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Organizational and environmental conditions associated with AI adoption intent: A sector-level TOE analysis

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Abstract

This study examines organizational and environmental conditions associated with artificial intelligence (AI) adoption intent using a sector-level application of the Technology-Organization-Environment (TOE) Framework and data from the United States Census Bureau Business Trends and Outlook Survey (BTOS). Prior research has identified technological readiness, organizational resources, and external pressures as important drivers of AI adoption; however, much of the literature relies on firm-level perceptual survey data and gives limited attention to objective indicators of environmental turbulence. This study addresses that gap by examining the prevalence of AI adoption intent across sector-size-period groups. Using 1,284 observations, the study constructs nine standardized aggregate condition measures—organized conceptually under the TOE organizational and environmental contexts—from workforce, operational, supply-chain, pricing, and financial-stress indicators. Multiple regression analysis was used to evaluate relationships among these aggregated conditions and the percentage of firms reporting AI adoption intent. The findings indicate that industry sector and firm size were the strongest predictors of adoption intent prevalence, with information-intensive and knowledge-oriented sectors demonstrating significantly higher levels of intent. After controlling for sector and firm size, interest-rate-related financial stress demonstrated a positive relationship with AI adoption intent prevalence, suggesting that AI may be viewed as a strategic response to operational uncertainty and economic pressure.

Keywords: artificial intelligence adoption intent, technology-organization-environment framework, sector-level analysis, business trends and outlook survey (BTOS), environmental turbulence

Introduction

There is a growing assumption that artificial intelligence (AI) can generate operational improvements, create new business opportunities, and provide a potential source of competitive advantage (Jöhnk et al., 2021). However, organizational adoption of AI remains uneven across sectors and firm sizes. This unevenness suggests that adoption patterns may depend not only on the characteristics of the technology itself, but also on organizational conditions and environmental pressures. As organizations face increasing uncertainty associated with supply disruptions, economic volatility, and external shocks, understanding the conditions associated with AI adoption intent has become increasingly important. To address this issue, this study applies the Technology-Organization-Environment (TOE) Framework to examine the prevalence of AI adoption intent using sector-level data from the Business Trends and Outlook Survey (BTOS).

Prior research has identified a variety of factors associated with AI adoption, including technological readiness, organizational resources, managerial support, and external environmental pressures. Studies using the TOE Framework have provided important insights into how technological, organizational, and environmental conditions shape adoption decisions. However, much of this literature relies on cross-sectional survey designs, emphasizes managerial perceptions rather than objective indicators, and gives limited attention to how environmental turbulence such as supply disruptions, interest-rate pressures, and external shocks may influence adoption patterns across sectors. As a result, there remains limited empirical evidence regarding AI adoption intent using sector-level panel data and objective measures of environmental conditions. This study addresses that gap by extending TOE logic to examine how aggregated organizational and environmental conditions are associated with variation in AI adoption intent prevalence across sector-size groups. In doing so, the study also develops an explicit theoretical rationale for treating the sector-size group as a meaningful unit of analysis, rather than as a purely practical accommodation to the structure of the available data.

This study seeks to make three contributions to existing literature. First, it extends TOE-based research on AI adoption intent by applying TOE logic to aggregated sector-by-size-period data and by incorporating environmental turbulence as a theoretically relevant contextual condition. Second, it contributes empirical evidence using archival sector-level data from the BTOS, offering an alternative to the survey-based designs that dominate prior research. Third, it provides practical insights into how organizational structure, sector context, and environmental pressures may shape the prevalence of AI adoption intent across sectors and firm sizes.

Literature Review

Artificial intelligence (AI) is increasingly viewed as a transformative technology capable of improving organizational efficiency, supporting decision-making, and generating competitive advantage (Davenport & Ronanki, 2018). As a general-purpose technology, AI can be applied across a wide range of organizational functions including operations, supply chain management, forecasting, and strategic planning, and its strategic use has become a central theme in the information systems literature (Borges et al., 2021). Despite the potential benefits of AI, organizational adoption remains uneven across industries and firm sizes; recent sector-focused studies continue to document substantial variation in AI implementation readiness and outcomes (Ouanhlee, 2026). Prior research suggests that AI adoption is influenced not only by technological capabilities, but also by organizational readiness and external environmental conditions (Jöhnk et al., 2021; Merhi, 2023; Phuoc, 2022).

The Technology-Organization-Environment Framework provides a widely used lens for examining organizational technology adoption. Originally proposed by Tornatzky and Fleischer (1990), TOE suggests that adoption decisions are influenced by technological, organizational, and environmental contexts. The technological context captures characteristics of the innovation itself, while the organizational context reflects internal conditions such as firm size, operational readiness, and resource availability. The environmental context includes external pressures such as competition, uncertainty, regulation, and market conditions.

Prior TOE research has consistently found that organizational characteristics influence adoption of emerging technologies. Larger firms are generally more likely to adopt complex technologies because they possess greater financial resources, technical expertise, and implementation capacity (Lin & Lin, 2008). Organizational flexibility and operational readiness may also influence adoption by affecting a firm's ability to adjust workflows, allocate resources, and integrate new technologies into existing processes (Phuoc, 2022). Research further suggests that organizations with stronger operational capabilities are better positioned to absorb implementation costs and adapt to technological change.

The environmental context of TOE has traditionally focused on competition and regulatory pressures. More recent research suggests that broader environmental turbulence, including supply disruptions, demand volatility, economic instability, and external shocks, may also influence organizational technology adoption decisions (Ismatullaev & Kim, 2022). Such conditions may simultaneously create operational constraints while increasing incentives for automation, forecasting, and data-driven decision-making. Organizations experiencing heightened turbulence may therefore view AI adoption as a mechanism for improving efficiency, resilience, and operational adaptability.

