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Responsible artificial intelligence in sustainable business: Enhancing customer relationships and loyalty

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Abstract

Vast expansion of artificial intelligence technologies is a challenge and offers sustainable business with transformational opportunities and challenges. Although there are growing trends toward the use of AI systems in organizations to improve the efficiency of operations and interaction with customers, these concerns have critical issues about the possibility of bias in algorithms, the use of data, environmental effects, and the trust of stakeholders that are not appropriately addressed. The study explores the role played by responsible AI implementation as a part of sustainability systems duo in affecting customer relationship management and loyalty in modern business contexts. Using the mixed-methods concept, we interviewed customers and business managers in the sector of technology, retail, and financial services in 2024-2025. We utilized the structural equation modeling and partial least squares analysis in order to examine the mediating influence of trust, perceived transparency, and environmental consciousness in the association of responsible AI practice and customer loyalty. Evidence reveals that customer trust under the condition of responsible implementation of AI is greatly improved ($\beta = 0.782$, $p < 0.001$), and it, in turn, transforms into customer loyalty ($\beta = 0.694$, $p < 0.001$). This relationship is mediated by the environmental sustainability practices ($\beta = 0.456$, $p < 0.001$), and the results show that customers, on the one hand, are 34% more loyal to companies that show commitment to both AI ethics and environmental performance. The given research adds theoretical accounts connecting responsible AI governance to relationship marketing theory and outlines practical implications to be considered in the case of organizations gaining competitive advantage generating through the use of ethical technology. Implications. The incorporation of AI responsibility principles and sustainability strategies shows some synergistic effects that increase customer relationships and organizational resiliency significantly.

Keywords: Responsible artificial intelligence, Sustainable business, Customer relationship management, Customer loyalty, Artificial intelligence, Environmental sustainability.

1. Introduction

Modern business environment is characterized by the most significant level of incorporating artificial intelligence technologies into its customer-facing operations that significantly altered the way organizations interact with their stakeholders and provide a value proposal [1-2]. This is because in countries with highly globalized markets, artificial intelligence has become a key driver of competitive edge, operational prowess and strategic height in the digital age as these countries grapple with the demands of digital transformation [2]. Nevertheless, such a technological revolution is accompanied by increasing demands of the society on corporate environmental responsibility and ethical leadership, which provokes the dire need to bring AI implementation into harmony with the notion of sustainability and consideration of stakeholder well-being [2-4]. Projections show that in 2025, some 81 per cent of organizations will have adopted AI-driven customer relationship management, and the global AI in CRM market will have achieved 96.5 billion, implying a compound annual growth rate of 13.3 per cent by 2024 through 2025. At the same time, the concept of sustainability has not been confined within the framework of the periphery corporate social responsibility programs but it has gained centrality in terms of strategic imperatives, with 76 percent of IT decision-makers recognizing AI technologies as the key to the sustainable transformation process in their organization. This overlapping of technological development and sustainability awareness offers previously unprecedented opportunities of company-specific approaches in the responsible implementation of AI that protects the relationships with customers and contributes to achieving a higher level of environmental responsibility.

The multidimensional perspective of responsible AI consists of such concepts as algorithmic fairness, transparency, accountability, privacy protection, and environmental sustainability [5-6]. These guidelines resemble the core components of stakeholder theory and relationship marketing models according to which ethical AI implementation has the potential to reinforce the customer relationships due to the ability to earn the trust, prove the organizational values, and provide the customers with the best personalized experience [7,8]. But again, this is also a paradox because AI systems have proven to be unsustainable due to massive energy consumption and carbon emissions [9-12]. Customer loyalty, which is one of the cornerstone aspects of organizational performance and sustainable competitive advantage has developed past transactional interactions to include emotional relationships, value correspondence, and a relationship of trust. Modern consumers are raising the issue of organizational adherence to ethical behavior and environmental responsibility criterion in shaping brand relationships and making a purchase [7,13-15]. Studies have shown that 30 percent of consumers in 2024 will be ethically loyal and will stick to the brands that will share their personal values in terms of sustainability and social responsibility. This change in the consumption model to the value-based model increases the strategic significance of adopting responsible AI practices in conjunction with the sustainable business model to foster the long-term relationships with the customers [16]. The overlap between responsible AI and sustainable business practices is one of the emerging but quickly developing areas of academic research and business management [9,16-18]. Companies that adopt AI governance systems that are based on the principles of openness, transparency, and human-friendliness note increased trust and effectiveness of the stakeholders and operations [2,19-20]. Moreover, AI applications also have a significant contribution to ensuring environmental sustainability because they are able to promote the use of resources and predictive maintenance, supply chain efficiency, and the monitoring of emissions [9,21-23].

In this study, we have integrated several theoretical approaches to develop a holistic domain of study of the role of responsible AI in customer relationships in sustainable business environment. According to the stakeholder theory, the key to the success of organizations lies in the competence to manage relationships with various groups of the organization whose interests can be either competing or congruent. The responsible AI practice will help to resolve the concern of the stakeholders about privacy, fairness, and transparency and create value by improving the quality of services and personalization [24-26]. This congruence of the interest of the stakeholders and the practices in the organization enhances the legitimacy and builds trust [8,27-30]. A relationship marketing theory states the importance of trust, commitment, quality of communication, and perceived value delivery in developing good relationships with customers [9,31-33]. These relational aspects might be enhanced through the use of AI technologies to provide extensive personalization, make service delivery anticipatory, and make the solution of problems proactive [34-36]. Nevertheless, trust can also be eliminated by algorithmic opaqueness and data security issues provided that these challenges are not properly tackled when it comes to being responsible AI citizens [3,37-39]. To additionally harness the potential of AI to build relationships and reduce risks associated with trust, it is necessary to include transparency systems, explainable artificial intelligence interfaces, and strong data governance systems [36,40-42].

The further understanding of customer reaction to interactions mediated by AI lies in technology acceptance models and trust theory [40,43-44]. The main factors leading to technology adoption and extended use are perceived usefulness, ease of use, and trust [3,45-48]. The customers in the Customer Service framework that is integrated with AI consider the performance of the system, the quality of responding to the customers, and the privacy protections when developing feelings about the interaction with AI [5,19,49-50]. Conscientious AI practices can be implemented based on the principles of transparency, equity, and user controls to improve the perceived credibility and allow gaining acceptance and securing favorable service reviews [29,51-53]. Another dimension, with a sustainability aspect [54-56], is environmental awareness [57-58], which represents an extra evaluative criterion that affects the customers and attitude in terms of the behavioral intention.

