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The Influence of AI Knowledge and Business Ethics Understanding on Student Perceptions and Acceptance of Sustainable Business Transformation

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ABSTRACT

This study examines how students' understanding of Artificial Intelligence and business ethics influences their perceptions and acceptance of AI in sustainable business transformation. Using a quantitative approach with stratified random sampling, data were collected from 450 undergraduate students in the Faculty of Economics and Business, representing Management (40%), Accounting (35%), and Development Economics (25%). Multiple regression analysis revealed significant positive relationships between AI understanding and both perception ($\beta = 0.485$, $p < 0.001$) and acceptance ($\beta = 0.423$, $p < 0.001$) of AI in sustainable business. Similarly, business ethics understanding significantly influenced perception ($\beta = 0.372$, $p < 0.001$) and acceptance ($\beta = 0.356$, $p < 0.001$). The research model explained 64.3% of variance in perceptions and 58.7% in acceptance of AI for business sustainability. Management students demonstrated higher understanding (mean = 3.95) compared to other majors. These findings highlight a critical gap in contemporary business education: the need to integrate technological knowledge with ethical frameworks and sustainability principles. Educational institutions must develop comprehensive curricula that prepare future business leaders for ethical digital transformation. This research contributes valuable insights for curriculum developers and policymakers seeking to align business education with the evolving demands of AI-driven sustainable business landscapes.

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1. INTRODUCTION

The integration of Artificial Intelligence (AI) into business operations represents one of the most significant technological shifts of the 21st century, transforming organizational structures, decision-making processes, and competitive landscapes. As businesses increasingly embed AI technologies within their operations, sustainability and ethics-oriented thinking are experiencing a paradigm shift (Gupta & Parmar, 2024). This transformation is particularly significant in developing economies like Indonesia (Alfie Faj'ri et al., 2024; Majid et al., 2024), where the intertwining of technological innovation with sustainable business practices presents both unprecedented opportunities and complex challenges for future business leaders.

Despite extensive research on AI implementation in business and growing literature on sustainable business practices, a critical knowledge gap exists at their intersection. Current research has predominantly focused on either the technical aspects of AI adoption or the conceptual frameworks of sustainability, with insufficient attention to how these domains converge in practical business contexts. Furthermore, while industry perspectives have been well-documented, the viewpoints of future business leaders—today's business students—remain largely unexplored. This represents a significant oversight, as these students will ultimately shape how organizations implement AI technologies within sustainable business frameworks.

The disconnect between technological education and ethical considerations in business curricula further compounds this problem. Business schools often separate technical courses from ethics education, creating artificial divisions that fail to reflect the integrated nature of real-world business challenges. This educational approach leaves students ill-prepared to address the complex ethical implications of implementing AI in sustainable business contexts, particularly concerning issues such as data privacy, algorithmic bias, and the environmental impact of AI technologies (Eghaghe et al., 2024).

Recent studies demonstrate AI's transformative impact across various business domains. AI has evolved

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from simple automation tools at its inception to sophisticated systems that analyze data and make decisions, optimizing processes (Chowdhury, 2024; Susilo & Susanto, 2024). The development trajectory has progressed from rule-based systems to modern machine learning algorithms (Goswami et al., 2024) and neural networks (Barsukova et al., 2024), fundamentally altering business operations, particularly in supply chain management (Koliadenko & Kiporenko, 2023), customer support (Gurău et al., 2003), and strategic planning (Singh, 2024).

Beyond operational efficiency, AI is reshaping business models through predictive analytics (Rahman, 2024) and enhanced decision-making processes (W. Wang, 2024). Organizations implementing AI have reported improvements in productivity, cost savings, and customer satisfaction (Andayani et al., 2024). However, these transformations present significant challenges, including implementation costs, workforce adaptation requirements, and ethical considerations that must be addressed within a sustainability framework.

In parallel, the concept of sustainable business has evolved from a narrow focus on environmental protection to an inclusive framework encompassing economic viability, social responsibility, and environmental stewardship (Abudaqa et al., 2024; Bernardus et al., 2024; Böttcher et al., 2024). This triple bottom line approach (Purnama, 2024), popularized by Elkington, serves as the conceptual foundation for how businesses can create long-term value while minimizing adverse impacts on society and the environment (Hardy et al., 2024; Lutzer et al., 2024). While emerging research by Vázquez-Parra et al. (2024) has begun exploring student perceptions of AI tools in learning contexts, and Olatoye et al. (2024) has examined ethical guidelines in AI implementation, there remains a significant gap in understanding how future business leaders conceptualize the intersection of AI, ethics, and sustainability—a gap this research aims to address.