AI Adoption in the Context of Prior Technology Adoption Waves

Situating AI within the broader history of organizational technology adoption helps clarify which patterns observed in this study are general features of technology diffusion and which may be distinctive to AI. Earlier waves of enterprise technology adoption exhibited several regularities that TOE research has repeatedly documented. Studies of e-business diffusion found that firm size, technical resources, and industry context were strong predictors of adoption depth and breadth (Lin & Lin, 2008), and research on enterprise resource planning systems emphasized that successful adoption depended heavily on organizational readiness, top-management support, and implementation capacity rather than on characteristics of the technology alone (Nah et al., 2001). In both waves, adoption clustered in information-intensive industries first and diffused unevenly toward operationally oriented sectors, and larger firms adopted earlier because they could better absorb fixed implementation costs.

The sector and size gradients observed for AI adoption intent in this study are therefore consistent with well-established diffusion patterns rather than unique to AI. At the same time, AI differs from earlier enterprise technologies in ways that may accentuate these patterns. AI applications are unusually data-intensive, which advantages sectors whose core production processes already generate structured digital data (e.g., information, finance, and professional services). AI also depends on scarce specialized skills, reinforcing size and sector advantages. Conversely, the delivery of AI capabilities through cloud-based services lowers infrastructure barriers relative to earlier on-premises technologies such as ERP, which may eventually compress adoption gaps across firm sizes. Finally, AI adoption is occurring during a period of pronounced economic turbulence, raising the possibility—examined directly in this study—that environmental stress itself functions as an adoption stimulus in a way that was less salient in earlier adoption waves.

Sector-Level Analysis as a Theoretically Meaningful Unit

Although TOE was originally developed to explain technology adoption at the level of the individual organization, there are strong theoretical grounds for treating the industry sector as a meaningful unit for studying adoption prevalence, beyond the practical fact that BTOS data are released in aggregated form. Institutional theory argues that organizations within the same field are subject to shared coercive, normative, and mimetic pressures that produce convergent behavior (DiMaggio & Powell, 1983). Firms in the same sector face common regulatory environments, common customer and supplier markets, common labor pools, and highly visible competitor behavior; when prominent firms in a sector adopt a technology, mimetic pressure encourages others in that sector to follow. Sectors also differ systematically in task environments—in the data intensity of production, the routineness of work, and exposure to demand and supply volatility—which shapes the objective payoff to AI across entire industries rather than firm by firm. Diffusion research has long documented that technology adoption exhibits pronounced industry-level clustering consistent with these mechanisms (Lin & Lin, 2008). Sector-size groups therefore represent coherent populations of organizations facing similar adoption incentives and pressures, and the prevalence of adoption intent within such groups is a theoretically interpretable quantity: it reflects the aggregate response of a population of similarly situated firms to shared organizational and environmental conditions.

Although prior TOE studies provide important insights into AI adoption, several limitations remain. Much of the existing literature relies on cross-sectional survey data and perceptual measures, limiting the ability

to examine adoption patterns across sectors and over time. In addition, relatively limited attention has been given to objective indicators of environmental turbulence such as supply disruptions, pricing pressures, and financial stress. This study addresses these limitations by applying TOE as a guiding theoretical framework for examining sector-size-level patterns in AI adoption intent. Because the BTOS data are aggregated, the analysis does not directly observe individual firm-level adoption decisions. Rather, it examines whether TOE-relevant organizational and environmental conditions are associated with the prevalence of AI adoption intent within aggregated business groups.

This distinction is important theoretically and methodologically. TOE was originally developed to explain organizational technology adoption at the firm level. In this study, TOE is used to structure the selection and interpretation of aggregate predictors rather than to claim direct firm-level causal inference. The unit of analysis is the sector $\times$ firm size $\times$ biweekly period, and the dependent variable represents the percentage of firms within each group reporting intent to use AI. Therefore, the hypotheses are framed as aggregate prevalence hypotheses: they examine whether sector-size groups characterized by particular organizational and environmental conditions demonstrate higher or lower levels of AI adoption intent prevalence. The following research questions and hypotheses guide the analysis; Figure 1 summarizes the research model, including the hypothesized direction of each association and the level of support each hypothesis ultimately received.

RQ1: To what extent are aggregated organizational conditions associated with the prevalence of AI adoption intent across sector-size groups?

H1: Sector-size groups representing larger businesses will demonstrate higher prevalence of AI adoption intent than groups representing smaller businesses.

H2: Greater aggregate organizational capacity, reflected in labor and operational flexibility, will be positively associated with the prevalence of AI adoption intent across sector-size groups.

RQ2: To what extent are aggregated environmental pressures, including supply disruptions, economic volatility, and external shocks, associated with the prevalence of AI adoption intent across sector-size groups?

H3: Greater aggregate supply disruptions will be positively associated with the prevalence of AI adoption intent across sector-size groups.

H4: Greater aggregate environmental turbulence will be positively associated with the prevalence of AI adoption intent across sector-size groups.

Methodology

This study examines organizational and environmental conditions associated with the prevalence of artificial intelligence (AI) adoption intent using sector-level data from the Business Trends and Outlook Survey (BTOS). Drawing on the Technology-Organization-Environment Framework, the study investigates how aggregated organizational and environmental conditions are associated with AI adoption intent prevalence across sector-size groups during a period characterized by economic uncertainty and rapid technological change.

Data Source

This study uses sector-level data from the United States Census Bureau Business Trends and Outlook Survey (BTOS), a high-frequency survey designed to capture near real-time business conditions across

sectors of the U.S. economy. The analysis utilized aggregated sector-by-size data from the final two periods of 2025 through 2026 year-to-date. The unit of analysis was sector $\times$ firm size $\times$ biweekly period. Firm-size categories (Size A through Size G) follow the Census Bureau's BTOS employment-size classifications, with Size A representing the smallest firms and Size G the largest [authors: insert the specific employment ranges for each size class]. The final dataset consisted of 1,284 observations and 44 variables. Each observation represented aggregated responses for businesses within a given sector, firm-size category, and survey period.