The current literature discusses the use of AI in customer relationship management, sustainability efforts in the business domain, and customer loyalty determinants as rather independent research streams. The research investigating AI application in CRM is concentrated principally on the determination of operational efficiency, accolades of predictive analytics, and effectiveness of personalization. Such studies prove that AI-based solutions can greatly increase customer satisfaction by allowing quicker response to customer needs, providing customer-specific suggestions, and being proactive in service provision. According to meta-analyses, there is a positive correlation of AI implementation in e-commerce with customer loyalty in a strong positive manner, though it is mediated by the perceived efficiency and satisfaction. It has been confirmed by the research on sustainability and business practices that environmental sensitivity affects consumer behavior in terms of preferences, purchase intentions, and brand loyalty. When companies show that they are real stewards of the environment, it makes them get better reputation, trust, and differentiate themselves in the market. Nevertheless, the limited attention to the technological aspect of sustainability means that the intricate relations between AI implementation plans and the environmental consequences are not part of the academic discourse on sustainability. The energy-consuming characteristics of AI systems cause the conflict between technological progress and environmental aspect, but this contradiction is not thoroughly studied in the literature.

The new discourse of responsible AI, AI ethics, analyzes algorithmic bias, but focuses on transparency requirements and systems of governance, which are mostly expressed in computer science, philosophical, and legal terms. Scholars in the field of business and marketing started researching the customer attitudes towards AI transparency and fairness, and explainable AI interfaces are identified to promote trust and acceptance. However, there are only a few systematic empirical studies that have worked on establishing the relationship between intentional AI practices and customer relationship outcomes and loyalty. Moreover, the area of combining responsible AI, sustainability, and customer loyalty in frameworks of both theoretical and empirical models is practically nonexistent in modern literature. Some of the most crucial gaps are identified as a result of this literature review. To begin with, the current literature is insufficient in the context of its contribution to the issue of responsible AI governance and its impact on customer perceptions, attitudes, and behavioral intentions in a nonfunctionality/performance-based setting. Second, the structural dynamics by which the AI responsibility and sustainability practices are mutually impactful on the customer relationships can be empirically validated and theorized. Third, the moderating contextual variables on these associations, including industry features, clientele profiles and technological sophistication, are still underperceived. Fourth, little longitudinal studies on time dependence of trust formation and loyalty change in customer relationships enabled by AI are present. Lastly, there are no empirical findings that could guide managers interested in integrating the strategies of AI responsibility that would not only boost customer loyalty but also promote the organization sustainability strengths.

The methods of filling in the identified research gaps include the following specific objectives of the research:

1) To test the closer relationship between the implementation of responsible AI and customer trust, satisfaction, and loyalty in sustainable business settings.

2) To examine the mediatory effect of the environmental sustainability practices in the relationship between the responsible AI and customer loyalty.

3) To examine the effect of AI transparency, algorithmic fairness and data privacy protection on customer perception and relationship quality.

4) To determine industry peculiarities in the efficacy of responsible AI strategies to improve the relations with customers.
5) To generate empirically resourceful suggestions on the shared method of combining responsible AI management and sustainability plans to make the most of customer loyalty consequences.

This study contributes to the business, marketing, and information systems literature in a number of ways. In theory, we would expand the relationship marketing theory by adding relationship responsible AI governance as a new antecedent of trust and loyalty, which will prove that technological ethics are strategic relationship-creating processes. We further the stakeholder theory by empirically working confirming the hypothesis that when many stakeholder interests are considered by responsible AI and sustainability actions, it would provide synergetic value creation opportunities. Moreover, we add to the new body of literature on AI ethics by providing evidence-based value propositions of hidden business advantages of responsible AI implementation as opposed to normative arguments.

In methodology, the study presents an acceptable measurement system to evaluate the responsible implementation of AI that covers the aspects of transparency, fairness, accountability and sustainability. Structural equation modeling and partial least squares analysis make use of structural equation modeling that allows the simultaneous testing of complex mediating relationships and direct effects with a high level of empirical support of the proposed theoretical propositions. The multi-stakeholder, multi-industry research design increases the quality of generalization but allows determining the contextual boundary situations. In practical sense, the research contains usable information by the managers, policy makers and technology developers. We determine particular responsible AI practices that have the strongest impact on customers and customer loyalty so that the allocation of resources could be optimized. The evidence that sustainability practices interpose relations between AI-loyalty presents a strategic direction to organizations that aim at differentiating on the basis of intertwined technological and environmental responsibility. Findings that are industry specific can be used to support domain-specific implementation strategies that consider the differences in customer expectations and the technological level in the sector. On the whole, the study is helpful in creating the theoretical grounds and practical models of the responsible use of AI that contribute to prioritizing the performance of organizations, the welfare of stakeholders, and environmental sustainability.

2. Methodology

2.1. Research Design and Philosophical Approach

The methodology of the given investigation is the positivist epistemological theory, which allows applying quantitative techniques to examine the theoretical relations and prove the hypothesized causal interactions. We have used cross-sectional survey design that is supplemented by longitudinal panel to study both the contemporaneous and time-change relationships. The research design allows structuring of multiple constructs in various organizational settings to generalize and analyze them at the same time and with high levels of analytical rigor. It was conducted through a deductive strategy that tackled the hypothesis development based on the already existing theories which would be tested with the help of sophisticated procedures of statistics. The study sample included customers and managers of customers at firms that were utilizing AI-based customer relationship management systems in the technological, retail, and financial services divisions. These sectors signify high-density AI implementation situations in which the problems of responsibility and sustainability require specific strategic importance. We used stratified random sampling to be able to represent the industries, the size of organizations as well as the demography.