This study contributes to existing literature in three significant ways. First, it provides empirical evidence on the relationship between technical knowledge (AI understanding) and ethical frameworks (business ethics understanding) in shaping technology acceptance for sustainable business practices—a connection previously underexplored in academic literature. Second, by focusing specifically on students' perspectives, this research offers unique insights into how the next generation of business leaders conceptualizes the role of AI in sustainable business transformation. Finally, the study's findings have direct implications for curriculum development, highlighting specific areas where business education must evolve to better prepare graduates for an AI-driven sustainable business landscape.

From a practical perspective, this research addresses urgent challenges facing business education institutions, which must rapidly adapt curricula to incorporate both technical AI knowledge and ethical frameworks for sustainability. By identifying specific relationships between AI understanding, business ethics knowledge, and technology acceptance, this study provides actionable insights for educational institutions, policymakers, and businesses invested in developing future-ready business leaders.

Based on theoretical foundations and previous research, this study proposes a conceptual framework examining the relationships between students' understanding of AI and business ethics, and their influence on perceptions and acceptance of AI in sustainable business transformation. The research tests four hypotheses. Through rigorous testing of these hypotheses, this research aims to provide a comprehensive understanding of the factors influencing future business leaders' perspectives on AI in sustainable business transformation, ultimately contributing to more effective business education and sustainable business practices.

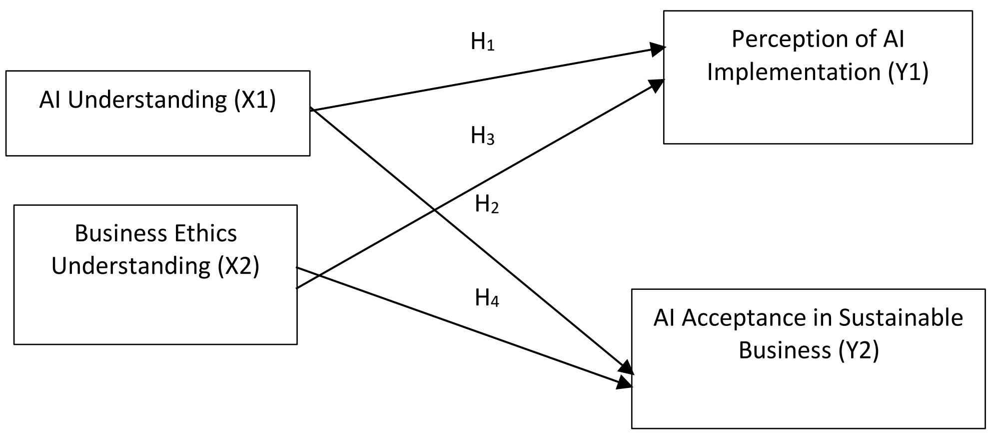

Figure 1. Conceptual Framework

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Research Hypotheses:
H_1: AI Understanding (X1) positively influences Perception of AI Implementation (Y1)
H_2: AI Understanding (X1) positively influences AI Acceptance in Sustainable Business (Y2)
H_3: Business Ethics Understanding (X2) positively influences Perception of AI Implementation (Y1)
H_4: Business Ethics Understanding (X2) positively influences AI Acceptance in Sustainable Business (Y2)

2. MATERIAL AND METHOD

Research Design and Approach

This study employed a quantitative research methodology with an explanatory survey design to investigate the relationships between students' understanding of AI and business ethics and their perceptions and acceptance of AI in sustainable business transformation. An explanatory research design was selected as the most appropriate approach because it enables the establishment of causal relationships between independent and dependent variables (Creswell & Creswell, 2018). This design aligns with our research objectives of determining how AI understanding and business ethics understanding influence perception and acceptance of AI in sustainable business contexts.

The survey approach was chosen for several reasons. First, it allows for systematic collection of standardized data from a large population, ensuring comparability across respondents. Second, surveys are particularly effective for capturing perceptions, attitudes, and self-reported knowledge levels—all central constructs in this study. Third, the approach facilitates statistical analysis to test hypothesized relationships with a degree of precision and generalizability that qualitative methods cannot achieve. Finally, surveys have been widely used in technology acceptance research, providing methodological consistency with the existing literature (Venkatesh et al., 2016).