Variable Construction

The dependent variable was AI adoption intent prevalence, operationalized as the percentage of firms within a sector-size-period grouping reporting intent to use artificial intelligence technologies during the next six months (BTOS Question 24). Consistent with the Technology-Organization-Environment Framework, nine aggregate condition measures were constructed from BTOS items related to workforce conditions, operational flexibility, supply disruptions, pricing changes, financial stress, and environmental disruptions, and were organized conceptually into two groups corresponding to the TOE organizational and environmental contexts.

Organizational variables included:

- paid employee changes (Q5),
- hours worked changes (Q6),
- and inventory conditions (Q9).

Environmental variables included:

- supplier delivery delays (Q8),
- demand changes (Q10),
- prices charged (Q11),
- prices paid (Q12),
- interest-rate impacts (Q13),
- and extreme weather disruptions (Q14).

Two clarifications about these groupings are important. First, the organizational and environmental groupings function as conceptual categories that organize the selection and interpretation of predictors under the TOE framework; each condition measure was entered individually in the regression model rather than being collapsed into estimated composite scores. Second, the measures within each grouping are treated as formative-style indicators of their respective TOE contexts: each captures a distinct, non-interchangeable facet of organizational or environmental conditions (Diamantopoulos & Winklhofer, 2001). Under a formative logic, indicators define a construct rather than reflect it, and they are not assumed or required to intercorrelate. This is why, for example, supplier delivery delays exhibit near-zero correlations with workforce measures, and interest-rate stress correlates negatively with them: these measures capture different, partially independent dimensions of the environment rather than manifestations of a single underlying factor. Accordingly, internal-consistency statistics such as Cronbach's alpha, which presuppose reflective measurement, are not appropriate validity criteria for these groupings; content coverage of the TOE contexts is the relevant criterion instead.

Because BTOS reports responses as percentage distributions across categorical response options, ordered response categories were transformed into weighted ordinal composite measures suitable for statistical analysis (Allen & Seaman, 2007; Lindner & Lindner, 2024). For each item, ordered numeric values were assigned to the response categories (for example, "Increased" = 1, "No change" = 0, and "Decreased" = -1 for three-category items, with analogous symmetric codings for five-category items), and each group's

composite score was computed as the sum of the reported category percentages multiplied by their assigned values. The resulting score is a continuous measure of the net direction and intensity of the condition within each sector-size-period group. A worked numerical example of this procedure is provided in Appendix D. Multi-response financial stress items associated with interest-rate impacts (Q13) were aggregated into a single composite financial-stress measure, treated formatively. All condition measures were then standardized (z-scores) across the full analytical sample of 1,284 observations prior to analysis [authors: please confirm that standardization was performed at the full-sample level rather than within sector-size groups].

These condition measures should be interpreted as aggregate indicators describing conditions within sector-size-period groups rather than as direct measures of any individual firm's capacity or turbulence exposure. Firm-size and sector dummy variables were also included to control for structural differences across organizations and industries. Biweekly time-period controls were included to account for temporal variation in business conditions and AI adoption trends.

Analytical Approach

The study employed multiple linear regression analysis to examine relationships between aggregated organizational conditions, environmental conditions, and AI adoption intent prevalence. Let i index industry sector, s index firm-size category, and t index biweekly survey period. The estimated model was:

$$AI\ Adoption\ Intent\ Prevalence = \beta_0 + \beta_1(OCI) + \beta_2(ETI) + \beta_3(Sector\ Controls) + \beta_4(Firm-Size\ Controls) + \beta_5(Time\ Controls) + \epsilon_{ist}$$

where OCI represents the aggregated Organizational Capacity Index and ETI represents the aggregated Environmental Turbulence Index.

This estimated model can be further explained as :

$$Y_{ist} = \beta_0 + \sum_k \beta_k ORG_{k,ist} + \sum_m \gamma_m ENV_{m,ist} + \sum_i \delta_i SECTOR_i + \sum_s \lambda_s SIZE_s + \sum_t \theta_t PERIOD_t + \epsilon_{ist}$$

where Y_{ist} is AI adoption intent prevalence (the percentage of firms in sector i , size class s , and period t reporting intent to use AI); ORG_k ($k = 1, \dots, 3$) denotes the three standardized organizational condition measures (Q5, Q6, Q9); ENV_m ($m = 1, \dots, 6$) denotes the six standardized environmental condition measures (Q8, Q10–Q14); $SECTOR$, $SIZE$, and $PERIOD$ are dummy-variable sets for two-digit NAICS sector, firm-size class, and biweekly period, respectively; and ϵ_{ist} is the error term. The hypothesized (pre-analysis) signs were $\beta_k > 0$ for the organizational measures (H2), $\gamma_m > 0$ for supplier delays (H3) and the remaining turbulence measures (H4), and λ_s increasing in firm size (H1). The estimated (post-analysis) coefficients are reported in Table 3 and Appendix C.

Prior to regression analysis, correlation and collinearity diagnostics were conducted. Variance Inflation Factor (VIF) values were examined to evaluate multicollinearity among predictors. All variables demonstrated acceptable multicollinearity levels, with VIF values remaining below commonly accepted thresholds. Because the analysis is based on grouped data, the results are interpreted as associations between aggregate conditions and adoption intent prevalence, not as direct evidence of individual firm-level adoption decisions.

Data Preparation

The BTOS data required preprocessing prior to analysis due to its aggregated categorical response structure. First, variables relevant to AI adoption intent, workforce conditions, operational performance, supply disruptions, pricing changes, and financial stress were retained for analysis. The data were organized at the

sector $\times$ firm size $\times$ biweekly period level. Ordered response categories were transformed into weighted ordinal composite measures using the procedure described above and illustrated in Appendix D. Missing or suppressed values were treated as missing data and excluded from composite calculations. The final analytical dataset consisted of 1,284 observations and 44 variables. All constructed variables represent group-level prevalence or condition measures rather than firm-level observations.

