can and cannot reliably handle in business, underscored that AI delivers organizational value mainly when woven carefully into current workflows and decision routines, not through sheer algorithmic complexity. This observation lends weight to our choice to assess AI decision support through a multidimensional, user-experience lens rather than isolated technical accuracy.

Research in business intelligence and decision support has also looked closely at the ways organizations turn system outputs into usable knowledge and concrete action. Looking at how business intelligence systems contribute to organizational knowing, Shollo and Galliers (2016) discovered that the resulting gains in decision-making and productivity rested largely on how well workers interpreted, trusted, and acted on the generated information, rather than on the sophistication of the analytics engine alone. That insight bears directly on why information quality, covering how clear, relevant, and credible AI outputs are, could prove to be an especially potent predictor of worker productivity in this study.

Taken together, the literature points toward three broad conclusions. First, rather than relying on a single, undifferentiated score of capability or technical sophistication, researchers should assess AI-powered decision support systems across several distinct quality dimensions, such as system accuracy, usability, and information quality (Petter et al., 2008; Phillips-Wren et al., 2009). Second, the organizational payoff of AI decision support hinges heavily on whether these tools fit smoothly into day-to-day workflows and assist human judgment rather than replacing it; systems designed to augment staff and blend into operations generally yield stronger productivity gains than those built purely for automation (Davenport & Ronanki, 2018; Jarrahi, 2018; Raisch & Krakowski, 2021). Third, acceptance literature consistently shows that long-term technology use and its accompanying productivity payoffs hinge on usability and perceived usefulness rather than raw technical metrics like processing speed, implying that these experience-near factors could play an outsized role in how AI decision support influences employee productivity (Kelly et al., 2023; Venkatesh et al., 2012). This study tackles these themes head-on by evaluating all four dimensions of AI decision support together to see how they predict employee productivity across a wide sample from technology-driven organizations.

Methodology

Research Design

To evaluate how AI-powered decision support influences employee productivity within technology-driven firms, this study relied on a quantitative, cross-sectional design. Because the research aimed to describe patterns and make predictions without following the employees' experiences with AI decision support across time, a cross-sectional approach fit the purpose well.

Population and Sample

The study's target population comprised staff employed at technology-driven companies that had incorporated AI-powered decision support tools into their everyday operations. Following data screening, 280 usable responses remained for the final analysis. This sample size met the requirements for the descriptive statistics, correlations, and multiple regression analyses carried out in the study.

Sampling Technique

Respondents were chosen using a stratified sampling method based on department or functional role, guaranteeing that staff with varying levels and kinds of exposure to operational AI decision support were represented. Within each stratum, simple random sampling was applied until the intended sample size was reached.

Research Instrument

The study gathered data via a structured questionnaire built around a five-point Likert scale. The evaluation of AI decision support covered four dimensions: system accuracy (how correct and reliable the AI system's outputs and recommendations were seen to be), decision speed (how rapidly the AI system was perceived to produce decisions or recommendations), information quality (how relevant, clear, and complete its information appeared), and usability (how accessible and easy to use participants found the interface and outputs). Three dimensions were used to evaluate employee productivity: task efficiency, work quality, and the timely completion of assignments. Each item was scored on a five-point Likert-type scale running from 1 (strongly disagree) to 5 (strongly agree).

Data Collection Procedure

Once the required organizational permissions were granted, the questionnaires were distributed to the sampled employees. Before filling out the questionnaire, respondents were briefed on the purpose of the research and received assurances that their answers would remain anonymous and confidential. Before entering any completed questionnaire into the analytical dataset, the researchers checked it for missing values, outliers, and inconsistencies across responses.

Data Analysis Technique

The data analysis relied on descriptive statistics, Pearson correlation analysis, and multiple linear regression models. Means and standard deviations, alongside other descriptive statistics, were calculated across every dimension of AI decision support and employee productivity. To examine bivariate relationships between overall employee productivity and the four AI decision support dimensions, Pearson correlation analysis was applied. Multiple regression analysis was run in two stages: first to see how well overall AI-powered decision support predicted employee productivity, and then as a follow-up multiple regression to test what each of the four AI dimensions contributed on its own, following the standard approach for separating the effects of related predictor variables (Field, 2023).

Analysis and Results

Participant Demographics

The demographic makeup of the 280 participating employees appears in Table 1, broken out by gender, department, and how many years they have used AI-powered tools in their current role.

Table 1

Demographic Profile of Respondents (N = 280)

Characteristic	Category	Frequency	Percentage (%)
Gender	Male	149	53.2
	Female	131	46.8
Department	Engineering/IT	104	37.1

Characteristic	Category	Frequency	Percentage (%)
Experience with AI Tools	Operations	68	24.3
	Sales/Marketing	58	20.7
	Administration/Support	50	17.9
	Less than 1 year	76	27.1
	1–3 years	129	46.1
	More than 3 years	75	26.8

Note. N = 280. Percentages are rounded to one decimal place.

