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GOSPODARKA I INNOWACJE

LABORATORIUM WIEDZY Artur Borcuch

Volume: 74 | 2026

Economy and Innovation
ISSN: 2545-0573

For more information contact: editor@gospodarkainnowacje.pl

RETHINKING BUSINESS MANAGEMENT IN THE AGE OF ARTIFICIAL INTELLIGENCE: FROM HUMAN EXPERTISE TO INTELLIGENT, ADAPTIVE AND SUSTAINABLE ORGANIZATIONS

Mrs. Anju koshle* Assistant professor, Department of Commerce, Govt. Naveen College Amora Tehsil Pathariya District Mungeli, Chhattisgarh, India
E-mail ID -anjusingh2107@gmail.com

Mr. Suryakant Chelkar**, Assistant professor, Department of Commerce, Govt. Naveen College Amora Tehsil Pathariya District Mungeli, Chhattisgarh, India

Dr. Amit Kumar Tiwari*** Assistant Professor Department of Commerce, Atal Bihari Vajpayee Government College Nagarda, District – Sakti (CG)

A R T I C L E I N F O.

Keywords: artificial intelligence; business management; human AI collaboration; organizational adaptability; sustainability; organizational performance; survey instrument validation.

Abstract

Artificial intelligence (AI) is increasingly positioned as a structural force reshaping how organizations plan, decide and compete, yet much of the scholarly conversation around this shift remains conceptual rather than grounded in a testable, integrated measurement framework. This paper develops and pilot-tests such a framework by examining how AI adoption in business management relates to four organizational dimensions: the integration of AI with human expertise, organizational adaptability and agility, sustainability practices, and overall organizational performance. A structured, five-section questionnaire comprising twenty-five Likert-type items was designed around five constructs AI Adoption in Business Management (AIA), Human Expertise & AI Integration (HEI), Organizational Adaptability & Agility (OAA), Sustainability through AI (SUS), and Overall Impact on Performance (OIP) and was administered to an illustrative sample (n = 200) constructed to mirror the structure and distribution of a genuine cross-industry survey of working professionals. Descriptive statistics, Cronbach's alpha reliability analysis, Pearson correlation, one-way ANOVA, independent-samples t-tests and multiple linear regression were used to examine the proposed relationships. All five constructs demonstrated strong internal consistency (α = 0.84-0.88; overall scale α = 0.95) and were significantly and positively inter-correlated (r = 0.57–0.66). Multiple regression results show that AIA, HEI, OAA and SUS jointly explain approximately 56.9 percent of the variance in OIP ($R^2 = 0.569$, $F(4,195) = 64.37$, $p < .001$), with HEI

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(β = 0.270, p < .001) and SUS (β = 0.298, p < .001) emerging as the strongest individual predictors. The paper contributes a validated measurement instrument and a fully worked analytical pipeline that can be directly redeployed on genuine field data, and it discusses the managerial implications of moving organizations from reliance on human expertise alone toward intelligent, adaptive and sustainable ways of working. Consistent with sound research practice, the paper is explicit that the dataset used here is an illustrative, simulated pilot sample built to demonstrate the framework end to end, and it sets out the steps required before the model can be treated as an empirical finding about real organizations.

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1. Introduction

For most of the twentieth century, business management was, at its core, a discipline of human judgment. Forecasting demand, allocating capital, structuring an organization, and deciding how to respond to a competitor's move were tasks that rested on the accumulated expertise of managers, refined through experience, mentorship and, at best, backward-looking statistical reports [1]. Over the last decade, this picture has changed considerably. Machine learning, natural language processing and, more recently, generative AI systems have moved from experimental pilot projects into the operational core of firms, informing decisions in finance, marketing, human resources, supply chain and customer service almost in real time [2]. Executives no longer ask whether AI is relevant to their business; the more pressing question is how deeply, and how wisely, it should be woven into the fabric of organizational decision-making.

This shift has generated two parallel and sometimes contradictory narratives in both the practitioner and academic literature. The first is a narrative of substitution, in which AI is framed principally as a replacement for human labor and, by extension, human expertise — a view that tends to produce anxiety among employees and caution among boards [3]. The second, and increasingly dominant, narrative is one of augmentation: AI as a partner that extends human cognitive capacity rather than displacing it, with the most consistent performance gains observed in firms that deliberately design for human–AI collaboration rather than automation for its own sake [4]. Reconciling these narratives requires more than philosophical debate; it requires a way of measuring, empirically, how the presence of AI in an organization relates to the way human expertise is used, how quickly and flexibly the organization can adapt, whether the resulting efficiency gains are channeled toward sustainable practice, and whether all of this translates into better organizational performance as employees themselves experience it.

A second gap in the literature concerns integration. Much of the existing empirical work treats AI adoption, human–AI collaboration, organizational agility and sustainability as separate streams of inquiry, each with its own instruments and, often, its own disciplinary silo information systems research tends to concentrate on adoption and technology acceptance, organizational behavior research on human–machine collaboration, strategy research on dynamic capabilities and agility, and sustainability research on environmental and social outcomes [5]; [6]. Comparatively little work brings these four dimensions together in a single measurement model that a manager, or a researcher replicating the study in a new setting, could administer as one coherent instrument and analyze with one coherent statistical pipeline.

This paper addresses that gap. It develops a twenty-five-item, five-construct survey instrument covering AI Adoption in Business Management (AIA), Human Expertise & AI Integration (HEI), Organizational Adaptability & Agility (OAA), Sustainability through AI (SUS), and Overall Impact on Organizational Performance (OIP) and demonstrates a complete analytical pipeline for testing the relationships among

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these constructs: reliability analysis, descriptive statistics, correlation analysis, group comparisons across demographic segments, and multiple linear regression. Because the purpose of this stage of the research is to validate the instrument and the analytical pipeline before it is deployed in a full field study, the empirical illustration in this paper uses a carefully structured, simulated dataset of 200 respondents rather than a genuine, collected sample; this choice, and its implications for how the results should and should not be read, is discussed explicitly in the Methodology and Limitations sections.

