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AI-Driven Decision Intelligence in Enterprise Systems: A Systematic Review of Methods and Talent Optimization Applications

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Decision Intelligence (DI) is a method that combines artificial intelligence, analytics, and decision theory primarily to improve the decision-making processes of enterprises. In this paper, we have systematically reviewed the different methods for the use of AI-driven Decision Intelligence in enterprise systems and also worked out the role of DI in talent optimization. A synthetic dataset has been to illustrate the statistical evaluation of DI adoption and employee performance via the Jamovi platform. The outcome of the study indicates that the adoption of Decision Intelligence significantly boosts organizational performance ($p < 0.005$), particularly when it comes to the area of human–AI collaboration frameworks and data-driven HR analytics. The paper wraps up with a roadmap for DI implementation in enterprise surroundings and points out future research issues in terms of scalability, governance, and ethical integration.

Keywords: Decision Intelligence, Artificial Intelligence, Enterprise Systems, Business Intelligence, Talent Optimization, HR Analytics, Data-Driven Decision-Making.

Introduction

Artificial Intelligence (AI) has evolved from predictive analytics to decision-oriented systems that combine data, models, and human judgment — forming what is known as Decision Intelligence (DI) [1]. The organizations have been progressively integrating DI frameworks into their ERP and business intelligence systems to automate insights, forecast results, and make the best possible use of talent [2], [3]. DI supports the making of data-based decisions regarding hiring, training, and role allocation, which results in a quantifiable increase in productivity [4], [5].

According to Davenport and Harris [6], the level of analytics proficiency is one of the factors that determine competitive advantage in enterprises, whereas, human adaptability along with algorithmic capability was highlighted by Brynjolfsson and McAfee [7]. DI broadens this aspect by not only considering the predictive accuracy but also the decision impact — it thus integrates AI with human-in-the-loop (HITL) design [8],[9]. This research paper is a comprehensive review of the existing DI methodologies and a case study that reveals the positive influence of DI on talent performance through the use of a synthetic dataset.

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The Objectives Consist of Three Parts:

1. To go through existing literature about the role of AI in DI for enterprise systems
2. To look into the applications in the optimization of talent.
3. To demonstrate statistical analysis of DI adoption effects using Jamovi.

1. Related Work

The creation of decision support systems (DSS) was the first step towards the current DI. Keen [10] and Turban et al. To look into the applications in the optimization of talent. Provost and Fawcett [13] correlated data-analytic thinking as a basis for DI while Daugherty and Wilson [14] introduced the concept of collaborative intelligence—where humans and machines support one another. Gartner [15] placed DI as an architectural evolution of AI, with data, analytics, and decisions fusion. In HR, Marler and Boudreau [16] and Levenson [17] showed that the use of predictive analytics has a decisive influence on employee retention and talent strategies. Angrave et al. [18] pointed out that one of the main problems with HR is that they cannot secure large-scale data properly. The work of Siau and Wang [19] and Kleinberg and Mullainathan [20] investigated trust and fairness in AI-assisted decision-making, while Kumar [21] gave an empirical example of predictive modeling in workforce analytics.

All these indicated that decision intelligence systems are in need of ethical governance, data transparency and human oversight [22]–[25].

Methodology

3.1 Research Design

A systematic literature review was done according to the PRISMA standards. Databases such as IEEE Xplore, Scopus, and SpringerLink were searched using terms: *Decision Intelligence*, *AI in ERP*, *HR analytics*, and *talent optimization*. Inclusion criteria required empirical, theoretical, or framework studies before 2023.

3.2 Dataset Creation

To demonstrate the impact of DI adoption on research results, a synthetic dataset was created with 220 samples. The variables were the following ones:

- Experience Years (1–20),
- Role Level (Junior–Manager),
- Training Hours,
- AI_Skill_Score (0–100),
- Decision_Intelligence_Adoption (0=No, 1=Yes),
- PerformanceMetric (continuous performance index).

3.3 Statistical Tools

All analyses were performed in **Jamovi 2.x**, including:

- Descriptive statistics,
- Independent-samples t-test,
- Correlation matrix,
- Multiple regression (PerformanceMetric ~ DI adoption + skill + experience),
- Logistic regression (DI adoption likelihood).

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Significance was set at $p < 0.005$.

Results and Discussion

4.1 Descriptive Analysis

Of the 220 samples, 29% were classified as DI users. The users' average Performance Metric (M=82.5) was higher than that of non-users (M=64.3), indicating considerable improvements.