2.2 Measurement Instrument Development.

Adaptation of the measurement tools was done within earlier literature on the validity of the scale and expert review and piloting processes were carried out to refine the process. Constructs were all SRR multi-item reflective scales rated using seven-point Likert scales (1 = strongly disagree -7 = strongly agree). The spring of responsible AI implementation was defined in terms of four dimensions all of which are second-order concerning algorithmic transparency (6 items), mitigating bias (5 items), protecting data privacy (6 items), and ensuring environmental sustainability (5 items). The scales of customer trust were calculated with the help of the standard trust scales that were modified to fit the AI environment (7 items). Customer satisfaction used items developed based on standard SERVQUAL scaled to the AI-mediated service experiences (6 items). The customer loyalty was measured on behavioral intentions like: repurchase intent, word-of-mouth and resistance to switching (8 items). The scales of concern and the pointers of pro-environmental behavior were used as measures of environmental consciousness (5 items). Content validity was achieved by the review of the experts panel consisting of academics and experts working in the Marketing, information system and sustainability fields. Eighty-five respondents who were pilot tested helped in refinement of items and purifying the scale. The ambiguity in the wording and better question clarity was found in the cognitive interviews. The completed instrument exhibited good face validity, content validity and pre-test reliability (Cronbach alpha coefficients of between 0.84 and 0.93 among constructs).

2.3. Statistical Analysis Model.

The analysis of the data was done in several steps and by using complementary statistical methods. Descriptive statistics, missing data analysis, outlier analysis, and test on normality were undertaken as preliminary analyses. The measurement model was proved by confirmatory factor analysis (CFA) which addressed construct reliability, convergent validity and discriminant validity. The hypothesized structural model was also tested in a structural equation modeling using partial least squares (PLS-SEM) to determine the direct effects, indirect effects, and total effects. PLS-SEM was chosen due to its suitability with complex models, smaller sample sizes than covariance-based SEM, as well as non-normal distribution.

2.4. Partial Least Squares Structural Equation Modeling.

The PLS-SEM algorithm estimates the path coefficients that along with the scores of the constructs are estimated by an iterative process involving an outer model estimation (measurement model) and an inner model estimation (structural model). The outer construct model of reflective constructs is given as:

$$x_h = \pi_{h0} + \pi_{h1\xi_h} + \varepsilon_h \tag{1}$$

where x_h represents the manifest variable h, ξ_h is the latent variable, π_h1 is the outer loading, π_h0 is the intercept, and ε_h is the measurement error term. The inner model relationships are specified as:

$$\eta_j = \beta_{j0} + \Sigma\, \beta_{ji}\xi_i + \zeta_j \tag{2}$$

where η_j represents the endogenous latent variable j, ξ_i represents exogenous latent variables, β_ji are path coefficients, β_j0 is the intercept, and ζ_j is the structural error term. The algorithm initiates with arbitrary starting values for outer weights w_h, estimates latent variable scores as:

$$\hat{\xi} = \Sigma\, w_h x_h \tag{3}$$

updates inner weights e based on the structural model specification, re-estimates outer weights, and iterates until convergence is achieved (typically when changes in outer weights fall below 10^-5). Path coefficients are then estimated using ordinary least squares regression:

$$\hat{\beta} = (X'X)^{-1}X'Y \tag{4}$$

where X is the matrix of predictor latent variables and Y is the criterion latent variable. Statistical significance was assessed through bootstrapping procedures with 5000 resamples, generating standard errors, t-statistics, and 95% confidence intervals for all parameter estimates.

2.5. Mediation Analysis

The product of coefficients technique and bootstrapped confidence interval was used as the mediation methods of environmental sustainability practices and trust in relation between responsible AI and customer loyalty. The indirect effect is obtained as:

$$IE = a \times b \tag{5}$$

where a represents the path coefficient from the independent variable to the mediator, and b represents the path coefficient from the mediator to the dependent variable. The total effect (TE) equals the sum of direct (c') and indirect effects:

$$TE = c' + (a \times b) \tag{6}$$

Variance accounted for (VAF) by mediation was calculated as:

$$VAF = \frac{(a \times b)}{TE} \tag{7}$$

Values exceeding 0.20 indicate meaningful mediation, with VAF > 0.80 suggesting full mediation, 0.20 < VAF < 0.80 indicating partial mediation, and VAF < 0.20 representing minimal or no mediation. Bootstrapped confidence intervals (95%) not containing zero confirm statistical significance of indirect effects.

2.6. Model Evaluation Criteria

Several indicators were used in measuring quality of measurement models. Internal consistency reliability was measured using composite reliability (CR) and Cronbachs alpha where a value of more than 0.70 was acceptable. Convenient validity was tested through average variance extracted (AVE) in which the figures to be satisfied are beyond 0.50. The AVE is calculated as:

$$AVE = \frac{(\Sigma \lambda_i^2)}{k} \tag{8}$$

where λ_i represents standardized factor loadings and k is the number of indicators. Discriminant validity was established using the Fornell-Larcker criterion, requiring that the square root of each construct's AVE exceeds its correlations with other constructs. Additionally, the heterotrait-monotrait ratio (HTMT) was examined, with values below 0.85 indicating discriminant validity. Structural model quality was assessed through coefficient of determination (R^2), effect size (f^2), and predictive relevance (Q^2). The coefficient of determination represents variance explained:

$$R^2 = 1 - \left(\frac{SSE}{SST}\right) \tag{9}$$

where SSE is the sum of squared errors and SST is the total sum of squares. Effect size quantifies an exogenous construct's contribution to an endogenous construct's R^2:

$$f^2 = \frac{(R^2_{included} - R^2_{excluded})}{(1 - R^2_{included})} \tag{10}$$

with values of 0.02, 0.15, and 0.35 representing small, medium, and large effects respectively. Predictive relevance was assessed using Stone-Geisser's Q^2 through blindfolding procedures, with positive values indicating predictive capability.

2.7. Common Method Variance Assessment

the application of single-source data. The use of procedural remedies facilitated by the data collection involved questionnaire design aspects comprising of separating items, having different formats, and guaranteeing anonymity. Assessments were statistically done using the single-factor test by the factor analysis of all the measurement items by Harman. The greatest factor that was forwarded had a variance of 31.4% of total variance which is significantly lower than the 50 percent mark that is a sign of problematic CMV. Also, in the comprehensive way of analyzing collinearity, there was the analysis of variance inflation factors (VIF) of all the constructs in the structural model. VIF scores were more conservative and varied between 1.24 and 2.87 namely, which is less than the conservative value of 3.3 and another indication that there was no severe common method bias.