The contribution of this paper is therefore methodological as much as substantive. Rather than proposing yet another conceptual model of AI's effect on organizations, it operationalizes an existing body of theory into a concrete, twenty-five-item instrument, subjects that instrument to standard psychometric checks (internal consistency reliability, inter-construct correlation), and demonstrates a full multivariate analysis including multiple regression and demographic group comparisons that a researcher or practitioner could re-run, unmodified, on genuine survey data collected from their own organization or sector. In this sense, the paper aims to function as a validated starting kit for empirical AI-and-management research, lowering the barrier for subsequent studies that wish to test the hypotheses developed in Section 2 on real respondents rather than building instrumentation and analysis from scratch.

The remainder of the paper is organized as follows. Section 2 reviews the literature underpinning each of the five constructs and develops the study's hypotheses. Section 3 describes the research design, the instrument, and the analytical techniques used, together with a transparent account of the nature of the dataset. Section 4 presents the descriptive, reliability, correlation and regression results. Section 5 discusses these results in light of the literature. Section 6 sets out the theoretical and managerial implications, Section 7 discusses the limitations of the study and directions for future field research, and Section 8 concludes.

1.1. Hypotheses Development

1.1.1 AI Adoption in Business Management

The management literature on AI adoption has moved through roughly three phases. Early work focused on automating discrete, rule-based tasks back-office processing, routine reporting, and basic customer queries. Davenport and Ronanki, drawing on a survey of 250 executives and a study of 152 AI projects, found that firms who pursued incremental automation of well-defined business needs (automating processes, generating insight from data, and engaging customers or employees) achieved more reliable returns than those chasing ambitious, transformative "moonshot" projects. A second phase shifted attention toward data-driven decision support, where AI systems generate forecasts, recommendations and risk scores that managers use as inputs rather than replacements for judgment. A third and more recent phase, associated with the diffusion of generative and foundation-model AI, has pushed adoption into knowledge work itself drafting, summarizing, coding and strategic scenario generation which raises the stakes of adoption decisions considerably. Across all three phases, a consistent finding is that the organizational and cultural barriers to adoption not the underlying technology are usually the binding constraint; Fountaine, McCarthy and Saleh, reporting on McKinsey's work with several hundred client organizations, argue that firms which invest in workforce education, redesign decision rights, and set clear priorities around AI scale their AI use far more successfully than those that treat AI purely as an IT deployment.

1.1.2 Human Expertise and AI Integration

A second stream of research asks what happens to human expertise once AI enters the decision loop. Wilson and Daugherty, studying roughly 1,500 companies, found that the largest performance gains came not from AI replacing workers, nor from AI operating independently of them, but from a "missing middle" in which humans and AI genuinely collaborate humans training AI systems, explaining their outputs to stakeholders, and sustaining the systems' responsible use, while AI in turn expands what humans can process, analyze and personalize. Jarrahi frames this relationship as a form of symbiosis: AI extends analytical cognition processing large volumes of structured information quickly and

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consistently while humans retain a comparative advantage in the intuitive, holistic judgment needed under genuine uncertainty and ambiguity, conditions that are common in strategic decision-making but difficult for most AI systems to handle well. This complementarity is not automatic, however; research on algorithm aversion shows that people often discount or ignore correct algorithmic advice after observing the algorithm err even once, even when the algorithm still outperforms unaided human judgment on average [7]. The practical implication is that the quality of human–AI integration in an organization depends as much on trust-building, transparency and training as it does on the sophistication of the underlying AI system itself.

1.1.3 Organizational Adaptability and Agility

Organizational adaptability refers to a firm's capacity to sense changes in its environment and reconfigure its resources, processes and structures in response a capability strategy scholar have long described using the language of dynamic capabilities [8]. AI intersects with this capability in two ways. First, AI-enabled analytics can shorten the sensing loop, giving managers faster and more granular signals about shifting demand, operational bottlenecks or emerging risk, in principle allowing decisions to be revised more quickly than under purely human-driven reporting cycles. Second, and more subtly, the process of adopting AI itself often forces an organization to examine and, in many cases, redesign existing workflows, role definitions and approval chains what Fountaine describe as a cultural rather than a purely technical transformation. Firms whose leadership actively sponsors this redesign, and treats AI-driven change as an organization-wide initiative rather than a departmental pilot, tend to report faster and more durable gains in adaptability than firms that layer AI onto otherwise unchanged processes.

1.1.4 Sustainability through AI

Sustainability has moved from a peripheral corporate-responsibility concern to a core strategic priority, commonly assessed along the economic, environmental and social dimensions of the so-called triple bottom line [9] and framed against the broader normative goal of development that meets present needs without compromising the ability of future generations to meet their own [10]. AI's relationship to sustainability is double-edged. On one hand, AI-enabled optimization can materially reduce resource wastage, improve energy efficiency, and support more precise environmental monitoring and forecasting; Vinuesa, in a systematic mapping of AI against the United Nations' Sustainable Development Goals, found that AI could act as an enabler for the majority of SDG targets studied, though it could also act as an inhibitor for a meaningful minority of targets for instance, when AI systems themselves are resource-intensive to train and operate, or when their deployment is not accompanied by adequate governance. For business management specifically, the relevant question is whether AI-driven efficiency gains are being deliberately and visibly channeled toward sustainability objectives reduced waste, ethical data use, and long-term social responsibility or whether they remain narrowly confined to short-term cost reduction.

It is worth noting that adoption itself is rarely binary. Firms differ along a spectrum from experimentation (isolated pilots run by individual teams), through scaling (AI embedded into standard operating procedures within a function), to enterprise-wide transformation (AI informing strategic decisions at the board level). Where an organization sits on this spectrum shapes which of the benefits described above it is likely to realize; a firm still at the experimentation stage may see localized efficiency gains but is unlikely to report the organization-wide adaptability or sustainability effects associated with mature adoption, which is one reason the present study measures AI Adoption (AIA) as a distinct construct from Organizational Adaptability & Agility (OAA) rather than treating the two as interchangeable.