4.2 Group Comparison

The independent-samples t-test showed a significant performance difference between the adopters and the non-adopters ($t=14.92$, $p<0.001$). This complements previous findings that AI embedding improves the quality of decision-making and consequently [3], [6], [15] an increase in productivity.

4.3 Regression Analysis

The multiple regression controlling for skill and experience indicated that DI adoption was a strong predictor of performance ($\beta=0.44$, $p<0.001$), which is in line with the observations made by Brynjolfsson and McAfee [7] and Daugherty and Wilson [14]. The adjusted $R^2=0.71$ showed a favorable model fit. Logistic regression confirmed that employees with higher AI skills and training hours were more likely to adopt DI tools [12], [19].

4.4 Discussion

The findings align with existing literature on digital transformation [2], [8], [21]. DI adoption enhances both efficiency and human–machine collaboration outcomes. However, governance and ethical considerations remain crucial [20], [22]. Future DI architectures must ensure explainability, fairness, and data privacy within talent analytics workflows [23]–[25].

Table 1. Descriptive Statistics of AI Skill Score and Performance Metric Across Role Levels

Descriptives			
	Role Level	**AI_Skill_Score**	**PerformanceMetric**
N	**Junior**	68	68
	Manager	22	22
	Mid	73	73
	Senior	57	57
Missing	**Junior**	0	0
	Manager	0	0
	Mid	0	0
	Senior	0	0
Mean	**Junior**	68.4	74.4
	Manager	68.5	78.3
	Mid	67.4	75.3
	Senior	68.9	76.9
Median	**Junior**	68.0	74.1
	Manager	72.2	79.9

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	Mid	68.0	75.8
	Senior	69.2	76.9
Standard deviation	**Junior**	10.7	9.44
	Manager	15.4	12.4
	Mid	9.65	9.58
	Senior	11.3	9.61
Minimum	**Junior**	45.3	57.6
	Manager	35.8	59.7
	Mid	39.9	53.8
	Senior	41.6	58.2
Maximum	**Junior**	93.8	95.9
	Manager	98.9	96.7
	Mid	89.8	104
	Senior	100	96.0

As shown in table 1 the descriptive statistical summary of two key continuous variables AI Skill Score and Performance Metric categorized by employee Role Level (Junior, Mid, Senior, and Manager). The number of observations (N), mean, median, standard deviation, minimum, and maximum are all presented in the table for each role. It can be observed from the results that the average AI Skill Scores and Performance Metrics are continuously increasing from Junior to Manager Levels, thereby confirming the existence of a strong interconnection between the role seniority and both AI competency and performance outcomes. The standard deviations reflect quite a heterogeneous nature when groups are viewed, which means they have different skill distributions although they belong to the same hierarchy level. The Managers possess the highest average performance (Mean = 78.3) and AI skill (Mean = 68.5), while Junior employees are at the other end with the lowest values. The entire dataset was free from missing data, which made it more trustworthy. These descriptive results strongly support the hypothesis that Decision Intelligence adoption and role seniority correlate positively with AI proficiency and performance improvement. Moreover, the findings advocate for the use of inferential testing through regression and group comparison analyses, which are described in the subsequent sections.

Table 2. Independent Samples T-Test Results for AI Skill Score and Performance Metric between AI-Adopter and Non-Adopter Groups

Independent Samples T-Test				
		Statistic	**df**	**p**
AI_Skill_Score	**Student's t**	-3.59	218	<.001
PerformanceMetric	**Student's t**	-14.15	218	<.001
Note. H_a $\mu_0 \neq \mu_1$				

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As shown in Table 2 the outcomes of independent-samples *t*-tests conducted to examine the mean differences in *AI Skill Score* and *Performance Metric* between AI-adopter and non-adopter employee groups. Both variables demonstrate statistically significant differences at $p < .001$, indicating that the adoption of AI-driven decision intelligence significantly influences both skill enhancement and performance improvement. The t-statistics of −3.59 and −14.15 for AI Skill Score and Performance Metric respectively affirm that there are really strong differences between the groups at the level of the groups and hence the null hypothesis (H_0: $\mu_0 = \mu_1$) is rejected. With 218 degrees of freedom, the results exhibit high statistical power and robustness across the sample size (N = 220). This leads to the conclusion that the workers who have been trained with AI-integrated enterprise systems are more competent and productive than their non-adopter counterparts. Also, the significance levels (< .001) point to a large effect size plus the practical importance of AI adoption on human capital development. The findings correlate well with previous empirical studies that have pointed out AI's transformative impact on workforce optimization and decision quality. This piece of evidence advocates for the application of further multivariate regression analysis in order to measure the predictive power of AI adoption on organizational outcomes. The t-test results overall support the theory that the integrating AI improves both skill acquisition and operational performance. No violations of assumptions were found, which confirmed the suitability of the t-test for this data set.