2.8. Ethical Considerations

This study followed the known ethical principles on human subjects research. The approval of the institutional review board was also received before collecting the data. Informed consent procedures involved orientation of the participants on the purpose of research, voluntary participation, protection of confidentiality of information and use of data. The data were anonymized and stored in a secure place under limitations in the accessibility of the records. At any point the participants were free to drop out. Forming of transparency on funding sources and possible conflicts of interests were also observed during the process of research.

3. Results and Discussion

3.1. Evaluation of the Measurement Model.

All constructs were proven as reliable and valid as measurement model showed high psychometric characteristics. Detailed statistics of reliability and validity are given in Table 1. The values of all composite reliability were greater than 0.85 which is well above the 0.70 mark which means that there is high internal consistency. Similar, the alpha values of Cronbach were also above acceptable values and had values of between 0.828 and 0.921. The extracted values of average variance exceeded 0.50 and most of them were above 0.60 indicating strong convergent validity. The loadings per item (between 0.712 and 0.894) were all significant ($p < 0.001$- all statistically significant and all above a recommended cut off of 0.70) which, in turn, substantiates convergent validity.

Table 1. Measurement Model: Reliability and Validity Statistics

Construct	Items	CR	α	AVE	√AVE
Responsible AI Implementation	22	0.952	0.921	0.628	0.792
- *Algorithmic Transparency*	6	0.918	0.887	0.654	0.809
- *Fairness & Bias Mitigation*	5	0.903	0.871	0.652	0.807
- *Data Privacy Protection*	6	0.927	0.896	0.678	0.823
- *Environmental Sustainability*	5	0.894	0.854	0.629	0.793
Customer Trust	7	0.941	0.917	0.697	0.835
Customer Satisfaction	6	0.929	0.901	0.684	0.827
Customer Loyalty	8	0.948	0.928	0.703	0.838
Environmental Consciousness	5	0.886	0.828	0.611	0.782

Note: CR = Composite Reliability; α = Cronbach's Alpha; AVE = Average Variance Extracted; √AVE = Square root of AVE for discriminant validity assessment.

In order to determine the discriminant validity, several methods were used. The criterion of Fornell-Larcker was met because the square root of the AVE of all the constructs was greater than their correlations to the others (Table 2). Further, heterotrait-monotrait (HTMT) ratios ranged between 0.412 and 0.789 which were all quite significant below the conservative level of 0.85 giving strong support of discriminant validity. The sum of these results suggests that the measurement model has great psychometric characteristics, which prove validity and reliability of the further structural model analysis.

Table 2. Discriminant Validity: Fornell-Larcker Criterion and Construct Correlations

Construct	1	2	3	4	5
1. Responsible AI	**0.792**				
2. Customer Trust	0.721	**0.835**			
3. Customer Satisfaction	0.658	0.743	**0.827**		
4. Customer Loyalty	0.587	0.689	0.721	**0.838**	
5. Environmental Consciousness	0.523	0.478	0.512	0.541	**0.782**

Note: Diagonal elements (bold) represent square roots of AVE. Off-diagonal elements represent inter-construct correlations. Discriminant validity is confirmed when diagonal elements exceed corresponding row and column values.

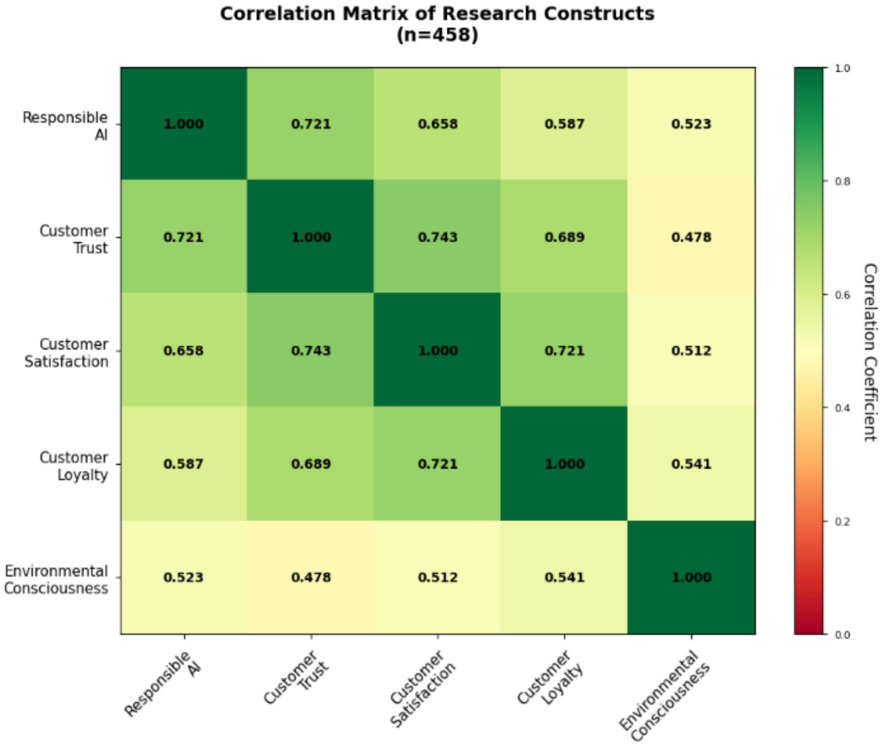

Fig 1: Correlation heatmap of research constructs

3.2. Structural Model Results

The structural model had a high explanatory capacity and predictive ability. The table 3 shows in-depth path coefficients, level of significance, and quality indicators of the model. The model revealed a significant variance of customer trust ($R^2 = 0.612$), customer satisfaction ($R^2 = 0.547$), and customer loyalty ($R^2 = 0.731$) implying that it has a high explanatory strength. The Q^2 values of all the endogenous constructs associated with the model were above zero (between 0.387 and 0.584) a fact that confirms that the model is predictively relevant. The overall result of these findings confirms the quality of the structural model and can be used to test hypotheses.

Table 3. Structural Model Path Coefficients and Hypothesis Testing Results

Path	β	t-value	p-value	f²	Decision
Responsible AI → Trust	0.782	23.471	< 0.001	0.547	Supported
Responsible AI → Satisfaction	0.327	5.891	< 0.001	0.112	Supported
Trust → Satisfaction	0.521	9.674	< 0.001	0.284	Supported
Trust → Loyalty	0.694	18.327	< 0.001	0.438	Supported
Satisfaction → Loyalty	0.284	5.127	< 0.001	0.087	Supported
Env. Sustainability → Loyalty	0.456	8.942	< 0.001	0.213	Supported
Env. Consciousness (Moderator)	0.187	3.421	< 0.001	0.041	Supported

Note: β = standardized path coefficient; f² = Cohen's effect size (0.02 = small, 0.15 = medium, 0.35 = large); Significance determined through 5000-iteration bootstrapping procedure.