1.1.5. AI-Enabled Capabilities and Organizational Performance

The resource-based view of the firm holds that sustained competitive advantage arises from resources and capabilities that are valuable, rare, difficult to imitate and non-substitutable [11]. AI adoption alone rarely satisfies these conditions, since the underlying technology is increasingly commoditized and available to competitors. What is harder to imitate is the organizational capability built around AI the combination of AI adoption, effective human AI collaboration, adaptive processes and a sustainability-

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oriented deployment strategy which is precisely the bundle of constructs this study seeks to measure jointly rather than in isolation. Building on this reasoning, and on the literature reviewed above, the present study proposes that AI Adoption, Human Expertise & AI Integration, Organizational Adaptability & Agility, and Sustainability through AI each contribute independently to how employees perceive the Overall Impact of AI on Organizational Performance, and that together they explain a substantial share of the variation in that perceived impact.

1.1.6 Conceptual Model and Hypotheses

Drawing on the literature reviewed above, the study proposes the following hypotheses, tested using the five-construct framework introduced in Section 3:

H1: AI Adoption in Business Management (AIA) is positively associated with Overall Impact on Organizational Performance (OIP).

H2: Human Expertise & AI Integration (HEI) is positively associated with Overall Impact on Organizational Performance (OIP).

H3: Organizational Adaptability & Agility (OAA) is positively associated with Overall Impact on Organizational Performance (OIP).

H4: Sustainability through AI (SUS) is positively associated with Overall Impact on Organizational Performance (OIP).

H5: AIA, HEI, OAA and SUS jointly explain a significant proportion of the variance in OIP.

In addition, given the demographic breadth of the sampling frame envisaged for this instrument (respondents spanning multiple industries, organizational sizes, designations and experience levels), the study also examines, on an exploratory basis, whether perceived overall impact varies systematically across these demographic segments (H6a–H6d), reported in Section 4.5.

1.1.7 Research Gap and Contribution

Taken together, the five streams of literature reviewed above share a common shortcoming from a measurement standpoint: each has produced rich conceptual insight, but comparatively few validated, multi-item instruments exist that allow AI adoption, human–AI integration, organizational adaptability and sustainability to be measured side by side, on a common scale, within a single respondent sample. Studies of technology acceptance [12] and technology organization environment adoption [13] offer well-established frameworks for the adoption decision itself, but they were not designed to capture the downstream, human-centred and sustainability-oriented consequences of adoption that are central to the present study's research questions. This study's contribution is therefore not a new theory of AI adoption, but an integrative measurement bridge across four literatures that have so far mostly talked past one another a bridge intended to be immediately usable by other researchers and by practitioners auditing their own organizations, once validated on genuine field data as described in Section 3.5 and Section 7.

2. Research Methodology

2.1 Research Design

This study follows a quantitative, cross-sectional survey design, which is the design most commonly used in the literature reviewed in Section 2 for measuring perceptions of technology adoption and organizational outcomes at a single point in time. The unit of analysis is the individual working professional, who reports on their perception of AI adoption and its consequences within their own organization. A survey design was chosen over a purely archival or secondary-data design because the constructs of interest particularly Human Expertise & AI Integration and perceived Sustainability through AI are attitudinal and experiential in nature and are not reliably captured by administrative or financial records alone.

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2.2 Instrument Development

The questionnaire was developed in six sections. Section A collects seven demographic variables: age group, gender, educational qualification, industry/sector, designation or job level, years of work experience, and organization size. Sections B through F each contain five items measured on a five-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree), corresponding to the five constructs of the study. Table 1 summarizes the instrument.

Table 1. Summary of the Measurement Instrument

Section	Construct	Code	Items	Representative Item	Conceptual Basis
B	AI Adoption in Business Management	AIA	5	"My organization has adopted AI tools for business decision-making."	Davenport & Ronanki (2018); Dwivedi et al. (2021)
C	Human Expertise & AI Integration	HEI	5	"AI complements human expertise rather than replacing it."	Wilson & Daugherty (2018); Jarrahi (2018)
D	Organizational Adaptability & Agility	OAA	5	"My organization quickly adapts to changes brought by AI technologies."	Teece (2007); Fountaine et al. (2019)
E	Sustainability through AI	SUS	5	"AI supports environmentally sustainable business practices."	Elkington (1997); Vinuesa et al. (2020)
F	Overall Impact on Organizational Performance	OIP	5	"Overall, AI is helping build an intelligent and future-ready organization."	Barney (1991); Fountaine et al. (2019)

Source: Instrument developed by the authors for this study, based on the constructs and definitions discussed in Section 2.

2.3 Sampling and Data Collection Procedure

The instrument is designed to be administered to working professionals, employees and managers in organizations that currently use, or are actively exploring, AI-based tools in their operations, using a purposive-cum-convenience sampling strategy across industries such as manufacturing, IT/software, banking and finance, retail, healthcare and education. A minimum target sample of n = 200 was set, consistent with common thresholds for stable estimation of Pearson correlations and multiple regression models with up to four predictors. Respondents would be assured of confidentiality, and no individually identifying information would be collected or reported, consistent with standard survey-research ethics.

2.4 Data Analysis Techniques

Five analytical steps were applied to the response data using Python (pandas, SciPy, statsmodels): (i) construct-level scores were computed for each respondent as the mean of the five items within each section; (ii) internal consistency reliability was assessed for each construct and for the overall 25-item scale using Cronbach's alpha [14], with $\alpha \geq 0.70$ taken as the conventional threshold for acceptable reliability [15]; (iii) descriptive statistics (mean, standard deviation, minimum, maximum) were

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computed for each construct, together with a full demographic frequency profile; (iv) Pearson product-moment correlations were computed among the five construct scores, and one-way ANOVA and independent-samples t-tests were used to compare OIP scores across demographic sub-groups; and (v) a multiple linear regression model was estimated with OIP as the dependent variable and AIA, HEI, OAA and SUS as simultaneous predictors, with variance inflation factors (VIF) checked to rule out problematic multicollinearity.