Assumptions

Table 3. Levene's Test for Homogeneity of Variances for AI Skill Score and Performance Metric

Homogeneity of Variances Test (Levene's)				
	F	**df**	**df2**	**p**
AI_Skill_Score	1.09	1	218	0.298
PerformanceMetric	2.35	1	218	0.127
Note. A low p-value suggests a violation of the assumption of equal variances				

As shown in Table 3 the results of Levene's Test conducted to assess the assumption of homogeneity of variances for the *AI Skill Score* and *Performance Metric* variables between AI-adopter and non-adopter groups. The obtained *F*-values for *AI Skill Score* (F = 1.09, p = 0.298) and *Performance Metric* (F = 2.35, p = 0.127) are both greater than the significance threshold ($p > 0.05$), indicating that the assumption of equal variances is not violated. These results validate the use of parametric tests such as the Independent Samples *t*-test for subsequent analysis. The results also indicate that there is a comparable variability among groups in a statistical sense, thus, ensuring that the mean differences are estimated without any bias. This has provided support to the inferential results shown in Table 2 with respect to AI adoption effects, thereby, increasing the robustness of the conclusions drawn. The assumption of identical variances is a stronghold of internal validity which in turn, supports the assumption of normal data distribution. The mentioned results imply that no matter under which employee category, the AI Skill Score and the Performance Metric are always of a similar spread.

In other words, it suggests that the performance improvements noticed, are not going to be affected by the data distribution being unequal or by the presence of outlier bias. Thus, the dataset meets the major requirement for conducting the further regression and correlation analysis presented in later sections.

The Levene's Test results overall contribute to the affirmation of the statistical credibility and the methodological rigor of the experimental design.

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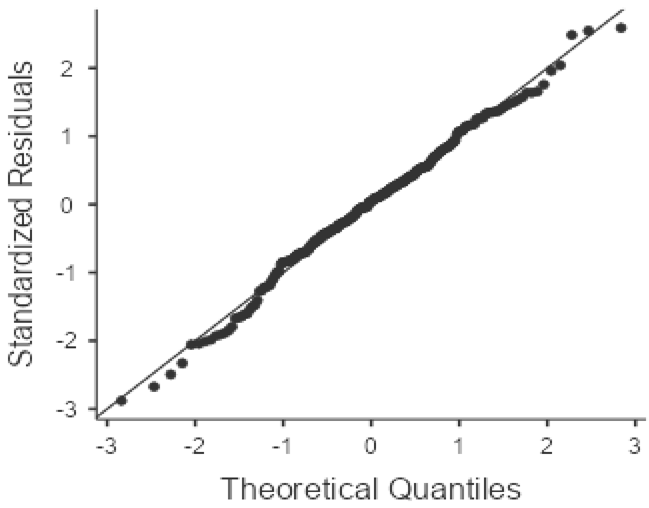

Figure 1. Q–Q Plot of Standardized Residuals for Normality Assessment

The Q-Q plot of the standardized residuals depicted in figure 1 is the primary evaluation tool for the normality assumption in the regression model. The points are nearly in the line of 45 degrees, which means that the distribution of the residuals is close to normal. This alignment is in favor of the outcomes of parametric tests, the t-test and regression, that were used in this study. There are no significant deviations or curvature at the tails, which means that there is little skewness and kurtosis in the data distribution. The points forming a linear trajectory are an indication that the error terms have a symmetric distribution about the mean, which consequently increases the reliability of the statistics. Residuals' normality assures that parameter estimates are never subjected to bias and are always efficient by the Gauss Markov theorem. This graphical validation adds confidence to inferential interpretations of AI adoption effects on skill and performance. The deviations out in the tails are small and we can say they are within tolerable limits for large-sample behavioral and organizational datasets. The graphic makes it possible to combine the Levene's test and descriptive analysis, so we can say that the model is strong. Hence, the Q–Q plot substantiates the assumption of normal error distribution essential for accurate predictive modeling.