Analysis

Collinearity diagnostics were conducted to evaluate overlap among predictors. Variance Inflation Factor (VIF) values ranged from 1.37 to 2.78, remaining below commonly accepted thresholds for multicollinearity concerns. Tolerance values also remained within acceptable ranges. These results suggest that the predictors contributed sufficiently distinct explanatory information and that multicollinearity was not a major concern within the final regression model. The full results are shown in Appendix B.

Pearson correlation analysis was conducted to examine relationships among organizational conditions, environmental conditions, and AI adoption intent prevalence. Several sector and firm-size variables demonstrated statistically significant relationships with AI adoption intent prevalence. Information-intensive sectors such as Information (51), Finance and Insurance (52), and Professional and Technical Services (54) demonstrated positive relationships with AI adoption intent prevalence, while operational and service-oriented sectors demonstrated negative relationships. Organizational and environmental measures including workforce conditions, inventory conditions, pricing pressures, financial stress, and extreme weather disruptions also demonstrated significant bivariate relationships with AI adoption intent prevalence. Correlation coefficients among the independent variables generally remained below levels associated with severe multicollinearity concerns, supporting their inclusion in subsequent regression analysis. Table 1 shows the variables significantly correlated with the dependent variable, and Table 2 shows the correlations among the organizational and environmental condition measures..

Table 1. Significant Correlation Coefficients for AI Adoption Intent Prevalence vs Independent Variables

Variable	Coefficient	Significance Level
Period 202601	.052	.032
Period 202604	-.046	.049
Sector 11 (Agriculture)	-.224	< .001
Sector 21 (Mining)	-.281	< .001
Sector 22 (Utilities)	-.217	< .001
Sector 23 (Construction)	-.111	< .001
Sector 31 (Manufacturing)	-.052	.030
Sector 48 (Transportation/Warehousing)	-.161	< .001
Sector 51 (Information)	.399	< .001
Sector 52 (Finance and Insurance)	.279	< .001
Sector 53 (Real Estate)	.064	.011
Sector 54 (Professional/Technical Services)	.309	< .001
Sector 61 (Educational Services)	.141	< .001
Sector 72 (Accommodation/Food Services)	-.209	< .001
Sector 81 (Other Services)	-.119	< .001
Size G	.253***	< .001
Size B	-.182***	< .001
Size C	-.101***	< .001
Size E	.111***	< .001

Variable	Coefficient	Significance Level
Size F	.191***	< .001
Paid Employee Changes (Q5)	.214***	< .001
Hours Worked Changes (Q6)	.282***	< .001
Inventory Conditions (Q9)	.361***	< .001
Demand Changes (Q10)	-.121***	< .001
Prices Charged to Customers (Q11)	-.228***	< .001
Prices Paid for Goods/Services (Q12)	-.139***	< .001
Interest-Rate Impacts (Q13)	-.232***	< .001
Extreme Weather Disruptions (Q14)	.282***	< .001

Table 2. Correlations Among Organizational and Environmental Condition Measures

Variable	(Q5)	(Q6)	(Q8)	(Q9)	(Q10)	(Q11)	(Q12)	(Q13)
Hours worked changes (Q6)	.57***							
Supplier delays (Q8)	0.03	0.02						
Inventory conditions (Q9)	.23***	.25***	0.02	--				
Demand changes (Q10)	.44***	.56***	0.002	.37***	--			
how the prices this business charges (Q11)	-.053*	-.050*	.30***	-.12***	-.12***	--		
how did the prices (Q12)	-.14***	-.10***	.33***	-.26***	-.23***	.56***	--	
Interest-rate impacts (Q13)	-.23***	-.24***	.14***	-.26***	-.30***	.34***	.36***	--
Extreme weather disruptions (Q14)	-.09***	-0.045	.11***	-.26***	-.11***	.29***	.33***	.26***

* $p < .05$. ** $p < .01$. *** $p < .001$. Q5 = paid employee changes; Q6 = hours worked changes; Q8 = supplier delays; Q9 = inventory conditions; Q10 = demand changes; Q11 = prices charged; Q12 = prices paid; Q13 = interest-rate impacts; Q14 = extreme weather disruptions.

Regression Model Results

The regression model was statistically significant ($F = 77.09$, $p < .001$) and demonstrated strong explanatory capability, with an adjusted R^2 of .718. Industry sector and firm size emerged as the strongest predictors of AI adoption intent prevalence. Information (Sector 51), Finance and Insurance (Sector 52), and Professional and Technical Services (Sector 54) demonstrated significantly higher AI adoption intent prevalence, while Agriculture (11), Mining (21), Utilities (22), Transportation and Warehousing (48), and Accommodation and Food Services (72) demonstrated lower levels of intent prevalence. Table 3 presents a consolidated summary of the regression results for the condition measures, firm-size effects, and selected sector effects; the full model, including all sector and period coefficients, appears in Appendix C.

Firm-size variables demonstrated significant positive relationships with AI adoption intent prevalence, with coefficients increasing monotonically from Size C through Size G, indicating that sector-size groups representing larger organizations had higher percentages of firms reporting intent to adopt AI technologies. Among the environmental measures, interest-rate impacts (Q13) remained positive and statistically significant ($\beta = .055$, $p = .007$), suggesting that groups experiencing greater financial stress also reported higher AI adoption intent prevalence conditional on sector and firm size. Notably, the sign of this relationship reverses between the bivariate and multivariate analyses: interest-rate stress correlates negatively with adoption intent prevalence at the bivariate level ($r = -.232$, Table 1) but positively in the full model. The remaining organizational and environmental measures demonstrated significant bivariate

correlations with AI adoption intent prevalence but became non-significant after controlling for sector, firm size, and period. Both of these patterns are examined in the Discussion.