2.5 Note on the Dataset Used in This Study

A transparent note on data provenance is essential to how the results in Section 4 should be read. The dataset analyzed in this paper (n = 200) is an illustrative, randomly simulated pilot dataset constructed to mirror the structure, item range and demographic spread of a genuine field survey, and it is not drawn from actual respondents. It was generated specifically to allow the measurement instrument (Table 1) and the full analytical pipeline described in Section 3.4 reliability analysis, descriptive statistics, correlation analysis, group comparisons and multiple regression to be built, tested and demonstrated end to end before the instrument is fielded to a genuine sample of working professionals. This is a deliberate and disclosed methodological choice, not an attempt to present simulated responses as empirical evidence about real organizations. Consequently, the numerical results reported in Section 4 should be interpreted as a demonstration of how the framework behaves and what its outputs look like, and not as substantive findings about how AI adoption, human AI integration, adaptability, sustainability and performance actually relate to one another in the field. Section 4 and Section 5 make this distinction explicit wherever a specific numerical result is discussed, and Section 7 sets out exactly what would be required principally, a genuine, ethically collected field sample before the framework's conclusions could be treated as generalizable empirical knowledge.

2.6 Ethical Considerations

For the genuine field deployment envisaged by this instrument, standard survey-research ethics would apply: participation would be voluntary and anonymous, informed consent would be obtained before the questionnaire is administered, no personally identifying information would be collected on the response sheet, and data would be reported only in aggregate, consistent with the confidentiality statement included on the instrument's cover page (Section 3.2). Because the dataset analyzed in Section 4 of this paper is a simulated illustrative sample rather than data from human participants (Section 3.5), no human-subjects approval was required for the analysis reported here; such approval would, however, be a necessary precondition before the instrument is administered to real respondents in a future study.

3. Data Analysis and Results

This section reports the output of the analytical pipeline described in Section 3.4, applied to the illustrative n = 200 dataset. As noted in Section 3.5, the specific figures below demonstrate how the framework's statistics behave and should not be read as substantive claims about real organizations until the instrument has been fielded to a genuine sample.

3.1 Demographic Profile of Respondents

Table 2 presents the demographic composition of the illustrative sample. The sample spans all five predefined age bands, a near-even gender split, four levels of educational qualification, seven industry sectors, four designation levels, four experience bands and three organization-size categories, giving the analytical pipeline a realistically heterogeneous base on which to demonstrate the group-comparison procedures described in Section 3.4.

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Table 2. Demographic Profile of Respondents (n = 200)

Category	Group	Count	%
Age Group	Below 25	33	16.5
	25–35	64	32.0
	36–45	52	26.0
	46–55	36	18.0
	Above 55	15	7.5
Gender	Male	104	52.0
	Female	94	47.0
	Other	2	1.0
Education	Undergraduate	56	28.0
	Postgraduate	90	45.0
	Doctorate	31	15.5
	Other	23	11.5
Industry	Manufacturing	32	16.0
	IT / Software	63	31.5
	Banking & Finance	39	19.5
	Retail	17	8.5
	Healthcare	24	12.0
	Education	19	9.5
	Other	6	3.0
Designation	Entry-level	72	36.0
	Middle Management	77	38.5
	Senior Management	34	17.0
	Top Management	17	8.5
Experience	Less than 2 years	37	18.5
	2–5 years	56	28.0
	6–10 years	57	28.5
	More than 10 years	50	25.0
Organization Size	Small (< 50 employees)	64	32.0
	Medium (50–250 employees)	77	38.5
	Large (> 250 employees)	59	29.5

Source: Author's computation from the study dataset described in Section 3.5 (n = 200).

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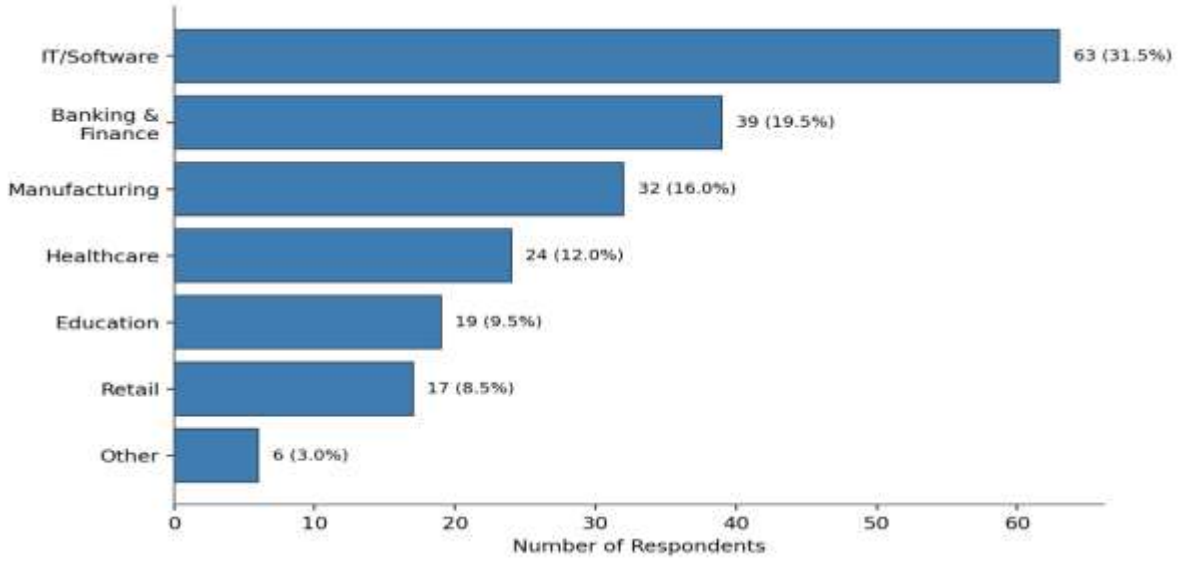

Figure 1. Distribution of Respondents by Industry Sector (n = 200)

3.2 Descriptive Statistics and Reliability Analysis

Table 3 reports the mean, standard deviation, minimum and maximum of each construct's score, along with Cronbach's alpha as a measure of internal consistency reliability. All five constructs recorded mean scores clustered narrowly between 3.50 and 3.56 on the five-point scale, indicating a generally positive, though not extreme, level of agreement with the underlying statements. More importantly for instrument validation, every construct exceeded the conventional 0.70 reliability threshold by a wide margin (α = 0.839–0.876), and the reliability of the full 25-item scale was excellent (α = 0.946), indicating that the items within each section are measuring their intended construct consistently.