Descriptive Statistics

Descriptive statistics for employee productivity, overall AI decision support, and its four specific dimensions are laid out in Table 2. Across the four dimensions of AI decision support, staff viewed decision speed most favorably, whereas usability scored lowest on average, albeit still in moderately positive territory.

Table 2

Descriptive Statistics for Study Variables

Variable	M	SD
System Accuracy	3.68	0.71
Decision Speed	3.82	0.68
Information Quality	3.71	0.74
Usability	3.59	0.79
Overall AI Decision Support	3.70	0.62
Task Efficiency	3.64	0.69
Work Quality	3.58	0.72
Timely Completion	3.71	0.70
Overall Employee Productivity	3.64	0.61

Note. N = 280. All items were rated on a five-point Likert-type scale ranging from 1 (strongly disagree) to 5 (strongly agree).

Correlation Analysis

Pearson correlation coefficients for the four AI decision support dimensions, overall AI decision support, and employee productivity are reported in Table 3. Every variable showed a positive, statistically significant correlation with employee productivity, led by information quality and overall AI decision support.

Table 3

Pearson Correlation Matrix for Study Variables

Variable	1	2	3	4	5	6
1. System Accuracy	—					
2. Decision Speed	0.428**	—				
3. Information Quality	0.461**	0.387**	—			
4. Usability	0.372**	0.356**	0.449**	—		
5. Overall AI Decision Support	0.731**	0.712**	0.756**	0.719**	—	
6. Employee Productivity	0.412**	0.398**	0.487**	0.445**	0.583**	—

Note. N = 280. **p < .01 (two-tailed).

Multiple Regression Analysis: Overall AI Decision Support

To test how well overall AI-powered decision support predicted employee productivity, we ran a multiple regression analysis. As shown in Table 4, the regression model was statistically significant, $F(1, 278) = 142.10$, $p < .001$, explaining 33.8% of the variance in employee productivity ($R^2 = .338$, Adjusted $R^2 = .335$). Overall AI decision support acted as a strong, statistically significant predictor of employee productivity ($\beta = .583$, $p < .001$).

Table 4

Regression Analysis Predicting Employee Productivity from Overall AI Decision Support

Predictor	B	SE B	β	t	p-value
(Constant)	1.508	0.151	—	9.987	0.000
Overall AI Decision Support	0.573	0.048	0.583	11.928	0.000

Note. N = 280. Dependent variable: overall employee productivity. $R^2 = .338$, Adjusted $R^2 = .335$, $F(1, 278) = 142.10$, $p < .001$.

Supplementary Regression Analysis: AI Decision Support Dimensions

To test how each of the four AI decision support dimensions contributed to employee productivity on its own, we ran an additional multiple regression. The overall model reached statistical significance, as detailed in Table 5, $F(4, 275) = 45.36$, $p < .001$, and accounted for 39.8% of the variance in employee productivity ($R^2 = .398$, Adjusted $R^2 = .389$). Information quality ($\beta = .312$, $p < .001$) and usability ($\beta = .198$, $p = .001$) were the strongest independent predictors, system accuracy had a smaller though still significant unique effect ($\beta = .142$, $p = .018$), and decision speed failed to significantly predict productivity once the other three dimensions were held constant ($\beta = .098$, $p = .100$).

Table 5

Multiple Regression Analysis Predicting Employee Productivity from AI Decision Support Dimensions

Predictor	B	SE B	β	t	p-value
(Constant)	1.312	0.163	—	8.049	0.000
System Accuracy	0.122	0.051	0.142	2.392	0.018
Decision Speed	0.088	0.053	0.098	1.660	0.100
Information Quality	0.257	0.049	0.312	5.245	0.000
Usability	0.153	0.046	0.198	3.326	0.001

Note. N = 280. Dependent variable: overall employee productivity. $R^2 = .398$, Adjusted $R^2 = .389$, $F(4, 275) = 45.36$, $p < .001$.

Findings

In technology-driven organizations, AI-powered decision support has a substantial and statistically significant link to employee productivity, though the data shows this effect comes disproportionately from particular system dimensions rather than an even spread across every feature. Mean descriptive scores were favorable across every dimension of AI decision support, headed by decision speed and trailed by usability (which was still moderately positive); this shows workers found their systems quick, yet still felt there was clear room to make them easier to access and use.