Table 3. Consolidated Regression Results for AI Adoption Intent Prevalence

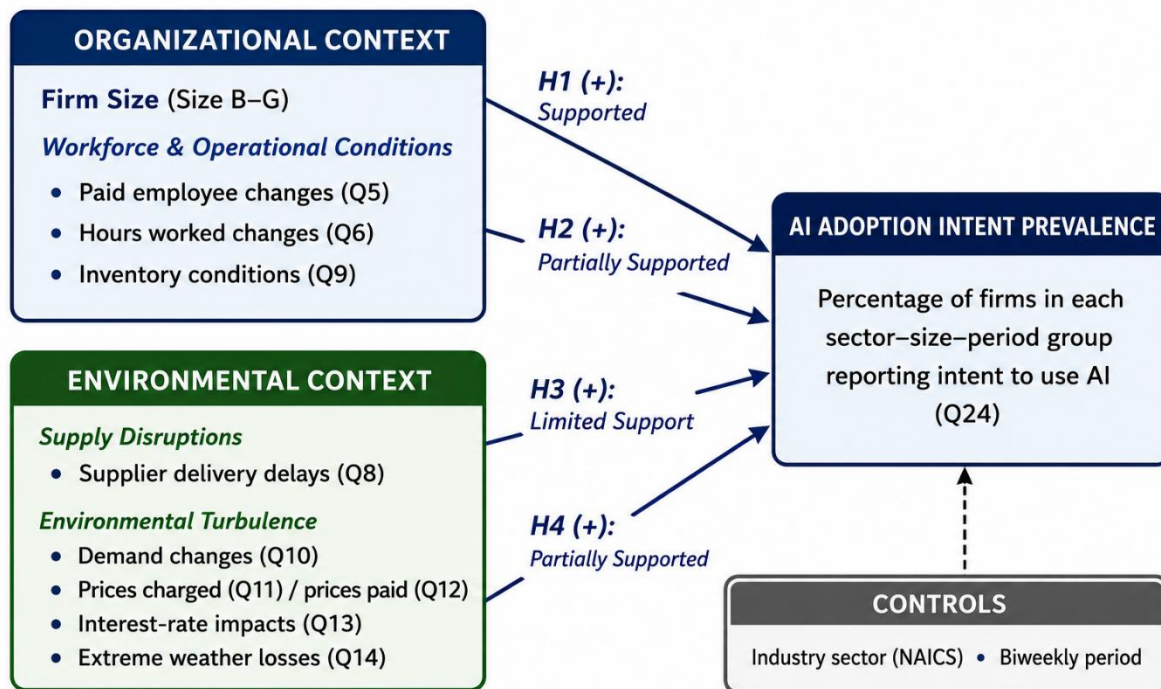
Predictor	B	SE	β	t	p
<i>Firm size (reference: Size A)</i>					
Size B	0.011	0.009	.023	1.202	.230
Size C	0.030	0.009	.065	3.251	.001
Size D	0.070	0.010	.149	7.253	< .001
Size E	0.116	0.011	.241	10.846	< .001
Size F	0.148	0.012	.299	12.665	< .001
Size G	0.190	0.013	.364	14.738	< .001
<i>Organizational condition measures</i>					
Paid employee changes (Q5)	0.008	0.033	.005	0.242	.809
Hours worked changes (Q6)	0.027	0.028	.021	0.938	.348
Inventory conditions (Q9)	−0.042	0.036	−.024	−1.157	.248
<i>Environmental condition measures</i>					
Supplier delays (Q8)	−0.012	0.055	−.004	−0.209	.835
Demand changes (Q10)	0.005	0.025	.005	0.205	.838
Prices charged (Q11)	0.026	0.041	.015	0.649	.517
Prices paid (Q12)	0.043	0.025	.038	1.752	.080
Interest-rate impacts (Q13)	0.061	0.022	.055	2.720	.007
Extreme weather disruptions (Q14)	0.062	0.043	.033	1.437	.151
<i>Selected sector effects (reference omitted; full set in Appendix C)</i>					
Sector 51 (Information)	0.295	0.016	.412	18.475	< .001
Sector 54 (Professional and Technical Services)	0.217	0.015	.308	14.116	< .001
Sector 52 (Finance and Insurance)	0.204	0.016	.290	12.672	< .001
Sector 61 (Educational Services)	0.110	0.016	.156	7.033	< .001
Sector 21 (Mining)	−0.170	0.019	−.189	−8.822	< .001
Sector 11 (Agriculture)	−0.161	0.021	−.150	−7.869	< .001
Sector 22 (Utilities)	−0.161	0.022	−.143	−7.462	< .001
Sector 72 (Accommodation and Food Services)	−0.150	0.017	−.213	−8.948	< .001
Sector 48 (Transportation and Warehousing)	−0.103	0.016	−.142	−6.433	< .001

Note. Model $F(43, 1240) = 77.09, p < .001$; adjusted $R^2 = .718$; constant = 0.136 ($SE = 0.019, p < .001$). B = unstandardized coefficient; SE = standard error; β = standardized coefficient. The model also includes biweekly period dummies and the full set of sector dummies; complete results appear in Appendix C.

Discussion

The findings as illustrated in Figure 1, generally support the proposed TOE-informed model of AI adoption intent prevalence, while also revealing patterns that carry important implications for how TOE logic operates at the aggregate level. Consistent with H1, sector-size groups representing larger organizations

demonstrated significantly greater prevalence of AI adoption intent than groups representing smaller firms, with a clear monotonic size gradient in the regression coefficients. H2 received partial support: the organizational condition measures demonstrated significant positive bivariate relationships with adoption intent prevalence, but none remained significant in the full regression model. H3 received limited support, as supplier delays were not significantly associated with adoption intent prevalence in either the bivariate or multivariate analysis in the hypothesized direction. H4 received partial support: among the environmental turbulence measures, interest-rate-related financial stress was positively and significantly associated with adoption intent prevalence in the full model, while the remaining turbulence measures were not.