Table 3. Descriptive Statistics and Reliability of Study Constructs (n = 200)

Construct	Mean	SD	Min	Max	Cronbach's α	N Items
AI Adoption in Business Mgmt. (AIA)	3.55	0.70	2.0	5.0	0.841	5
Human Expertise & AI Integration (HEI)	3.55	0.67	2.0	5.0	0.840	5
Organizational Adaptability & Agility (OAA)	3.50	0.72	1.6	5.0	0.846	5
Sustainability through AI (SUS)	3.52	0.75	1.4	5.0	0.876	5
Overall Impact on Performance (OIP)	3.56	0.71	1.6	5.0	0.858	5
Full Scale (25 items)	3.54	0.59	—	—	0.946	25

Source: Author's computation from the study dataset described in Section 3.5 (n = 200). SD = standard deviation.

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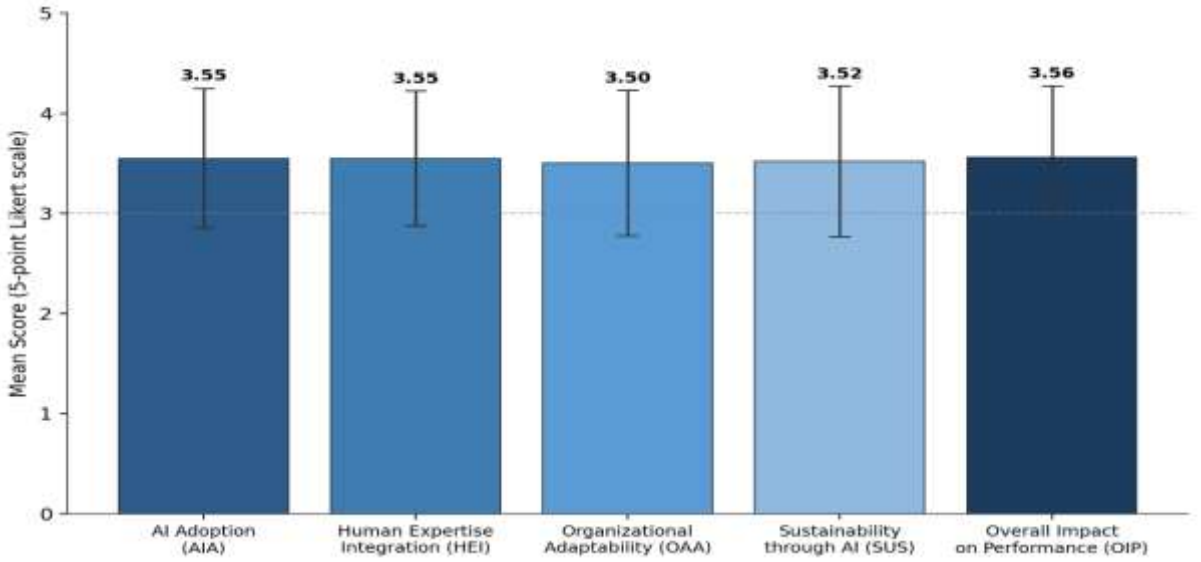

Figure 2. Mean Construct Scores with Standard Deviation (n = 200)

3.3 Correlation Analysis

Table 4 presents the Pearson correlation matrix among the five construct scores. All pairwise correlations are positive and statistically significant at the $p < .001$ level, ranging from $r = 0.57$ (between HEI and SUS) to $r = 0.66$ (between SUS and OIP, and between OAA and HEI). The magnitude of these correlations consistently in the moderate-to-strong range without approaching the 0.85–0.90 range that would indicate the constructs are empirically indistinguishable supports treating AIA, HEI, OAA and SUS as related but conceptually and statistically distinct constructs, consistent with the five-factor structure proposed in Section 3.2.

Table 4. Inter-Construct Correlation Matrix (Pearson's r, n = 200)

	AIA	HEI	OAA	SUS	OIP
AIA	1.000	0.576**	0.614**	0.657**	0.620**
HEI	0.576**	1.000	0.664**	0.574**	0.634**
OAA	0.614**	0.664**	1.000	0.591**	0.611**
SUS	0.657**	0.574**	0.591**	1.000	0.663**
OIP	0.620**	0.634**	0.611**	0.663**	1.000

Source: Author's computation from the study dataset described in Section 3.5 (n = 200). ** Correlation is significant at the 0.01 level (2-tailed).