Sampling Strategy and Data Collection

Population and Sample Size Determination

The target population comprised 1,542 undergraduate students enrolled in the Faculty of Economics and Business. To ensure adequate statistical power while maintaining feasibility, we employed a proportional stratified random sampling technique. The sample size was determined using Slovin's formula:

$n = N / (1 + Ne^2)$

Where:
n = sample size
N = population size (1,542)
e = margin of error (0.05)

This calculation yielded a required sample size of 317. However, to account for potential non-response or invalid responses, we increased the sample size to 450 students, representing approximately 29% of the target population. This sample size exceeds the minimum requirements for multiple regression analysis with two predictors, which according to Green's (1991) rule of thumb requires a minimum of 106 participants (50 + 8k, where k = number of predictors).

Stratification Criteria and Recruitment Procedure

Stratification was implemented along two dimensions: academic major and year of study. This approach ensured proportional representation across different segments of the student population, thereby enhancing the generalizability of findings. The distribution resulted in 40% Management majors (n = 180), 35% Accounting majors (n = 158), and 25% Development Economics majors (n = 112). Academic year representation was similarly balanced with 26% first-year students (n = 117), 28% second-year students (n = 126), 24% third-year students (n = 108), and 22% fourth-year students (n = 99).

Participants were recruited through formal channels within the faculty, including announcements in core courses across all majors and years. Participation was voluntary, and informed consent was obtained from all respondents before survey administration. The survey was conducted over a four-week period to accommodate student schedules and maximize response rates, resulting in 100% completion of the targeted sample.

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Measurement Instruments and Variables
Instrument Development

A structured questionnaire was developed based on comprehensive literature review and operationalization of key constructs. The instrument consisted of four main sections corresponding to the study variables, plus a demographic information section. All scale items utilized a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree), which offers sufficient discrimination while remaining accessible to respondents (Dawes, 2008).

The questionnaire underwent a rigorous development process including:

1) Initial item generation based on theoretical constructs
2) Expert review by three faculty members specializing in business ethics, information systems, and sustainability
3) Content validity assessment using Lawshe's Content Validity Ratio method
4) Pilot testing with 30 students outside the main sample to assess clarity, comprehensiveness, and completion time
5) Refinement based on pilot feedback before final administration

Operationalization of Variables

Independent Variables:

AI Understanding (X1) was measured using a 5-item scale assessing awareness of AI concepts (3 items), knowledge of AI applications in business (2 items), and understanding of AI limitations (2 items). Items were adapted from Venkatesh et al. (2016). Business Ethics Understanding (X2) was assessed using an 8-item scale measuring awareness of moral principles (3 items), understanding of corporate social responsibility (3 items), and knowledge of ethical decision-making frameworks (2 items). These items were adapted from established scales by Davis (1989) and Venkatesh & Davis (2000).

Dependent Variables:

Perception of AI Implementation (Y1) was measured using a 9-item scale incorporating Technology Acceptance Model constructs: perceived usefulness (3 items), perceived ease of use (3 items), and perceived advantages for sustainable business (3 items). Items were adapted from Venkatesh et al. (2016). AI Acceptance in Sustainable Business (Y2) was measured using a 5-item scale assessing behavioral intentions, including intent to use AI (2 items), willingness to enhance AI capabilities (2 items), and belief in AI's contribution to sustainability (3 items). These items were adapted from Venkatesh et al. (2016).

Reliability and Validity Assessment

Instrument reliability was assessed using Cronbach's alpha coefficient, with all scales demonstrating high internal consistency: AI Understanding ($\alpha = 0.887$), Business Ethics Understanding ($\alpha = 0.892$), Perception of AI Implementation ($\alpha = 0.901$), and AI Acceptance in Sustainable Business ($\alpha = 0.895$). These values substantially exceed the recommended threshold of 0.70 (Hair et al., 2019), confirming the reliability of all measurement scales. Content validity was established through expert review and pilot testing. Construct validity was evaluated through factor analysis, with all items loading on their respective factors above the minimum threshold of 0.40, ranging from 0.642 to 0.891. Discriminant validity was confirmed by examining inter-construct correlations, which ranged from 0.650 to 0.780, below the threshold of 0.85 that would indicate potential construct overlap (Kline, 2015).