Note. Model examines associations between aggregate organizational and environmental conditions and the prevalence of AI adoption intent across sector-size-period groups.

Figure 1. Research Model: Hypothesized Associations and Results

Note. Signs in parentheses indicate the hypothesized direction of association. Support levels reflect the full regression model, which controls for industry sector and biweekly survey period. All associations are interpreted at the level of sector-size-period groups, not individual firms.

Why Bivariate Relationships Attenuate: Sector Identity as a Carrier of TOE Conditions

A striking pattern in the results is that nearly every organizational and environmental condition measure was significantly correlated with AI adoption intent prevalence at the bivariate level (Table 1), yet almost all became non-significant once sector, firm-size, and period controls were included (Table 3). This pattern is theoretically informative rather than merely a statistical artifact. At the aggregate level, organizational and environmental conditions are not distributed randomly across the economy: workforce dynamics, inventory positions, pricing pressures, and turbulence exposure covary strongly with industry membership. When sector dummies are included, they absorb the stable, between-sector component of these conditions, leaving the condition measures to explain only the residual within-sector, within-size variation over time. The attenuation of the condition coefficients therefore suggests that sector identity subsumes much of what the organizational and environmental measures were expected to explain independently. In other words, at

the sector-size level, industry membership itself appears to function as a summary carrier of the organizational and environmental contexts that TOE treats as analytically distinct.

This interpretation has two implications for TOE theory applied to aggregate data. First, it suggests that studies applying TOE at aggregated levels should be cautious about treating sector controls as atheoretical nuisance parameters; in aggregate applications, sector effects are partly constituted by TOE conditions rather than independent of them. Second, it suggests that the appropriate test of organizational and environmental effects at the aggregate level may be a within-group (fixed-effects) test over time, which the present biweekly panel structure begins to enable but which a longer observation window would support more powerfully. The significant within-model effect of interest-rate stress, discussed next, illustrates that some environmental conditions retain explanatory power even after sector structure is absorbed.

The Sign Reversal for Interest-Rate Stress

Interest-rate impacts (Q13) present the most interesting single finding in the model: the bivariate correlation with adoption intent prevalence is negative ($r = -.232$), yet the coefficient in the full model is positive and significant ($B = 0.061$, $\beta = .055$, $p = .007$). This sign reversal is a classic suppression pattern and is readily interpretable given the structure of the data. Sectors and size classes that report the greatest interest-rate stress—such as construction, retail, accommodation, and smaller-firm groups—are also, for structural reasons unrelated to interest rates, the sectors and sizes with the lowest AI adoption intent. The negative bivariate correlation therefore largely reflects compositional confounding by sector and size. Once sector and size are held constant, the conditional relationship emerges: among comparable groups, those experiencing greater interest-rate-related financial stress report higher AI adoption intent prevalence. This conditional positive association is consistent with the theoretical argument that financial pressure functions as an adoption stimulus, motivating interest in AI as a means of improving efficiency and controlling costs under economic strain. It also illustrates the value of the multivariate design: reporting only the bivariate correlation would have led to the opposite—and likely incorrect—substantive conclusion.

Extreme Weather Disruptions: A Bivariate Association Only

Extreme weather disruptions (Q14) warrant explicit clarification, as the pattern of results could otherwise be misread. Weather-related monetary losses are positively and significantly correlated with adoption intent prevalence at the bivariate level ($r = .282$), but the coefficient is not statistically significant in the full regression model ($p = .151$). The study therefore does not conclude that weather disruption independently predicts AI adoption intent. The bivariate association most plausibly reflects sectoral and geographic composition: the sectors and firm-size groups most exposed to weather losses during the observation window may also, for unrelated structural reasons, differ in adoption intent, and once sector and size are controlled the residual association is indistinguishable from zero. To the extent a substantive mechanism exists—for example, disruption experiences prompting investment in forecasting and resilience technologies—detecting it would require firm-level or geographically disaggregated data.

Table 4. Research Questions Results

Research Question	Result
RQ1: To what extent are aggregated organizational conditions associated with the prevalence of AI adoption intent across sector-size groups?	Supported
RQ2: To what extent are aggregated environmental pressures, including supply disruptions, economic volatility, and external shocks, associated with the prevalence of AI adoption intent across sector-size groups?	Partially Supported

Note. RQ1 is supported through the firm-size effects (H1); the organizational condition measures contributed at the bivariate level only (H2). RQ2 is partially supported: interest-rate-related financial stress was significantly associated with adoption intent prevalence in the full model (H4), while supply disruptions (H3) and the remaining turbulence measures were not.

Table 5. Hypotheses Results

Hypothesis	Result
RQ1/ H1: Sector-size groups representing larger businesses will demonstrate higher prevalence of AI adoption intent than groups representing smaller businesses.	Supported
RQ1/ H2: Greater aggregate organizational capacity, reflected in labor and operational flexibility, will be positively associated with the prevalence of AI adoption intent across sector-size groups.	Partially Supported
RQ2/ H3: Greater aggregate supply disruptions will be positively associated with the prevalence of AI adoption intent across sector-size groups.	Limited Support
RQ2/ H4: Greater aggregate environmental turbulence will be positively associated with the prevalence of AI adoption intent across sector-size groups.	Partially Supported

Overall, the results suggest that AI adoption intent prevalence is shaped primarily by structural organizational characteristics—industry sector and firm size—with selected forms of environmental turbulence, particularly financial stress, retaining explanatory power conditional on that structure. Larger-firm groups and technology-oriented sectors demonstrated the strongest levels of AI adoption intent prevalence, while economic and financial pressure appeared to be associated with increased interest in AI solutions among otherwise comparable groups.