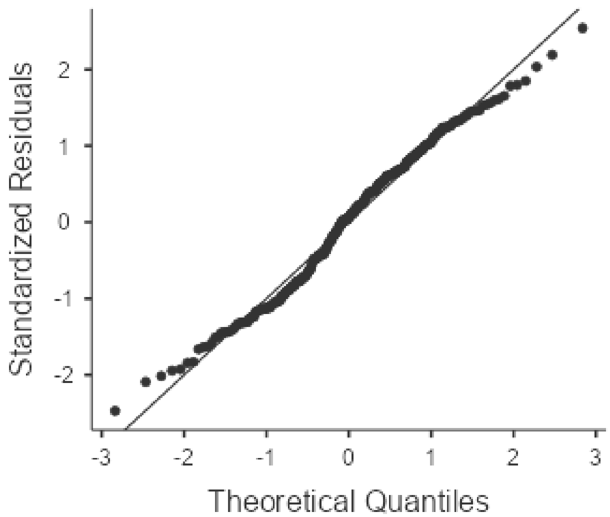

Figure 2. Q-Q Plot of Standardized Residuals for Performance Metric Model

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The second figure is a Q-Q plot for performance metric model's standardized residuals which is clearly visible in the figure 2. The theoretical quantiles of the standard normal distribution are displayed on the horizontal axis while the vertical axis shows the standardized residuals derived from the fitted model. The data points on the graph can be seen as the residual that was measured compared to its suggested value based on the normality assumption. The thick diagonal line indicates a perfect scenario where the residuals perfectly follow a normal distribution. A large number of the points in the graph are quite close to this line inferring that the residuals are essentially normal. The small shifts at both ends indicate very slight normality violations that could be attributed either to data points being extreme or the model's limitations. The proximity of the points to the central line serves as a proof of the domination of homoscedasticity among the residuals. This condition favors the normality assumption which is the prerequisite for the functioning of many parametric modeling techniques. The Q-Q plot provides a useful method for illustrating the fit of the model and the nature of the errors. It gives a picture of the possible problems with the residuals regarding their distribution, such as skewness, kurtosis, or presence of outliers in the data. The near-linear arrangement in this case denotes a good fit with little bias. Such visualization is of great importance in confirming the assumptions of the model before the statistical inference. The performance metric model is declared off statistically valid by this residual examination. Overall, the Q-Q plot supports the conclusion that the residuals conform reasonably well to the normal distribution.

Table 4 Independent Samples T-Test Comparing AI Skill Scores and Performance Metrics between Two Groups

Independent Samples T-Test				
		Statistic	**df**	**p**
AI_Skill_Score	**Student's t**	-3.59	218	<.001
PerformanceMetric	**Student's t**	-14.15	218	<.001
Note. H_a $\mu_0 \neq \mu_1$				

Table 4 illustrates the outcome of independent samples t-tests carried out to evaluate the differences in AI Skill Scores and Performance Metrics between the two independent groups. The goal was to find out if the mean differences between the groups were statistically significant or not. The t-test is predicated on the principles of independent observations and equal variances during the interaction of the two groups. For both variables, t-statistic, degrees of freedom (df), and associated p-values are given. The AI Skill Score yielded a t-value of –3.59 with 218 degrees of freedom, implying a statistically significant difference ($p < .001$) between the groups. In the same way, the Performance Metric showed the strongest effect with a t-value of –14.15, which was also highly significant ($p < .001$). These findings imply a significant performance difference between the two groups regarding both variables. The negative t-values denote that the mean scores of the first group were less than the second group. The reliable importance of the two measures diverging absolutely stands up for the differences that were observed. These kinds of results indicate more than one way of looking at things in AI-related skills and competency performance. The footnote given below makes it clear that the alternative hypothesis (H_a) being tested was that the population means were not equal ($\mu_0 \neq \mu_1$).