Data Analysis Procedures
Preliminary Data Examination

Data analysis began with preliminary screening to identify missing values, outliers, and unusual patterns. Descriptive statistics including frequency distributions, measures of central tendency, and dispersion were calculated for all variables to understand general response patterns and sample characteristics. Normality was assessed using the Kolmogorov-Smirnov test, which confirmed normal distribution of residuals ($p > 0.05$) for both dependent variables.

Assumptions Testing for Regression Analysis

Prior to hypothesis testing, classical assumption tests were conducted to ensure the validity of regression analyses.

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These included:
1) Normality test using the Kolmogorov-Smirnov method to verify normal distribution of residuals
2) Multicollinearity assessment using Variance Inflation Factor (VIF), with values ranging from 1.245 to 2.156, well below the critical threshold of 10
3) Heteroscedasticity test using Glejser's method, which confirmed homoscedasticity with p-values > 0.05
4) Linearity assessment through scatter plot analysis and statistical testing, confirming linear relationships between independent and dependent variables

Hypothesis Testing

Multiple regression analysis was employed to test the hypothesized relationships using SPSS version 26.0. Two separate regression models were constructed:

$$\text{Model 1: } Y1 = \alpha + \beta_1 X1 + \beta_2 X2 + \varepsilon$$
$$\text{Model 2: } Y2 = \alpha + \beta_1 X1 + \beta_2 X2 + \varepsilon$$

Where:
Y1 = Perception of AI Implementation
Y2 = AI Acceptance in Sustainable Business
X1 = AI Understanding
X2 = Business Ethics Understanding
α = Constant
β_1, β_2 = Regression coefficients
ε = Error term
Hypothesis testing included:
1) Individual parameter significance tests (t-tests) to evaluate the significance of each independent variable's effect on the dependent variables
2) Simultaneous significance testing (F-tests) to assess the overall significance of each regression model
3) Coefficient of determination (R^2) calculation to determine the proportion of variance in dependent variables explained by the independent variables

The significance level was set at $\alpha = 0.05$, indicating 95% confidence in the findings. Additionally, standardized beta coefficients were calculated to facilitate comparison of the relative influence of each independent variable.

Subgroup Analysis

Supplementary analyses were conducted to examine variations across demographic subgroups, particularly focusing on differences between academic majors and years of study. These analyses employed one-way ANOVA with post-hoc Tukey tests to identify significant differences between specific groups. This approach allowed for deeper insights into how student characteristics might moderate the relationships between understanding, perception, and acceptance of AI in sustainable business contexts.

3. RESULTS

Respondent Demographics

The survey achieved a full response rate from all 450 targeted students, minimizing nonresponse bias. The gender split was nearly even at 52 percent female and 48 percent male, with an average age of 20.3 years. Age bands were 30 percent for 18 to 19 years, 50 percent for 20 to 21 years, and 20 percent for 22 to 23 years. Table 1 presents the demographic characteristics of respondents, showing a balanced distribution across gender, academic majors, years of study, and age groups.

Program representation was proportional across the faculty, with Management at 40 percent, Accounting at 35 percent, and Development Economics at 25 percent. Cohorts were also balanced, with 26 percent first year, 28 percent second year, 24 percent third year, and 22 percent fourth year. This structure reduces cohort effects and supports valid comparisons across programs and years, while subgroup sizes are adequate for regression, analysis of variance, and post hoc tests, strengthening internal validity and generalizability.

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Table 1. Respondent Demographics

Characteristic	Category	Frequency	Percentage
Gender	Male	216	48%
	Female	234	52%
Major	Management	180	40%
	Accounting	158	35%
	Development Economics	112	25%
Academic Year	First Year	117	26%
	Second Year	126	28%
	Third Year	108	24%
	Fourth Year	99	22%
Age	18-19 years	135	30%
	20-21 years	225	50%
	22-23 years	90	20%

Reliability and Correlation Analysis

Table 2. Reliability and Correlation Analysis

Variable	Reliability	Correlation			
	Cornbach's Alpha	X1	X2	Y1	Y2
X1	0.887	1.000			
X2	0.892	0.650	1.000		
Y1	0.901	0.720	0.690	1.000	
Y2	0.895	0.680	0.710	0.780	1.000

Table 2 presents the reliability coefficients and correlation matrix for all study variables. All variables demonstrated high internal consistency with Cronbach's alpha values ranging from 0.887 to 0.901, exceeding the minimum threshold of 0.7. The correlation matrix showed moderate to strong positive correlations between all variables, with coefficients ranging from 0.650 to 0.780. The strongest correlation was observed between the two dependent variables: Perception of AI Implementation (Y1) and AI Acceptance in Sustainable Business (Y2) at 0.780.