Practical Implications

For managers, the findings carry three messages. First, the strong sector and size gradients indicate that AI adoption intent is diffusing along familiar lines: firms in information-intensive sectors and larger firms are moving first. Managers in lagging sectors and smaller firms should recognize that the competitive baseline in their industry may shift quickly if leading peers convert intent into implementation, and that the cloud-based delivery of AI capabilities lowers the infrastructure barrier that delayed smaller firms in earlier technology waves. Second, the conditional positive association between interest-rate stress and adoption intent suggests that financial pressure is prompting firms to consider AI as an efficiency and cost-control response rather than deferring technology investment until conditions improve. Managers facing similar pressures should evaluate AI initiatives explicitly as instruments of operational resilience, while remaining realistic about implementation capacity under financial strain. Third, because organizational conditions such as workforce flexibility did not independently predict adoption intent once sector and size were controlled, managers should not assume that favorable internal conditions alone will translate into adoption momentum; deliberate strategic commitment appears more decisive than ambient operational slack.

For policymakers, the pronounced size gradient—adoption intent prevalence rising monotonically from the smallest to the largest firm-size classes—signals a risk that AI diffusion will widen existing productivity gaps between large and small businesses, and between knowledge-intensive and operationally oriented sectors such as agriculture, mining, transportation, and accommodation and food services. Programs that reduce adoption costs for small firms (technical assistance, workforce training, shared data infrastructure) and sector-targeted diffusion initiatives would address the groups this study identifies as lagging. The findings also demonstrate that high-frequency public data such as the BTOS can serve as a near real-time monitoring instrument for tracking technology diffusion across the economy, offering policymakers a low-cost complement to periodic technology-use surveys.

For industry leaders and analysts, the sector-level estimates provide benchmarking context: an individual firm's adoption posture is best evaluated against its own sector-size peer group rather than against economy-wide averages. Leaders in high-intent sectors (information, finance and insurance, professional and technical services) should anticipate rapid movement from intent to implementation among peers, while

leaders in low-intent sectors may find early adoption a source of differentiation precisely because peer adoption pressure is currently weak.

Conclusion, Limitations, and Future Research

This study examined organizational and environmental conditions associated with AI adoption intent prevalence using sector-level data from the Business Trends and Outlook Survey (BTOS) and the Technology-Organization-Environment Framework. The findings suggest that AI adoption intent prevalence is strongly associated with structural organizational characteristics, particularly industry sector and firm size, while also being influenced by selected forms of environmental turbulence and financial pressure. Technology-oriented and knowledge-intensive industries demonstrated significantly higher levels of AI adoption intent prevalence, and sector-size groups representing larger organizations were more likely to report plans to adopt AI solutions than smaller-firm groups. The results further suggest that groups experiencing greater interest-rate-related financial stress may increasingly view AI adoption as a strategic response to operational uncertainty, efficiency challenges, and competitive pressures—an association visible only after sector and size composition is taken into account. Overall, the findings extend TOE-informed adoption research by highlighting the importance of environmental turbulence as a contextual factor associated with aggregate AI adoption intent patterns during periods of economic uncertainty and rapid technological change.

Several limitations should be considered when interpreting the findings of this study. First, and most importantly, the BTOS dataset is based on aggregated sector-level and firm-size-level survey responses rather than individual firm-level observations. As a result, the analysis does not directly test whether a specific firm's TOE conditions predict that firm's AI adoption decision. Instead, the study examines whether TOE-informed organizational and environmental conditions are associated with variation in the prevalence of AI adoption intent across aggregated sector-size-period groups. Therefore, the findings should not be interpreted as direct evidence of firm-level adoption behavior or firm-level causal mechanisms.

Second, the organizational and environmental condition measures are organized as conceptual, formative-style groupings under the TOE contexts rather than as psychometrically validated composite scales; because the underlying microdata are not publicly available, reflective reliability and dimensionality assessments (e.g., internal-consistency and factor-analytic diagnostics) could not be conducted and remain a task for research with firm-level data.

Third, several environmental and operational measures demonstrated moderate overlap due to the interconnected nature of economic turbulence, which may reduce the stability of individual regression coefficients, although collinearity diagnostics indicated acceptable levels overall. Fourth, the study focused on data from 2025 through 2026 year-to-date, representing a relatively short time horizon during a unique period characterized by elevated economic uncertainty and rapid expansion of AI technologies; the findings may reflect conditions specific to this period and may not fully generalize to other economic environments or longer-term AI adoption trends.

Finally, the study focused on organizational intent to adopt AI rather than actual implementation outcomes, meaning the findings capture reported adoption intent prevalence rather than realized organizational AI usage.

Future research could extend this study in several important ways. First, future studies with access to firm-level microdata could construct and psychometrically validate composite measures of organizational capacity and environmental turbulence, directly addressing the measurement questions that aggregated public data cannot resolve. Second, researchers could examine firm-level or longitudinal panel data to better evaluate causal relationships between environmental turbulence and organizational AI adoption over time,

including within-group fixed-effects designs that separate sector composition from condition dynamics. Third, future research could investigate sector-specific AI adoption patterns in greater depth, particularly among industries demonstrating either exceptionally high or low levels of AI adoption intent prevalence. Additional research could examine how different forms of environmental turbulence, such as supply disruptions, labor shortages, inflationary pressures, or financial uncertainty, differentially influence AI adoption decisions across organizational contexts. Finally, future studies could explore the relationship between AI adoption intent and actual organizational outcomes, including operational efficiency, resilience, innovation capability, and competitive performance, to better understand the long-term strategic implications of AI adoption under conditions of environmental uncertainty.