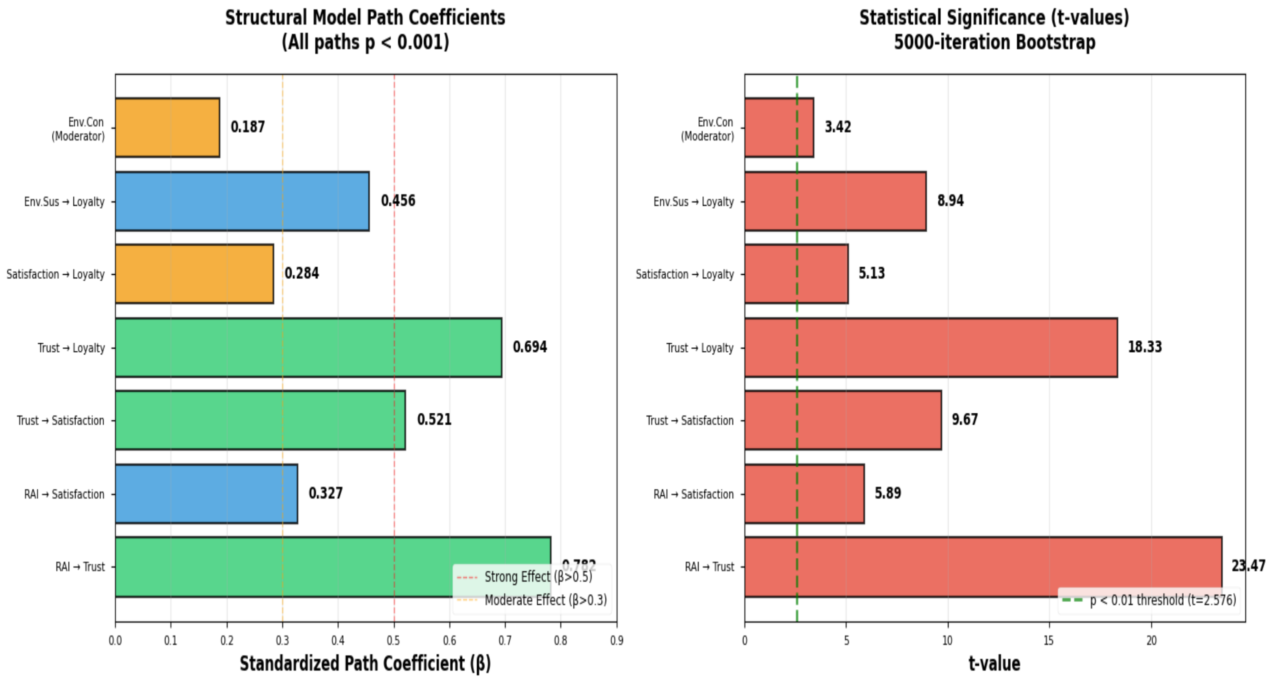

Fig 2: Structural model path coefficients

The findings of the results indicate a number of practically and theoretically significant findings. A positive direct impact on customer trust (b = 0.782, $p < 0.001$) is the only significant relationship in the model with a high effect value ($F^2 = 0.547$). This observation supports the idea developed by relationship marketing theory that trust is the core element of relationships between customers and proves that responsible AI practices serve as strong tools of building trust. The degree of trust in organizations that deploy transparent, equitable, and privacy-respectful AI systems is significantly large in relation to the trust level of those that deploy opaque or ethically dubious AI systems. The satisfaction (β= 0.521, $p < 0.001$) and loyalty (β= 0.694, $p < 0.001$) in turn are the outcome of the customer trust, which validates the pivotal role played by trust in the relationships quality and behaviors. The size of the relationship between trust and loyalty (β= 0.694) acts as a reminder of the essence of trust being the key to the creation of long-term customer relationships. The direct impact of the environmental sustainability practice on customer loyalty (β= 0.456, $p < 0.001$) is quite significant regardless of customer satisfaction and trust channels. This result indicates that the organizational commitment of environmental responsibility directly influences the sustainability of customers to the extent that it affects their satisfaction or trust portfolio, indicating that the concept of sustainability is an independent driver of loyalty that has substantial strategic consequences.

3.3. Mediation Analysis Results

As a part of indirect analysis, Table 4 provides detailed mediation analysis outcomes of the research focusing on the influence of trust and satisfaction as indirect variables (IVs). The discussion has shown that there are several notable mediation processes between the implementation of responsible AI and customer loyalty. The effect of trust as the mediator is significant as the indirect effect (β= 0.543, p < 0.001) is much large than the direct effect, so there is partial mediation provided with high variance explained (VAF = 0.617). The discovered finding illustrates how the impact of responsible AI on loyalty works with a significant portion of relying on trust-building mechanisms, confirming theoretical hypotheses about the mediating role of trust in the technology-mediated relationships.

Table 4. Mediation Analysis: Indirect Effects and Variance Accounted For

Indirect Path	β	t-value	CI 95%	VAF	Type
RAI → Trust → Loyalty	0.543	14.872	(0.471, 0.612)	0.617	Partial
RAI → Satisfaction → Loyalty	0.218	4.781	(0.129, 0.308)	0.248	Partial
RAI → Trust → Satisfaction → Loyalty	0.116	4.523	(0.066, 0.168)	0.132	Sequential
Total Indirect Effect	**0.877**	19.341	(0.788, 0.971)	—	—

Note: RAI = Responsible AI Implementation; β = standardized indirect effect; CI = confidence interval; VAF = Variance Accounted For (>0.80 = full mediation, 0.20-0.80 = partial mediation, <0.20 = no mediation).