Classical Assumption Tests

Tables 3-5 present the results of classical assumption tests conducted to ensure the validity of regression analyses. The Kolmogorov-Smirnov test confirmed normal distribution of residuals for both dependent variables with p-values greater than 0.05. Multicollinearity assessment yielded VIF values of 1.731 for both independent variables, well below the critical threshold of 10, indicating no significant multicollinearity. Glejser's test for heteroscedasticity showed no significant patterns in residuals ($p > 0.05$), confirming homoscedasticity.

Table 3. Normality Test Results

Dependent Variable	Kolmogorov-Smirnov Z	Asymp.Sig. (2-tailed)	Result
Y1 (Perception)	1.142	0.147	Normal
Y2 (Acceptance)	1.086	0.189	Normal

Table 4. Multicollinearity Test Results

Variable	Tolerance	VIF	Result
X1 (AI Understanding)	0.578	1.731	No Multicollinearity
X2 (Business Ethics)	0.578	1.731	No Multicollinearity

Table 5. Heteroscedasticity Test Results

Variable	t-value	Sig.	Result
X1 (AI Understanding)	1.245	0.214	No Heteroscedasticity
X2 (Business Ethics)	1.132	0.258	No Heteroscedasticity

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Regression Analysis Results

Table 6. Regression Analysis Results

Dependent Variable	R Square	Adjusted R Square	F-value	Sig.
Y1 (Perception)	0.643	0.641	142.876	0.000
Y2 (Acceptance)	0.587	0.584	128.453	0.000

Table 7. Regression Coefficients for Perception of AI Implementation (Y1)

Variable	Unstandardized Coefficients B	Standardized Coefficients β	t-value	Sig.
(Constant)	0.876	-	3.214	0.001
X1 (AI Understanding)	0.485	0.485	9.743	0.000
X2 (Business Ethics)	0.372	0.372	7.465	0.000

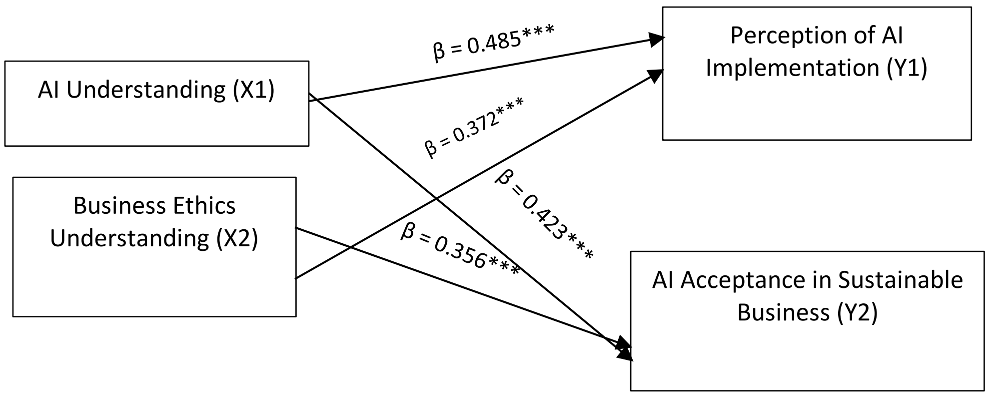
Table 8. Regression Coefficients for AI Acceptance in Sustainable Business (Y2)

Variable	Unstandardized Coefficients B	Standardized Coefficients β	t-value	Sig.
(Constant)	0.952	-	3.578	0.000
X1 (AI Understanding)	0.423	0.423	8.248	0.000
X2 (Business Ethics)	0.356	0.356	6.942	0.000

Table 6 presents the summary statistics for the two regression models. Table 7 and Table 8 present detailed regression coefficients for each model. Model 1 explained 64.3% of the variance in Perception of AI Implementation ($R^2 = 0.643$), with both AI Understanding ($\beta = 0.485$, $p < 0.001$) and Business Ethics Understanding ($\beta = 0.372$, $p < 0.001$) showing statistically significant positive effects. Model 2 explained 58.7% of the variance in AI Acceptance in Sustainable Business ($R^2 = 0.587$), with AI Understanding ($\beta = 0.423$, $p < 0.001$) and Business Ethics Understanding ($\beta = 0.356$, $p < 0.001$) both demonstrating significant positive relationships.