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Appendix A-BTOS Questions Used in the Study

Question ID	Question
5	In the last two weeks, how did this business's number of paid employees change?
6	In the last two weeks, how did the total number of hours worked by this business's paid employees change?
8	In the last two weeks, how did the time it takes for this business to receive deliveries from suppliers change?
9	How would you describe this business's current inventories?
10	In the last two weeks, how did demand for this business's goods or services change?
11	In the last two weeks, how did the prices this business charges for its own goods or services change?
12	In the last two weeks, how did the prices this business pays for goods or services change?
13	In the last six months, in what ways did changes to interest rates negatively impact this business?
14	In the last six months, did this business experience any monetary losses due to an extreme weather event (for example, hurricane, flood, drought, or heat wave)?
24	During the next six months, do you think this business will be using Artificial Intelligence (AI) in any of its business functions? (Examples of AI: machine learning, natural language processing, virtual agents, voice recognition, etc.)

Appendix B-Collinearity Results

Variable	Tolerance	VIF
Period 202525	0.536	1.866
Period 202526	0.546	1.832
Period 202601	0.496	2.015
Period 202602	0.521	1.92
Period 202603	0.484	2.065
Period 202604	0.453	2.208
Period 202605	0.449	2.226
Period 202606	0.463	2.161
Period 202607	0.451	2.216
Period 202608	0.424	2.358
Agriculture (11)	0.601	1.665
Mining (21)	0.479	2.088
Utilities (22)	0.596	1.677
Construction (23)	0.461	2.17
Manufacturing (31)	0.454	2.202
Wholesale Trade (42)	0.455	2.195
Retail Trade (44)	0.441	2.269
Transportation and Warehousing (48)	0.45	2.221
Information (51)	0.442	2.261
Finance and Insurance (52)	0.419	2.388
Real Estate (53)	0.473	2.113
Professional and Technical Services (54)	0.46	2.174
Administrative Services (56)	0.464	2.157

Educational Services (61)	0.446	2.243
Health Care and Social Assistance (62)	0.452	2.214
Arts and Entertainment (71)	0.472	2.117
Accommodation and Food Services (72)	0.388	2.574
and Other Services (81).	0.514	1.945
SizeG	0.36	2.775
SizeB	0.578	1.731
SizeC	0.556	1.797
SizeD	0.52	1.924
SizeE	0.443	2.256
SizeF	0.393	2.543
Paid employee changes (Q5)	0.614	1.628
Hours worked changes (Q6)	0.437	2.287
Supplier delays (Q8)	0.73	1.37
Inventory conditions (Q9)	0.517	1.936
Demand changes (Q10)	0.44	2.273
how did the prices this business charges (Q11)	0.434	2.302
how did the prices (Q12)	0.457	2.188
Interest-rate impacts (Q13)	0.543	1.841
Extreme weather disruptions (Q14)	0.419	2.389

Appendix C-Regression Model

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	26.114	43	0.607	77.09	<.001
	Residual	9.768	1240	0.008		
	Total	35.882	1283			

	Unstandardized B	Coefficients Std. Error	Standardized Coefficients Beta	t	Sig
(Constant)	0.136	0.019		6.964	<.001
Period 202525	-0.008	0.012	-0.013	-0.642	0.521
Period 202526	0.007	0.012	0.012	0.61	0.542
Period 202601	0.037	0.012	0.064	3.024	0.003
Period 202602	0.024	0.012	0.04	1.958	0.05
Period 202603	0.027	0.013	0.047	2.194	0.028
Period 202604	-0.02	0.013	-0.034	-1.548	0.122
Period 202605	-0.012	0.013	-0.021	-0.968	0.333
Period 202606	0.005	0.013	0.009	0.417	0.677
Period 202607	0	0.013	-0.001	-0.029	0.977
Period 202608	-0.005	0.012	-0.008	-0.362	0.717
Sector11	-0.161	0.021	-0.15	-7.869	<.001
Sector21	-0.17	0.019	-0.189	-8.822	<.001
Sector22	-0.161	0.022	-0.143	-7.462	<.001
Sector23	-0.065	0.015	-0.092	-4.237	<.001
Sector31	-0.031	0.015	-0.044	-2.003	0.045
Sector42	0.002	0.016	0.002	0.107	0.915
Sector44	-0.036	0.016	-0.051	-2.275	0.023
Sector48	-0.103	0.016	-0.142	-6.433	<.001
Sector51	0.295	0.016	0.412	18.475	<.001
Sector52	0.204	0.016	0.29	12.672	<.001
Sector53	0.068	0.016	0.091	4.216	<.001
Sector54	0.217	0.015	0.308	14.116	<.001
Sector56	0.002	0.015	0.003	0.16	0.873
Sector61	0.11	0.016	0.156	7.033	<.001
Sector62	0.019	0.016	0.027	1.235	0.217
Sector71	0.007	0.016	0.009	0.416	0.678
Sector72	-0.15	0.017	-0.213	-8.948	<.001
Sector81	-0.065	0.017	-0.081	-3.926	<.001
SizeG	0.19	0.013	0.364	14.738	<.001

	Unstandardized B	Coefficients Std. Error	Standardized Coefficients Beta	t	Sig
SizeB	0.011	0.009	0.023	1.202	0.23
SizeC	0.03	0.009	0.065	3.251	0.001
SizeD	0.07	0.01	0.149	7.253	<.001
SizeE	0.116	0.011	0.241	10.846	<.001
SizeF	0.148	0.012	0.299	12.665	<.001
Paid employee changes (Q5)	0.008	0.033	0.005	0.242	0.809
Hours worked changes (Q6)	0.027	0.028	0.021	0.938	0.348
Supplier delays (Q8)	-0.012	0.055	-0.004	-0.209	0.835
Inventory conditions (Q9)	-0.042	0.036	-0.024	-1.157	0.248
Demand changes (Q10)	0.005	0.025	0.005	0.205	0.838
how did the prices this business charges (Q11)	0.026	0.041	0.015	0.649	0.517
how did the prices (Q12)	0.043	0.025	0.038	1.752	0.08
Interest-rate impacts (Q13)	0.061	0.022	0.055	2.72	0.007
Extreme weather disruptions (Q14)	0.062	0.043	0.033	1.437	0.151