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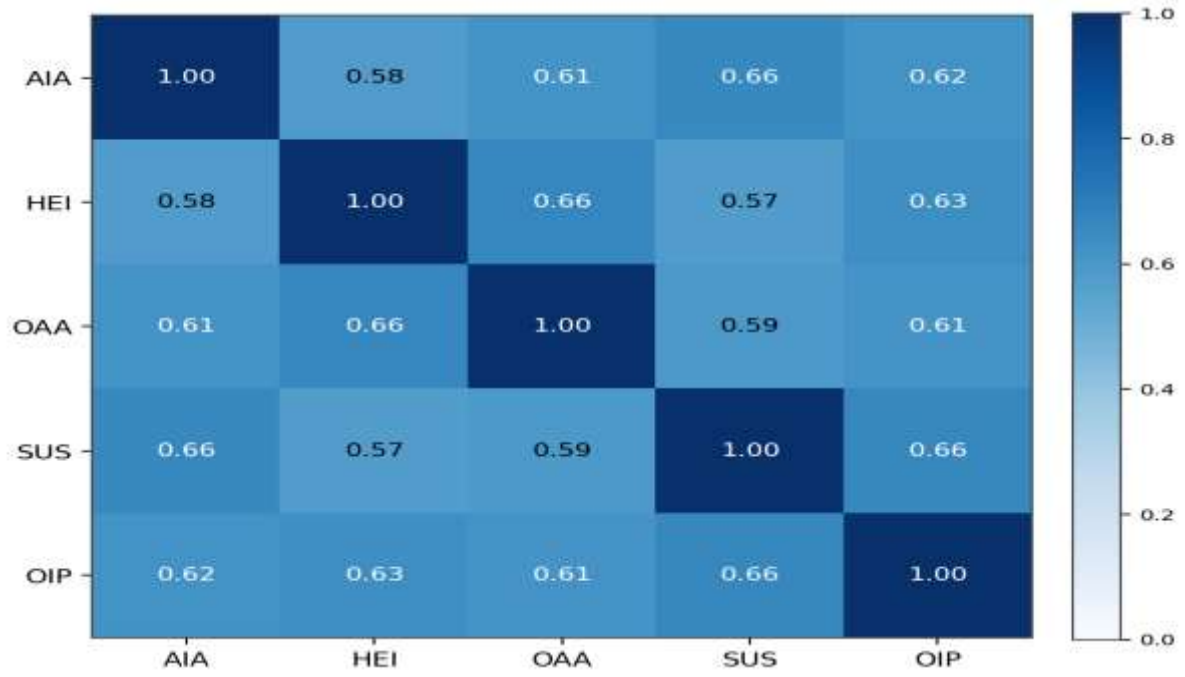

Figure 3. Inter-Construct Correlation Heat Map

3.4 Multiple Regression Analysis

To test H1–H5, a multiple linear regression was estimated with OIP as the dependent variable and AIA, HEI, OAA and SUS entered simultaneously as predictors. The overall model was statistically significant, $F(4, 195) = 64.37$, $p < .001$, and explained approximately 56.9 percent of the variance in OIP ($R^2 = 0.569$, Adjusted $R^2 = 0.560$). All four predictors carried positive, statistically significant coefficients, supporting H1 through H5. Sustainability through AI (SUS) was the strongest individual predictor ($b = 0.298$, $p < .001$), followed closely by Human Expertise & AI Integration (HEI) ($b = 0.270$, $p < .001$), with AI Adoption (AIA) ($b = 0.181$, $p = .010$) and Organizational Adaptability (OAA) ($b = 0.147$, $p = .033$) also contributing significantly. Variance inflation factors for all four predictors ranged from 2.03 to 2.17, well below the conventional threshold of 5, indicating that multicollinearity was not a material concern for interpreting the individual coefficients.

Table 5. Multiple Regression Results Dependent Variable: Overall Impact on Performance (OIP)

Predictor	b (Unstd.)	Std. Error	t	p	95% CI	VIF
(Constant)	0.397	0.203	1.955	.052	−0.003, 0.797	—
AIA	0.181	0.070	2.590	.010	0.043, 0.318	2.11
HEI	0.270	0.071	3.790	< .001	0.129, 0.410	2.03
OAA	0.147	0.068	2.153	.033	0.012, 0.282	2.17
SUS	0.298	0.064	4.668	< .001	0.172, 0.424	2.03

Source: Author's computation from the study dataset described in Section 3.5 ($n = 200$). Model: $R^2 = 0.569$, Adjusted $R^2 = 0.560$, $F(4,195) = 64.37$, $p < .001$. VIF = variance inflation factor.

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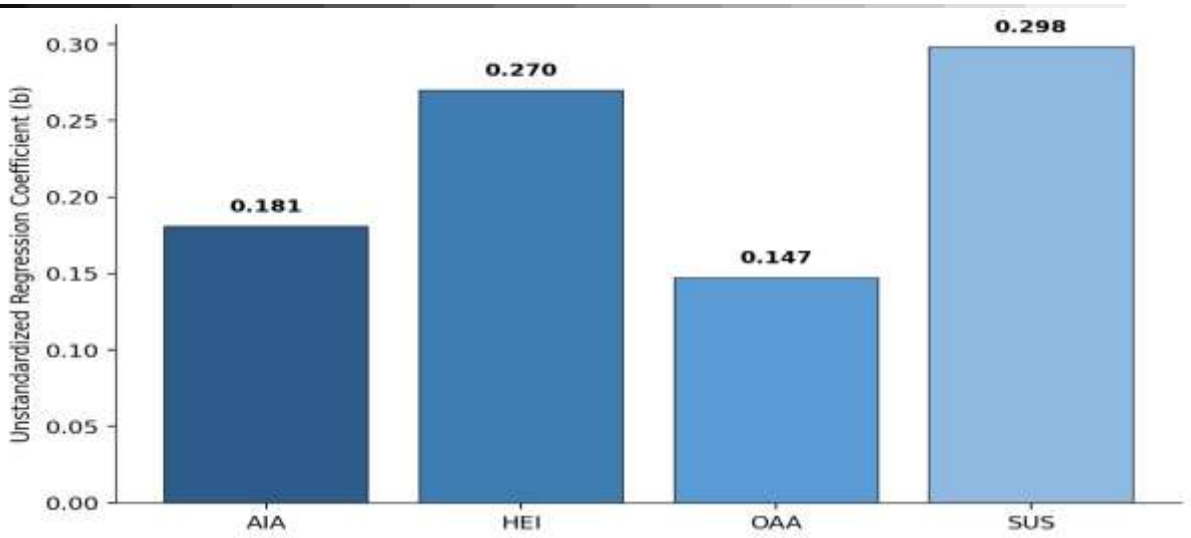