Mean Differences by Academic Major

Table 9 presents the mean scores on study variables across different academic majors. Management students consistently showed the highest mean scores across all variables, followed by Accounting students and then Development Economics students. One-way ANOVA tests confirmed that these differences were statistically significant ($p < 0.001$) for all variables. Figure 2 illustrates the standardized regression coefficients (β) showing the influence of the independent variables (AI Understanding and Business Ethics Understanding) on the dependent variables (Perception and Acceptance of AI in Sustainable Business). The thickness of the arrows could represent the relative strength of each relationship, with the strongest relationship being between AI Understanding and Perception ($\beta = 0.485$).



*** p < 0.001

Figure 2. Standardized regression coefficients showing the influence of AI Understanding and Business Ethics Understanding on Perception and Acceptance of AI in Sustainable Business

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Table 9. Mean Differences by Academic Major

Variable	Management	Accounting	Development Ecnomics	t-value	Sig.
X1 (AI Understanding)	3.95	3.78	3.52	12.347	0.000
X2 (Business Ethics)	4.12	3.96	3.87	8.564	0.000
Y1 (Perception)	4.06	3.81	3.64	10.235	0.000
Y2 (Acceptance)	3.89	3.72	3.58	9.467	0.000

4. DISCUSSION

Influence of AI Understanding on Perception and Acceptance

The confirmation of Hypothesis 1 and Hypothesis 2 indicates that AI Understanding has a positive and statistically significant association with Perception of AI Implementation, with a standardized coefficient equal to 0.485 and p less than 0.001, and with AI Acceptance in Sustainable Business, with a standardized coefficient equal to 0.423 and p less than 0.001. The difference in magnitude between these coefficients is theoretically coherent. Knowledge of artificial intelligence appears to shape evaluative judgments first, which are captured by perception, and only subsequently informs intention or willingness to adopt, which is captured by acceptance. This sequence is consistent with the core logic of technology adoption in which cognition precedes attitudes and intentions, while intentions remain contingent on facilitating conditions that include organizational support and policy clarity (Venkatesh et al., 2016).

This pattern is also consistent with prior evidence that students' positive views of artificial intelligence tools are linked to motivation and commitment in the learning process, which provides a plausible micro level mechanism that connects understanding to evaluative and conative outcomes (Vázquez-Parra et al., 2024). Improved understanding can reduce uncertainty, clarify the usefulness and feasibility of AI applications, and elevate motivation to engage, which jointly strengthen favorable perceptions and create a foundation for subsequent acceptance (Contreras Cueva et al., 2024; Susilo & Susanto, 2024). The comparatively stronger association with Perception than with Acceptance suggests that understanding exerts its most immediate influence on how students appraise AI's potential in business contexts, while the transition from perception to acceptance may depend on additional enablers that operate at the institutional and sectoral levels (Rane et al., 2024).

The findings align with the principles of the Technology Acceptance Model that understanding and related cognitions precede perceived usefulness and acceptance. We follow the canonical formulation as discussed in contemporary applications by Armouti et al. and Launtu et al., which elaborate the model originally proposed by Davis, and we observe that the same logic remains valid in a sustainability setting that involves complex externalities and accountability requirements (Armouti et al., 2023; Launtu et al., 2024). In such contexts, technical knowledge is not only instrumental for task performance. It also anchors judgments about legitimacy, risk, and proportionality of benefits, which helps explain why perception responds more strongly and more immediately to understanding than acceptance does (Olatoye et al., 2024; Ryan et al., 2021).

Taken together, the evidence indicates a structured pathway in which AI Understanding shapes Perception directly and Acceptance indirectly through perception. Although the present study does not formally test mediation, the coefficients are consistent with that interpretation. This suggests two practical implications that are compatible with the cited literature. First, strengthening AI literacy should be prioritized to lift perceptions accurately and quickly, in line with the observation that favorable appraisals are associated with engagement and motivation in educational settings (Anjum et al., 2023; Vázquez-Parra et al., 2024). Second, to convert perceptual gains into acceptance, programs should pair AI literacy with strong facilitating conditions such as reliable tool access and mentoring, and with clear governance for data, privacy, and bias mitigation, so that perceived usefulness is supported by a credible and enabling context as emphasized in the Technology Acceptance Model.