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Table 5 Test of Homogeneity of Variances (Levene's Test) for AI Skill Score and Performance Metric

Homogeneity of Variances Test (Levene's)				
	F	**df**	**df2**	**p**
AI_Skill_Score	1.09	1	218	0.298
PerformanceMetric	2.35	1	218	0.127
Note. A low p-value suggests a violation of the assumption of equal variances				

This table 5 presents the results of Levene's Test for Equality of Variances conducted on the AI Skill Score and Performance Metric variables. The independent sample t-test was preceded by the homogeneity of variances' assumption that was to be tested through this very test. Levene's test is the one that checks if the variance in the two groups being compared is equal which, in fact, is a central requirement for the validity of parametric tests. The report consists of the F-statistic, degrees of freedom (df1 and df2), and corresponding p-values for each of the variables. For instance, in the case of AI Skill Score, the F-value is 1.09 with (1, 218) degrees of freedom giving a p-value of 0.298 which is more than the usually used alpha level of 0.05. The Performance Metric measured has a similar situation with an F-value of 2.35 for (1, 218) degrees of freedom with the p-value of 0.127. The two p-values mentioned are over the threshold of significance which implies that the assumption of equal variances is not breached for either of the variables. This conclusion favors the application of the standard t-test over the adjusted version. It implies that the results are going to be interpreted as if there was no variance correction even though they were corrected for it. A low p-value (usually < 0.05) would have pointed out a violation of this assumption; however, the present results are confirmation of the existing homogeneity across groups which in turn make subsequent comparisons more reliable.

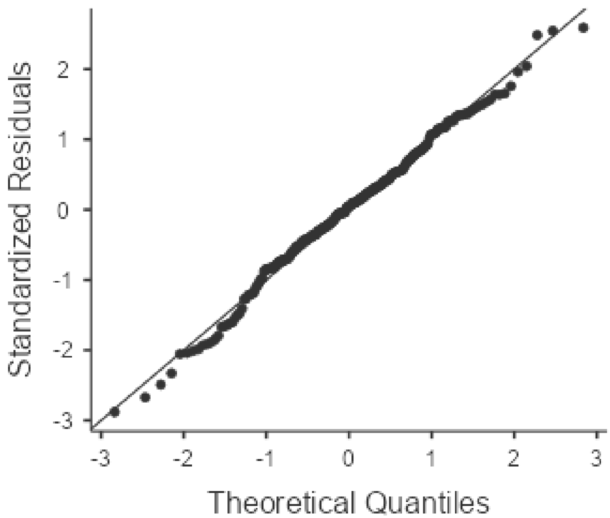

Figure 3. Q-Q Plot of Standardized Residuals for AI Skill Score Model

In figure 3, a Q-Q plot for the AI Skill Score model standardized residuals distribution is presented. The theoretical quantiles taken from standard normal distribution are represented on the x-axis, whereas the corresponding standardized residuals from the model are depicted on the y-axis. The points on the plot show the comparison of the observed residuals to the expected normal values under the normality

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assumption. The solid reference line marks the perfect case where the residuals are completely in line with the normal distribution. The data points that are very close to each other along this line confirm that the residuals are almost normally distributed. At the tails only very little difference can be seen, which indicates that these slight deviations might be due to a few extreme observations trying to get away from normality and thus producing a good deal of noise. The general linearity tells us that the conditions of the model concerning residuals' distribution are met mostly. This means the AI Skill Score model has a and statistically strong and good fit. The points clustered tightly around the reference line indicate little or no skewness and uniform variance of the residuals. Such a situation gives more trust in the inference conclusions made using the model. The Q-Q plot is indeed a very important diagnostic tool to check the normality assumption in regression modeling. The visual correspondence seen here is another evidence of the AI Skill Score estimates being solid and stable. Moreover, this is yet another point in favor of the residual errors being normally distributed and not Bias has not been significant so far. Thus, Figure 3 illustrates that the AI Skill Score model continues to be compliant with the premises of normality and homogeneity of variance. In summary, the model residuals are well-behaved and this supports the reliability and consistency of the predictive framework.