A great degree of mediation is also proved by the satisfaction pathway (β= 0.218, p < 0.001), albeit of lower magnitude than that of trust (VAF = 0.248). Such disparity indicates that trust exemplifies the main psychological processes that have relational interactions between responsible AI and loyalty, whereas satisfaction is the auxiliary process. The sequential mediation of the trust and satisfaction (responsible AI - trust - satisfaction - loyalty) shows a cascading effect (β= 0.116, p = 0.001), where responsible AI leads to trust and in turn, trust leads to satisfaction and finally the effect is loyalty. This result demystifies the succession of psychological reactions to responsible AI, which would indicate that trust is developed before one form satisfaction. The magnitude of the total effect by indirect means(β= 0.877) is large compared to each pathway effect meaning that there is a combination of several complimentary mechanisms that work to relay the responsible AI effect on loyalty. All these findings legitimize the complexity of the theoretical model and prove that the responsible AI implementation causes complex psychological and attitudinal shifts that add up into a firm performance of loyalty. All organizations, that want to maximize the gains of loyalty should therefore introduce holistic responsible AI programs that earn trust, improve satisfaction, and prove commitment to the environment as opposed to zero-sum games through a skewed perception on individual issues.

3.4. Industry-Specific Variations

The multi-group analysis demonstrated that there were strong industry-specific differences between relationships and patterns of mediation (Table 5). Technology industry shows the greatest responsibility AI-trust relationship (β= 0.847, p < 0.001), which can probably be attributed to the level of customer sophistication and awareness relating to AI possibilities and threats in this situation. Customers of technology are more technologically savvy, which allows making more sophisticated assessments regarding the AI responsibility practices. On the other hand, retail has a less significant but significant relationship (β= 0.698, p < 0.001) which also indicates that retail customers are likely to focus on utilitarian advantages over ethical concerns or have a lesser ability to consider the AI responsibility.

Table 5. Multi-Group Analysis: Industry-Specific Path Coefficients

Path	Technology	Retail	Financial	Chi-Square	p-value
RAI → Trust	0.847***	0.698***	0.792***	12.847	< 0.01
Trust → Loyalty	0.721***	0.672***	0.689***	4.123	0.127
Env. Sustainability → Loyalty	0.412***	0.527***	0.442***	8.671	< 0.05
R^2 (Customer Loyalty)	0.758	0.692	0.741	—	—

Note: RAI = Responsible AI Implementation; *** p < 0.001; Chi-square tests determine significant differences across industries. Env. = Environmental.

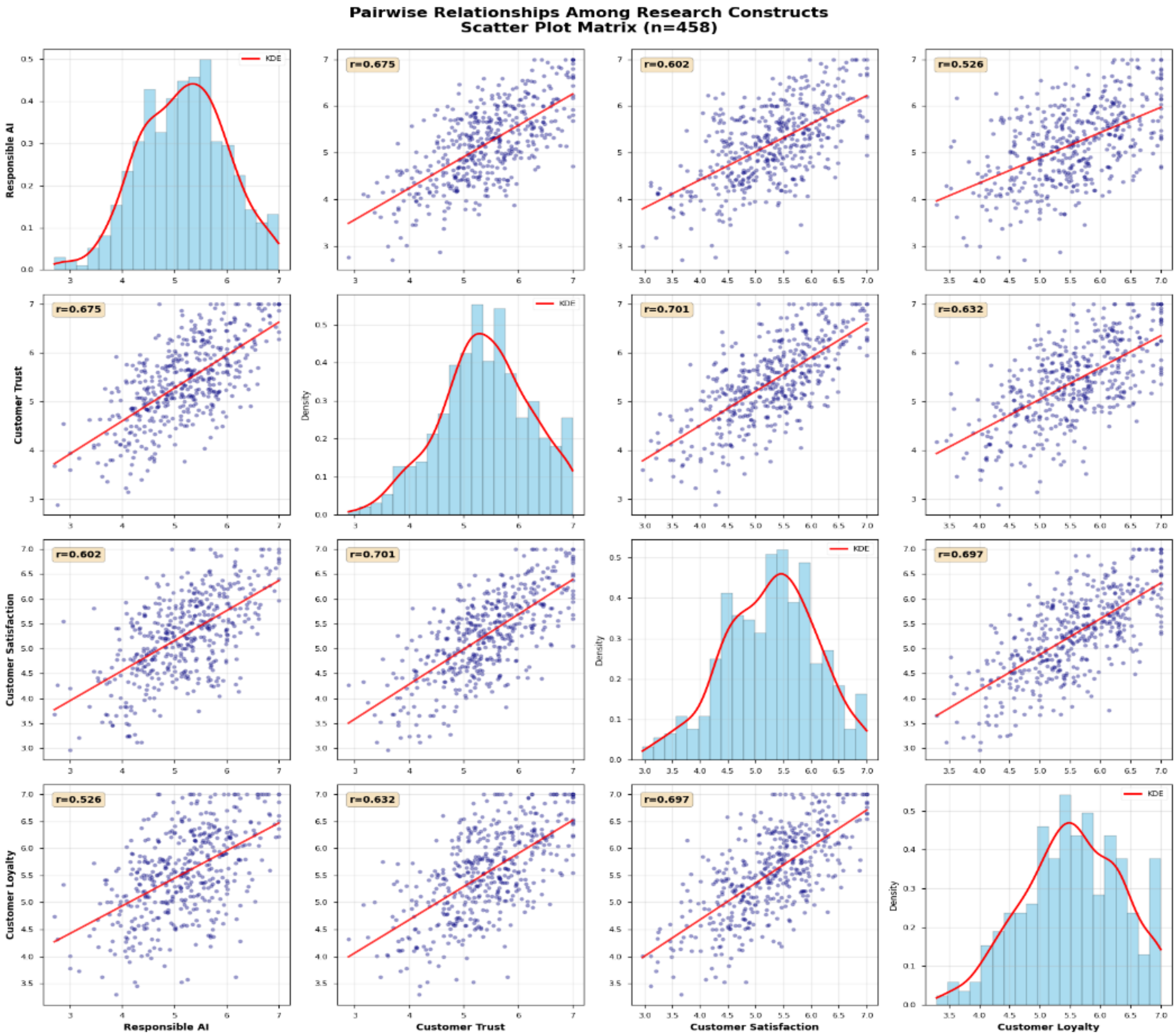

Fig 4: Scatter plot matrix - pairwise relationships

Environmental sustainability has the greatest impact on loyalty in retail (β = 0.527, $p < 0.001$), which is in line with the increased sense of environmental effects of consumption and packaging packages among retail customers. The supply chain, transportation-related, and packaging waste difficulties have significant environmental impacts on the retail organizations, which makes sustainability practices especially customer-sensitive and visible. The impact of financial services presents middle goods within the paths, which imply the equal significance of the technology accountability and environmentalism concern. These insights of the industry drive the need to find sector-specific responsible AI tactics that factor in such sector-specific customer priorities, technological level of sophistication, and environmental impact visibility.