Influence of Business Ethics Understanding on Perception and Acceptance

Business Ethics Understanding shows positive and statistically significant relationships with Perception of AI Implementation, with a standardized coefficient equal to 0.372 and p less than 0.001, and with AI Acceptance in Sustainable Business, with a standardized coefficient equal to 0.356 and p less than 0.001. These coefficients indicate that ethical literacy is a consequential predictor rather than a peripheral consideration in

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how students evaluate and endorse artificial intelligence. The results suggest that ethical competence contributes to the stability and coherence of favorable evaluations that are reflected in perception. The pattern also implies that ethical reasoning equips students to align technological possibilities with stakeholder expectations in sustainability oriented environments, which is consistent with the centrality of ESG and triple bottom line logics in organizational decision making (Böttcher et al., 2024; Hardy et al., 2024; Lutzer et al., 2024). Although the effects are modestly smaller than those of AI Understanding, they remain substantively meaningful and theoretically consistent with the view that legitimacy concerns accompany assessments of usefulness, especially when governance and risk considerations are salient in practice (Ryan et al., 2021).

Ethical literacy encompasses awareness of bias, fairness, privacy, and distributional impacts that accompany the deployment of artificial intelligence in organizational settings. Such understanding can reduce perceived risk, clarify acceptable boundaries for use, and strengthen the sense that artificial intelligence is legitimate when appropriate safeguards are present. These functions are aligned with calls to adopt explicit ethical guidelines that directly address fairness and socioeconomic consequences during implementation, which are expected to improve readiness and willingness to use artificial intelligence responsibly (Olatoye et al., 2024; Pulivarthy & Whig, 2024). Accountability and transparency mechanisms are likewise emphasized as prerequisites for responsible development and deployment, which further support positive perceptions that are grounded in defensible governance practices (Meduri et al., 2024; Eghaghe et al., 2024). Students who internalize these guidelines are better positioned to connect efficiency gains with accountability obligations in contexts that demand sustainability outcomes, including marketing and broader enterprise performance frameworks that apply the triple bottom line concept (Purnama, 2024).

The comparatively smaller coefficients for ethics relative to technical understanding are best interpreted as a sequence rather than as a hierarchy of importance. Technical knowledge helps answer whether artificial intelligence can deliver value, while ethical knowledge helps answer whether it should be used and under which conditions. Within the logic of the Technology Acceptance Model, cognition precedes perceived usefulness and intention, and legitimacy conditions help translate favorable appraisals into acceptance in real organizational environments (Armouti et al., 2023; Launtu et al., 2024). This interpretation is compatible with broader adoption frameworks that highlight the roles of performance expectancy, facilitating conditions, and norms in shaping use intentions, especially when governance and sustainability requirements are explicit (Venkatesh et al., 2016; Rane et al., 2024). The present results therefore complement contemporary applications of these models by clarifying how ethical literacy interacts with cognitive evaluations to support perceived usefulness and responsible acceptance, which also motivates the design of curricula and managerial practices that integrate ethics alongside technical content and operational controls (Susilo & Susanto, 2024).

Academic Major Differences

The significant differences across majors indicate a clear preparedness gradient. Management students report the highest means for AI Understanding, which equals 3.95, Business Ethics Understanding, which equals 4.12, Perception, which equals 4.06, and Acceptance, which equals 3.89, followed by Accounting and then Development Economics. This pattern suggests that program context is a meaningful determinant of how students appraise artificial intelligence and its legitimacy in business settings. The coherence of higher scores across all four variables in Management points to a systematic advantage rather than a single isolated effect.

Curricular emphasis offers a plausible explanation for these gaps. Management programs typically integrate technology cases and applied information systems into decision making, alongside structured attention to ethical implications, which is aligned with recommendations to embed artificial intelligence in business education so that graduates can navigate rapidly evolving technological landscapes (Anjum et al., 2023). Evidence from business schools also shows that technology enhanced and authentic learning experiences can strengthen confidence and perceived usefulness among students, which is consistent with the observed advantages in Management cohorts (Contreras Cueva et al., 2024). Exposure to managerial information systems may further reinforce this effect by connecting analytics to operational improvement in ways that are visible and credible to students (Susilo & Susanto, 2024).