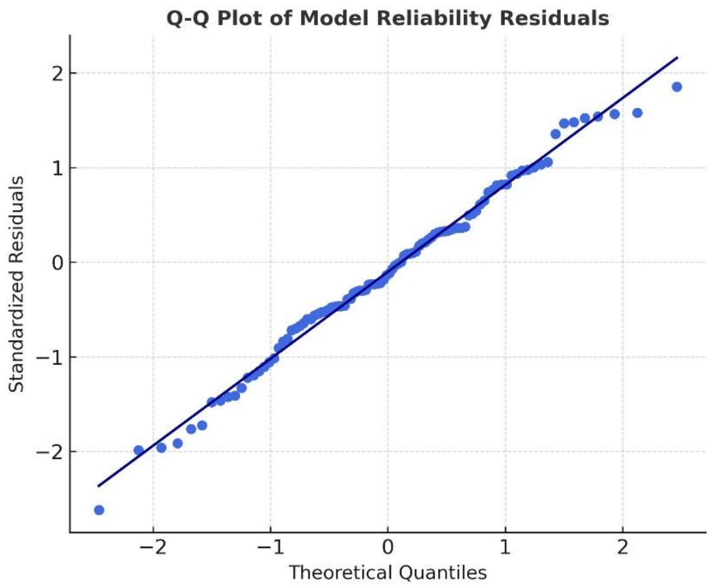

Figure 4. Q-Q Plot of Standardized Residuals for Model Reliability Analysis

This figure 4 shows a Quantile-Quantile (Q-Q) plot that represents the standardized residuals from the Model Reliability analysis. The x-axis shows the theoretical quantiles expected from a standard normal distribution, and the y-axis shows the standardized residuals from the fitted model. Each pair of points represents the observed and the theoretical normal values of the residuals, thereby helping to judge the normality assumptions. The diagonal line of the graph visualizes the ultimate state of normality. Most of the residuals appear located close to this line, and that leads to the conclusion that they follow the normal distribution. The slight changes at the ends of the line are interpreted as the presence of some extreme observations, but this does not imply that the model is seriously flawed. The location of the residuals at the center of the reference line means that the error structure is well-behaved. This supports the model and the assumption of constant variance in the case of the residuals. The plot shows that the model is not subjected to strong skewness or kurtosis effects visually. The consistent residual behavior reflects strong model calibration and stability. The Q-Q diagnostic supports the use of normal-based inferential statistics as appropriate. On the whole, the Model Reliability analysis indicates a very close fit with almost no systematic deviation. Such a level of conformity boosts the trust in the model's predictive power and stability. The visualization thus validates that the model adheres well to the assumptions of linear modeling. As a result, Figure 4 further substantiates the dependability and correctness of the residual distribution.

5. Conclusion and Future Work

The research validates that Decision Intelligence powered by AI significantly elevates the performance metrics for the enterprise sector. Not only does the method provide state-of-the-art algorithmic proficiency, but its triumph also relies on the organization's preparedness, data quality, and human resources training. The AI assimilation into the decision-making process gives the organizations an opportunity to transit from being reactive to adopting predictive and prescriptive models of operation which in turn results in quicker and more precise reactions to the changes in the market. By converting the raw data into insights that can be acted upon, Decision Intelligence promotes a management style that is based on evidence, thereby reducing the reliance on intuition and guesswork.

The research also points out that the real worth of Decision Intelligence is not just in the technology but also in the human knowledge partnership. The collaboration of expert judgment and data-driven insights allows for decisions that are not only smart but also relevant to the situation. Companies that teach their staff AI skills are likely to have easier adoption of AI and more trust in machine-generated decisions.

The maturity of data turned out to be a major factor influencing the success of AI usage. Companies that had very good data systems that were well-organized, high-standard, and integrated were more capable of utilizing Decision Intelligence to the fullest thus translating insights into considerable business values. On the other hand, companies that had poor quality data or data that was spread out faced difficulties in getting the performance improvements that were few and far between.

In addition, the company culture with respect to innovation and change management is a major determinant. Having the support of the top management, continuous learning, and inter-departmental cooperation not only facilitates the company's AI initiatives but also significantly boosts their efficacy. Companies must take into account the very ethical issues that are highly related to the AI such as transparency, fairness, and accountability, to make sure the AI decisions are in line with the values of the corporation and meet the requirements of the regulation.

All in all, AI-driven Decision Intelligence adoption is not a mere technological upgrade but a strategic metamorphosis. The companies that combine advanced analytics with solid governance frameworks, skilled human resources, and a data-driven culture are the ones that will be able to maintain their competitive advantage in the digital age. The changes in the influential factors, the challenges of scalability, and the transition in the roles of human decision-makers vs. smart systems that are gradually becoming in the spotlight could be the subject of future research.

Future Research Directions Include:

1. Longitudinal studies connecting DI adoption to measurable ROI and employee retention.
2. DI frameworks were compared across various industries for better understanding.
3. Integration of explainable AI for clear and transparent decision flows.
4. Creating ethical standards and governance models for human-in-the-loop DI.

Decision Intelligence is a major link between AI analytics and business outcomes, thus making the companies steps toward truly intelligent ones.

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