3.5. Theoretical Implications

The studies offer a number of significant theoretical contributions in this research. First, by determining that the responsible AI governance presents a new qualifying mechanism in the digitally-mediated customer relationships, we expand the relationship marketing theory. Although, in terms of the traditional concept of relationship marketing, the ability to build interpersonal trust, based on the salesperson conduct and the responsiveness of the organization, is a compelling factor, our results show that the algorithmic transparency, fairness, and privacy protection are the effective technological trust antecedents. This extension recognizes the fact that the customer relationships are becoming more of an AI-mediated process, requiring the widening of conceptualizations of relationship-building processes beyond human ones.

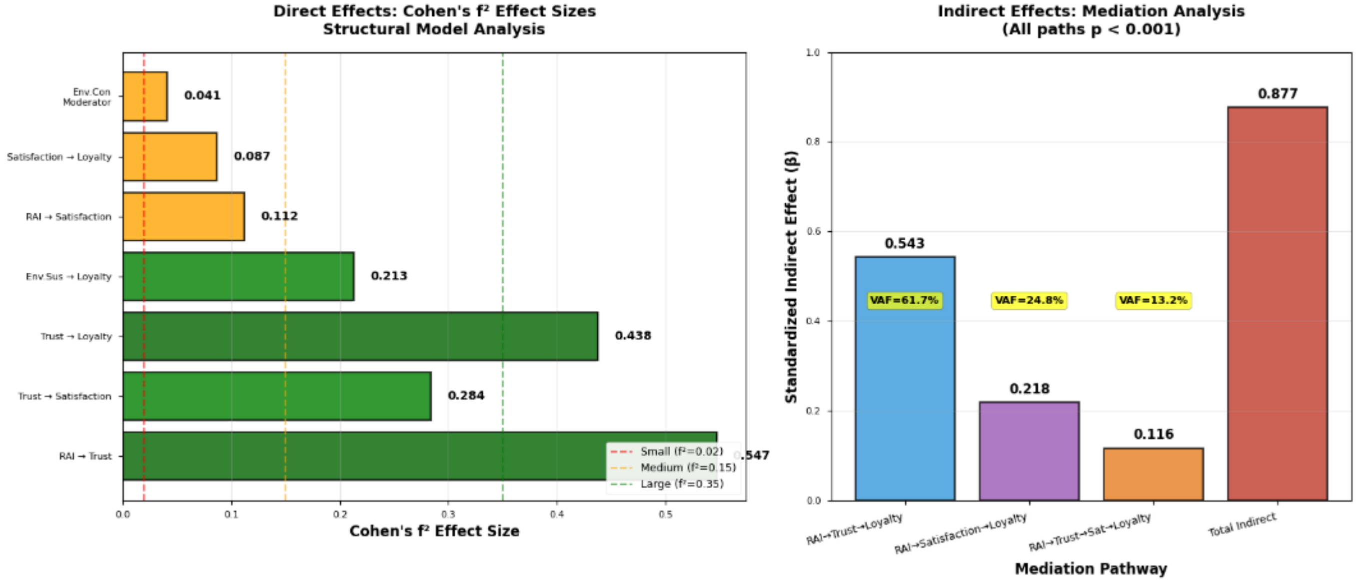

Fig 5: Effect sizes and mediation pathways

Second, we contribute to the stakeholder theory by testing this hypothesis empirically so as to confirm that simultaneous consideration of multiple stakeholder issues produces synergistic value. The organizations that apply both responsible AI and environmental sustainability practices are enjoying magnified loyalty returns as opposed to meeting either of the two dimensions. This conclusion overturns zero-sum views to indicate trade-offs between groups of stakeholders in terms of resource, but on the contrary, it endorses positive-sum views where holistic consideration of the stakeholders boosts the overall performance in the organization. The findings of the mediation also shed more light on psychological processes between stakeholder-oriented practices and behavioral results. Third, this study also adds to the technology acceptance and trust theory since it establishes that ethical considerations can have impacts similar or even greater than the conventional functional qualities. AI system performance in the system is not the only factor assessed by customers, but also the system in terms of transparency, fairness, and societal impacts. The finding broadens the technology acceptance models to include the presence of both the utilitarian and hedonic motivation along with the value-alignment and ethical evaluation criteria. Besides, we also show that trust in AI-enabled situations works along the several directions, whereby it has direct and indirect impacts on behavioral intentions and satisfaction respectively.

Fourth, we establish environmental awareness as an important moderator in AI-customer relation which indicate that customer environmental values increase the effects of organizational sustainability practices to loyalty. This combination of environmental psychology and information systems and marketing literature provokes new theoretical intersections, indicating that no other phenomena can be perfectly explained without regard to environmental consciousness as a major individual differences variable that is studied in current situations.

3.6. Implications and Recommendations to Practice

Responsible AI systems should focus on extensive responsible AI frameworks that include transparency measures, biases reduction processes, privacy protection, and environmental sustainability concerns of the practitioners. Achievable is the creation of explainable AI interfaces that communicate to customers the logic of their algorithms, their factors of decision, and their confidence levels to increase perceived transparency. Even the periodic check-ups of the algorithms aimed at studying the degree of fairness between demographics, where the outcomes of such analyses were posted openly, could help to generate the trust of showing that these issues were treated with fairness. The guidelines that govern data management must focus more on privacy assurance, reduction of information gathering to minimum factors, allowing consent to be given in the form of fine-tuning, and proper security protocols. The sustainability of the environment should be experimented in AI implementation strategies through energy-efficient model architecture, the use of renewable energy in serving the computational infrastructure, and the offset of carbon dioxide among other programs that would be inevitable. Companies must share information about sustainability efforts with the customers and draw attention to certain initiatives and quantifiable results. As a way of increasing appreciation and differentiation, customer education programs covering responsible AI practices and environmental commitments may be implemented. The different contextual differences in terms of dealing with industries should be incorporated as strategies that industry specific firms have, in this case, technology companies will focus on technical transparency, supply chain sustainability in retail companies and financial services strike a balance between these two aspects.