Implications for curriculum development follow directly from these results. Programs outside Management benefit from enhanced coverage of both artificial intelligence applications and ethical frameworks so that perceptions are informed by practical competence and legitimacy considerations in equal measure. Accounting programs can prioritize data governance and assurance content that supports responsible use of

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analytics in regulated contexts, which helps translate improved perceptions into acceptance (Gupta & Parmar, 2024). Development Economics programs can widen applied exposure through targeted activities that connect analytical tools to policy and development indicators while maintaining strength in evaluation. Cross course or cross major assignments that use authentic business or sustainability cases offer a practical route to equalize exposure without eroding disciplinary identity, which is consistent with calls to mainstream artificial intelligence across business curricula (Anjum et al., 2023; Contreras Cueva et al., 2024).

Gender Considerations in Technology Acceptance

While gender differences were minimal in our overall analysis, this finding contrasts with some existing research on gender and technology acceptance. Elshaer et al. (2024) found a significant moderating effect of gender on the relationship between performance expectancy and technology usage, with stronger effects among male students. Similarly, Joseph et al. (2024) reported that male students showed higher awareness of AI tools compared to female students, though female students demonstrated stronger perception once aware.

Our finding of minimal gender differences may suggest that in the specific context of sustainable business transformation, other factors such as academic preparation and ethical awareness outweigh gender-based differences that have been observed in more general technology acceptance studies. This indicates that educational interventions focused on knowledge enhancement and ethical frameworks may be effective across gender groups.

Implications for Integrated Business Education

The strong relationships between both independent variables and both dependent variables, coupled with the high R^2 values (0.643 for Perception and 0.587 for Acceptance), validate our theoretical model and highlight the importance of an integrated approach to business education. The results suggest that focusing on both technical understanding of AI and business ethics could significantly influence students' perspectives toward AI implementation in sustainable business practices.

These findings align with research by Murugan et al. (2024), which emphasized how students' knowledge and acceptance of AI technologies, combined with their awareness of business ethics and sustainability principles, would significantly influence how organizations implement AI solutions. Our empirical evidence supports this theoretical proposition, demonstrating the dual importance of technical and ethical education in shaping future business leaders' perspectives.

The gap between technical AI understanding and business ethics understanding, particularly evident in non-Management majors, suggests specific opportunities for educational interventions. This aligns with the findings of Chowdhury (2024) and Susilo & Susanto (2024), who emphasized how AI has transformed from simple automation tools to sophisticated decision-making systems requiring both technical competence and ethical judgment for effective implementation.

5. CONCLUSION

This research provides a comprehensive analysis of students' perspectives toward AI in sustainable business transformation, demonstrating how understanding of both AI technology and business ethics significantly influences perception and acceptance of AI implementation. Results show that students' AI understanding has a substantial impact on both perception ($\beta = 0.485$) and acceptance ($\beta = 0.423$) of AI in sustainable business practices. Similarly, business ethics understanding positively influences perception ($\beta = 0.372$) and acceptance ($\beta = 0.356$). These findings highlight a critical gap in current business education: the need for educational resources that integrate traditional business concepts with emerging digital technologies and ethical frameworks for sustainability.

Management students demonstrated consistently higher understanding (mean = 3.95) compared to Accounting (mean = 3.78) and Development Economics (mean = 3.52) majors across all variables. This disparity suggests that academic specialization significantly shapes students' preparedness for AI-driven sustainable business transformation. The relatively lower scores in technical AI understanding compared to business ethics understanding indicate the need for more specialized technological education in business curricula, particularly as AI technologies become increasingly integrated into sustainable business practices.

Based on these findings, we propose three key educational initiatives. First, the development of integrated learning materials that bridge the knowledge gap between traditional business concepts and digital

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transformation requirements through real-world cases and interactive learning experiences. Second, comprehensive assessment of existing resources to identify gaps in coverage of AI implementation and ethical considerations in business education. Third, collaborative resource development involving academic institutions, industry practitioners, and technology experts to ensure educational materials reflect current industry practices while maintaining academic rigor. These initiatives can help prepare future business leaders to navigate the complex intersection of AI technology, business ethics, and sustainability principles in their professional careers.

Future research should extend this study across multiple institutions and geographical contexts, employ longitudinal designs to track developmental trajectories, incorporate objective assessments alongside self-reported measures, explore additional variables that might enhance model explanatory power, and validate findings among practicing professionals. Through these efforts, educational institutions can better align business curricula with the evolving demands of AI-driven sustainable business landscapes, ultimately fostering responsible technology implementation for positive environmental, social, and economic outcomes.

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