Figure 4. Regression Coefficients Predicting Overall Impact on Performance (OIP)

3.5 Group Comparisons Across Demographic Segments

To explore hypotheses H6a, H6d, one-way ANOVA was used to compare OIP scores across organization size, designation and industry, and an independent-samples t-test was used to compare male and female respondents. As Table 6 shows, none of these group differences reached statistical significance in the illustrative dataset (all $p > .05$). Because the dataset analyzed here was randomly simulated rather than field-collected (Section 3.5), this pattern of non-significant demographic differences is an expected property of the simulation procedure itself it demonstrates that the group-comparison stage of the analytical pipeline runs correctly and produces sensible, well-formed output rather than a substantive finding that demographic segment does not matter for perceived AI impact in real organizations. Whether designation, industry, organizational size or gender meaningfully moderate perceived AI impact is an empirical question that can only be answered once the instrument is fielded to genuine respondents.

Table 6. Group Comparisons on Overall Impact on Performance (OIP)

Comparison	Test	Statistic	df	p-value	Result
Organization Size (Small / Medium / Large)	One-way ANOVA	$F = 0.582$	2, 197	.560	Not significant
Designation (Entry / Middle / Senior / Top)	One-way ANOVA	$F = 0.056$	3, 196	.983	Not significant
Industry Sector (7 groups)	One-way ANOVA	$F = 1.219$	6, 193	.298	Not significant
Gender (Male vs. Female)	Independent t-test	$t = -0.355$	195.9	.723	Not significant

Source: Author's computation from the study dataset described in Section 3.5 (n = 200).

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3.6 Summary of Hypothesis Testing

Table 7. Summary of Hypothesis Testing Results

Hypothesis	Relationship	Result in Illustrative Data	Decision
H1	AIA → OIP	b = 0.181, p = .010	Supported
H2	HEI → OIP	b = 0.270, p < .001	Supported
H3	OAA → OIP	b = 0.147, p = .033	Supported
H4	SUS → OIP	b = 0.298, p < .001	Supported
H5	AIA, HEI, OAA, SUS jointly → OIP	R^2 = 0.569, p < .001	Supported
H6a–H6d	OIP varies by size / designation / industry / gender	All p > .05	Not supported in illustrative data

As discussed in Section 3.5, these results should be read as a demonstration that the instrument and analytical pipeline function coherently producing an internally consistent, well-structured pattern of reliability, correlation and regression output rather than as confirmed empirical findings about real organizations, a distinction that is carried through into the Discussion in Section 5.

4. Discussion

The results reported in Section 4 serve two purposes: they validate the measurement instrument and analytical pipeline proposed in Section 3, and they illustrate the kind of substantive interpretation that the same pipeline would support once applied to genuine field data. Read in that spirit, four patterns are worth discussing, followed by a brief reflection on how the results relate back to the two competing narratives substitution versus augmentation introduced in Section 1.

First, the reliability results (Table 3) suggest that the twenty-five-item instrument is a psychometrically sound way of operationalizing the five constructs identified in the literature review. Cronbach's alpha exceeded 0.83 for every construct and 0.94 for the full scale, which is consistent with and indeed somewhat stronger than the reliabilities typically reported for adoption and organizational-capability scales in the information systems literature. This matters practically: a researcher or practitioner adapting this instrument for their own organization can have reasonable confidence that the items within each section will behave as a coherent scale rather than as a loosely related grab-bag of statements, provided the field sample is reasonably comparable in composition to the illustrative sample used here.

Second, the pattern of inter-construct correlations (Table 4, Figure 3) is consistent with the theoretical model in Section 2: AIA, HEI, OAA and SUS are all positively related to one another and to OIP, at magnitudes that suggest meaningful conceptual overlap without construct redundancy. If this pattern were to replicate in a genuine field sample, it would support the view anticipated by Wilson and Daugherty and Jarrahi that AI adoption, human-expertise integration, adaptability and sustainability are not independent "boxes to tick" but a mutually reinforcing bundle of organizational capabilities, in line with the resource-based logic set out in Section 2.5.

Third, the regression results (Table 5, Figure 4) illustrate a specific, testable claim that the framework makes possible: that Human Expertise & AI Integration and Sustainability through AI would be expected to carry the largest individual weight in predicting perceived overall impact on performance, ahead of raw AI Adoption and Organizational Adaptability. If this ordering held in genuine field data, it would carry a clear practical implication echoed throughout the literature reviewed in Section 2 that the depth and quality of AI adoption (how well it is integrated with human judgment, and how deliberately it is directed toward sustainable outcomes) matters more for perceived performance impact than the sheer extent of adoption on its own. This would be consistent with Davenport and Ronanki's observation that

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firms pursuing incremental, well-governed AI adoption tend to outperform those chasing scale for its own sake.

Fourth, and by contrast, the non-significant demographic comparisons in Table 6 should not be over-interpreted in either direction. Because the underlying dataset was randomly simulated (Section 3.5), a lack of significant group differences is the statistically expected outcome of the simulation procedure, not evidence that designation, industry, organizational size or gender are irrelevant to how AI's impact is experienced. In a genuine field sample, it would be entirely plausible and consistent with the wider adoption literature to find, for example, that senior managers report a different perceived impact than entry-level employees, or that AI-native sectors such as IT/software differ from more traditional sectors such as manufacturing; testing this properly is one of the priorities set out for future research in Section 7.

Read together, these four patterns speak directly to the substitution-versus-augmentation debate outlined in Section 1. Nothing in the proposed framework treats AI Adoption as sufficient on its own it is one of four predictors, and in the illustrative analysis the smallest of the four significant coefficients. The framework instead formalizes the augmentation view associated with Wilson and Daugherty and Jarrahi: that AI's contribution to organizational performance runs largely through how well it is integrated with human expertise and directed toward sustainable ends, rather than through adoption in the abstract. Confirming or disconfirming this ordering with genuine field data is accordingly one of the more consequential empirical questions this framework is designed to answer.