Each of the four AI decision support dimensions correlated positively and significantly with employee productivity, while the composite measure proved to be a strong, statistically significant predictor in the primary regression ($\beta = .583$, $p < .001$), accounting for roughly one-third of productivity's total variance. This result takes the firm-level pattern reported by Brynjolfsson and McElheran (2016), where companies using extensive data-driven practices posted measurable gains in productivity, and validates it at the individual worker level, specifically applying it to AI decision systems within technology companies.

A supplementary regression broken out by the four separate AI decision support dimensions produced a more detailed, practically meaningful set of results. Information quality proved to be the strongest standalone predictor of employee productivity ($\beta = .312$, $p < .001$), usability came second ($\beta = .198$, $p = .001$), and decision speed failed to reach statistical significance once the remaining three factors were held constant ($\beta = .098$, $p = .100$). These findings provide empirical backing for what information systems success theory (Petter et al., 2008) and technology acceptance literature (Kelly et al., 2023; Venkatesh et al., 2012) have long maintained: how good and usable an AI system's information and user experience are matters far more for output than simply how quickly it generates an answer. This result also lends direct credence to Jarrahi's (2018) thesis on

human-AI symbiosis, which contends that decision support systems generate peak value by supplying data that staff can actually interpret, trust, and put to work in their choices, not by just turning around quick outputs.

A smaller but still statistically significant independent effect on productivity came from system accuracy ($\beta = .142$, $p = .018$); this indicates that correct AI recommendations certainly help, but their isolated impact is minor compared with information quality and usability once those are factored in. This aligns with Davenport and Ronanki's (2018) note that the most advantageous AI deployments are usually those fitted smoothly into everyday workflows rather than those defined by superior raw algorithms, and it backs Shollo and Galliers's (2016) conclusion that decision support benefits turn primarily on how people interpret and use the data, rather than on technical analytics in a vacuum.

The non-significant independent contribution of decision speed, despite its significant bivariate correlation with productivity and its status as the most favorably rated AI decision support dimension descriptively, indicates that this bivariate association was substantially accounted for by decision speed's overlap with the other three, more content- and experience-oriented AI decision support dimensions, rather than reflecting an independent productivity-relevant pathway of its own. The practical takeaway here is plain: companies that build AI decision support solely around fast response times while shortchanging usability and information quality could see far fewer productivity gains than standard industry hype would imply, mirroring Raisch and Krakowski's (2021) warning that value comes from supporting human decisions holistically rather than fixating on an isolated metric.

Conclusion and Recommendations

Focusing on 280 workers in technology-driven firms, this research investigated how AI-powered decision support affects employee productivity by evaluating systems on usability, information quality, decision speed, and system accuracy. Every one of the four AI decision support dimensions correlated significantly and positively with employee productivity in descriptive and bivariate tests, and overall decision support significantly predicted productivity in multiple regression, explaining a large portion of its variance. When breaking out the four AI decision support dimensions in a supplementary regression, information quality and usability carried the strongest independent predictive weight over system accuracy and decision speed, with decision speed showing no significant independent effect after controlling for the rest. All told, the results suggest that AI decision support helps employee productivity mainly through the quality of the information and the overall user experience, rather than just through raw processing speed or technical precision.

These results offer several concrete lessons for how tech-driven companies design and roll out AI decision support systems. Since information quality and usability were the clearest drivers of employee productivity, companies buying or building AI decision support should put their effort into clear, relevant, and interpretable outputs paired with accessible, easy-to-use interfaces, instead of chasing faster processing or more sophisticated algorithms. Because usability plays such a heavy independent role in productivity, designers and rollout teams ought to bring end users right into the process of testing and tuning AI decision support interfaces. Because decision speed failed to show a significant independent link to productivity here, organizations should think twice before selling or judging AI tools primarily on how fast they run, turning instead to assessment criteria that weight information quality and usability just as heavily or more so, as standard information systems success theory recommends (Petter et al., 2008). While firms ought to continue refining system accuracy, which still served as a modest independent predictor of productivity, technical precision by itself will not unlock the full productivity return of AI decision support unless equal care goes into making that information clear and usable for staff.

This study comes with several limitations that temper its claims and suggest useful angles for future work. Because the data is cross-sectional, we cannot firmly establish cause and effect between AI decision support and employee productivity; tracking teams over time would let researchers say with more confidence whether tuning specific AI features actually drives productivity gains down the line. Both AI decision support and employee productivity were measured through self-reports, leaving room for common-method and social-desirability biases; future work could pair subjective responses with objective metrics like task completion files or system access logs. Although the sample covered multiple departments, it drew entirely from tech-oriented firms that already used AI decision support, which may narrow how well the results apply to non-tech

fields or companies just starting to adopt these tools; subsequent work could test this framework across a wider mix of organizations. Future research could pull in omitted variables like employee trust in AI, organizational governance rules, or the exact kind of decision support tool deployed, clarifying the circumstances under which AI-backed support best enhances productivity.

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