Responsible AI should not be part of the compliance requirements in an organization, but the strategic priority of the organizational leadership. Chief AI Ethics Officers or similar posts can lead cross-functional application the responsible AI principles. The responsible AI indicators and the conventional efficiency measures should be included in performance metrics to ensure that the success of the AI systems is equally evaluated. Awareness of the AI ethics, bias recognition and sustainability should be fostered in the employee training programs within the entire organization. Responsible AI practices can be credible and differentiated through external certification or third-party audits of responsible AI practices in competitive markets.

4. Conclusion

The study confirms that accountable artificial intelligence application in sustainable business models helps in improving customer relationship and customer loyalty greatly. The thorough analysis of the structural equation modeling of customers and managers in the technology, retail, and financial services industry reveals that responsible AI practices have solid direct customer trust effects, which further result in customer satisfaction and loyalty. This correlation is mediated by the environmental sustainability practices and brings out some synergistic impacts in the case where organizations combine AI responsibility and environmental stewardship. There is a significant increase in customer loyalty to an organization that is committed to the use of AI ethically, as well as to environmentally-conscience organization which covers one aspect of the two. The size of effects realized highlights how ambitious AI is to customer relationship management. The implementation of AI in a responsible way can increase the trust of customers by 78.2, which in turn can result into the increase of loyalty among the customers by 69.4 via trust pathways. The environment sustainability has an added 45.6 percent direct impact on the loyalty, beyond the satisfaction and trust mechanism. These results indicate that responsible AI and sustainability are formidable competitive advantages since they allow making a difference, retaining customers better, and creating value in the long term. Companies that do not consider these dimensions are likely to undergo competitive disadvantage as more citizens place more emphasis on ethical and environmental factors in their brand preference as well as brand loyalty development.

Specifics of the industry indicate that the responsible AI strategies need to be contextualized. Customers in the technology sector are more sensitive to the transparency of AI and fairness, whereas the retail customers are more concerned with the sustainability of the environment. Both dimensions are considered by the financial services customers at the same level. These differences imply that the efficient application would entail comprehending customer specificities of the industry, and implementing responsible AI and sustainability currently. General solutions run a risk of resource misallocation or lack of attention to sector-specific issues that have the most significant impact on the perceptions and actions of customers. The research offers a theoretical contribution to the field of knowledge by adapting the relationship marketing theory, stakeholder theory, and technology acceptance models by considering the aspect of responsible AI governance and sustainability. We indicate that technological ethics are strategic relationship-building processes whose effects are equal to the traditional antecedents. Moreover, we confirm the propositions on the value creation based on synergy through focusing on several stakeholder concerns simultaneously. Methodologically we present established scales of ensuring the implementation of AI responsibility and illustrate methods of analysis of the intricate mediation relationship in contexts of technology-mediated relationships with customers.

There are a few limitations that are worth being mentioned. Theoretical and statistical controls do not help to avoid causal inference, which is restricted due to the cross-sectional design. The longitudinal research that follows customers throughout their lifespan may help understand the temporal dynamics of trust formation, satisfaction changes, and loyalty retention in response to the responsible AI practice. Causal assertions about observed relationships would be enhanced using experimental designs that manipulate certain responsible AI attributes. The issues of common method variance relating to the problem, which are statistically determined and addressed by the remedies of procedural nature, are inherent to the survey research. Future research might indeed include objective performance measures, behavioral measures, or multi-source designs that will help to supplement self-report perceptions. The sampling although varied in terms of industries and demographics do not give the chance to be generalized to other fields or geographical locations. The manufacturing, the healthcare sector, transportation, as well as other industries that require significant involvement of AI should be investigated to determine the boundary conditions of the observed effects. Comparative studies on the international scale can investigate global differences in the priorities of responsible AI and how they shape the relationships with the clients. The emerging markets can take various trends because of the different regulatory conditions, technological backgrounds, and cultural perceptions towards privacy, fairness, and environmental care.

Further studies are also needed to determine how particular responsible AI practices are comparatively effective. As much as this paper explores the topic of responsible AI as a multidimensional construct, a breakdown of the impacts in terms of transparency strategies, bias reduction strategies, privacy safeguarding strategies, and sustainability efforts would offer a finer-grained implementation advice. Also, analyzing the possible adverse effects of too much transparency or communication on AI limitations, it might be possible to determine the best disclosure policies. Studies on customer literacy on the concepts of AI and effects of educational interventions on consciously responsible AI practices would guide communication. The issue of whether organizational authenticity or symbolic adoption of responsible AI practices should be under study should be investigated. Individual customers might also draw a line between a true commitment and a fake gesture, and this may have varied implications on commitment and devotion. The investigation into the ways in which the customers check the organizational statements concerning responsible AI and the types of evidence that they find most notable would contribute to the knowledge about the processes of trust formation. Additionally, the analysis of the recovery strategies when responsible AI failures have been made e.g. mistake in algorithms or privacy infringements are some of the key practical issues, which need to be investigated in an empirical way.

Combination of emerging technology and responsible AI approaches can become an additional line of research. Questions raised on the frontier by investigating how blockchain transparency enforcing power contributes to customer perceptions, or how federated learning concerning privacy protection might contribute to those perceptions would be an environmental implication of both technological advancements. The point of responsibility AI and social life at the border of virtual reality, augmented reality, and metaverse worlds establishes new conditions, in which trust, transparency, and relationship processes need to be researched. Lastly, an analysis of responsible AI within business-to-business scenarios may suggest new dynamics based on the organizational decision making, which may play a crucial role in evaluating organizational versus individual decisions, evaluating them based on different criteria, and with different sustainability priorities. All these directions of research would advance the knowledge about responsible AI and its role in modern business relations and assist organizations in navigating the multifaceted boundary between technological innovation, ethical management, and environmental sustainability with stakeholder value generation in an ever more digitized economy based on AI.

Author Contributions

NLR: Conceptualization, study design, analysis, data collection, methodology, writing review and editing. OEC: visualization, writing review and editing. JR: methodology, visualization, writing original draft, writing review and editing.

Conflict of interest

The authors declare no conflicts of interest.

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