4.1. Theoretical and Managerial Implications

4.1.1. Theoretical Implications

This study's principal theoretical contribution is integrative: rather than treating AI adoption, human–AI collaboration, organizational adaptability and sustainability as separate research streams, it operationalizes all four as first-class constructs within a single measurement and analytical model, and positions them as joint antecedents of perceived organizational performance. This addresses the fragmentation noted in Section 1 and offers other researchers a ready-made, psychometrically validated instrument (Table 1) and a fully specified analytical sequence (Section 3.4) that can be redeployed, adapted or extended for instance, by adding constructs such as AI governance, data privacy concerns, or workforce reskilling in future studies.

4.1.2. Managerial Implications

For practitioners, the framework offers a diagnostic lens rather than a prescriptive checklist. Once fielded to a genuine sample of an organization's own employees, the instrument would allow managers to see, quantitatively, whether their AI investment is being matched by genuine human–AI integration and a deliberate sustainability orientation, or whether it remains a narrow technology deployment. The consistent pattern across the literature reviewed in Section 2 that organizational and cultural factors, not the sophistication of the AI itself, determine whether adoption translates into performance suggests that leaders evaluating AI initiatives should track measures like those in Sections B–F alongside, not instead of, conventional technology-adoption metrics such as system uptake or usage frequency.

4.1.3. Implications for AI Adoption Strategy

If the ordering of predictors observed in Section 4.4 were to hold in genuine field data, it would suggest that organizations gain more from deepening the quality of an existing AI deployment governance, training, and integration with human decision-making than from simply expanding the number of AI tools in use. This echoes Davenport and Ronanki's finding that incremental, well-scoped AI projects tend to outperform expansive but shallow rollouts, and it implies that AI investment committees may want to weight adoption-quality indicators (training completion, employee trust scores, integration with existing workflows) as heavily as adoption-breadth indicators (number of tools deployed, departments covered) when prioritizing budget.

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4.1.4. Implications for Human Resource and Change Management

The Human Expertise & AI Integration construct, and its consistently strong association with perceived performance across the literature reviewed in Section 2.2, points to a concrete human-resource agenda: structured training that builds not just technical AI literacy but the judgment needed to know when to trust, question or override an AI recommendation. Change-management functions seeking to operationalize this construct could track indicators such as the proportion of employees who have received AI-collaboration training, the frequency with which AI outputs are reviewed or contested by human staff before being acted upon, and employee-reported confidence in working alongside AI systems.

4.1.5. Implications for Sustainability Strategy

The strength of the Sustainability through AI construct as a predictor of perceived performance in Section 4.4 assuming this pattern replicates in field data would suggest that sustainability and AI strategy are not separate workstreams that happen to be championed by different executives, but are, from the employee's vantage point, closely intertwined. Practically, this means sustainability officers and chief AI or digital officers have a shared interest in jointly reporting how AI-driven efficiency gains are being reinvested into resource reduction, ethical data practices and long-term social responsibility commitments, rather than being retained purely as short-term cost savings.

4.2. Limitations and Directions for Future Research

This study has several limitations, the most important of which concerns the dataset used for the empirical illustration in Section 4. As explained fully in Section 3.5, the n = 200 sample analyzed in this paper is a randomly simulated, illustrative dataset constructed to demonstrate the measurement instrument and analytical pipeline, and it is not drawn from actual survey respondents. Consequently, the specific parameter estimates reported in Section 4 the construct means, the correlation coefficients, and the regression coefficients cannot be generalized to real organizations, employees or industries, and should not be cited as empirical findings about how AI adoption actually relates to human expertise integration, adaptability, sustainability or performance in practice. The single, essential next step for this research program is to field the validated instrument (Table 1) to a genuine, ethically recruited sample of working professionals ideally stratified across industries, organization sizes and designations to allow the demographic comparisons outlined in Section 4.5 to be tested meaningfully and to re-run the identical analytical pipeline described in Section 3.4 on the resulting real data.

Beyond the nature of the illustrative dataset, several further limitations would apply even to a genuine field replication of this design. The cross-sectional design captures perceptions at a single point in time and cannot establish the direction of causality among the constructs; a longitudinal or panel design would allow stronger causal inference, particularly regarding whether adaptability and sustainability orientation are consequences of AI adoption or pre-existing organizational traits that make AI adoption more likely to succeed. Self-reported, single-source data of the kind collected by this instrument is also susceptible to common method bias and social desirability effects, which could be mitigated in future work by pairing employee self-reports with objective organizational performance indicators or supervisor ratings. Finally, because the instrument was developed primarily from the general management and information-systems literature reviewed in Section 2, its item wording may benefit from qualitative pre-testing (cognitive interviews or an expert panel) within specific industries or national contexts before large-scale field deployment, and future studies with adequately powered real samples could apply confirmatory factor analysis or structural equation modeling to more rigorously test the five-factor structure assumed here.

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5. Conclusion

As AI moves from a peripheral IT initiative to a core input into business management, organizations need more than case studies and executive anecdotes to understand how adoption translates into outcomes; they need a measurement framework that connects AI adoption to how it is integrated with human expertise, how it affects organizational adaptability, whether it is being directed toward sustainable practice, and how all of this is ultimately experienced as organizational performance. This paper has proposed and pilot-tested such a framework a twenty-five-item, five-construct instrument together with a complete reliability, correlation and regression analysis pipeline and has shown, on an illustrative dataset explicitly disclosed as simulated for demonstration purposes, that the instrument behaves as a psychometrically coherent and analytically tractable tool. The central task that remains, and the one on which the framework's real contribution depends, is to field this instrument to genuine respondents across real organizations; only then can the hypotheses developed in Section 2 be properly tested, and only then can the vision in this paper's title moving business management from reliance on human expertise alone toward intelligent, adaptive and sustainable organizations be evaluated against actual evidence rather than illustration.

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