Smart and Sustainable: Consumer Perceptions of AI-Based Green Logistics

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Abstract. There is a need to incorporate artificial intelligence based green logistics due to the increased reliance of e-commerce on environmental sustainability. This research measures consumer attitudes towards AI powered sustainable logistics through a structured questionnaire and provides advanced analysis using IBM SPSS Statistics v26 and AMOS v26. The regression analysis investigates the impact of environmental benefits, ease of use, and price sensitivity on their satisfaction. The results identify crucial issues that support adoption and innovative moves for business. The behavioral and technology adoption Rure Framework provides a fresh perspective on AI powered Green Logistics in e-commerce for e-commerce managers.

Keywords: AI-Based Sustainable Logistics, Consumer Trust in Green Logistics, Sustainability in Green Logistics.

1 Introduction

1.1 Background and Motivation

E-Commerce has transformed retail to ways never imagined possible, providing unmatched ease and accessibility to consumers across the globe. With all the benefits e-commerce brings, it also imposes a burden on the environment through greater transportation, packaging, and waste management requirements. (Rao et al., 2021) The over dependence on fossil fuels together with the inefficient delivery routes practices in traditional logistics adds significantly to carbon emissions and environmental damage. This results in a higher demand on sustainable solutions that would reduce the impact e-commerce has on the environment, and give us cleaner logistics. (Shageeva, 2023)

Green logistics is now a crucial area of activity not only for technology firms but also for other businesses and scientists, since it deals with ecologically secure practices of managing the whole supply chain Green logistics is one of the emerging marketing channels of catering which has tremendous prospects. (Mucowska, 2021)

AI can transform logistics by providing smart route planning, anticipating demand, and managing warehouses. Integrating AI into green logistics can further increase efficiency and help mitigate adverse impacts to the environment. AI systems can analyze

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traffic patterns during delivery and optimize the routes to reduce fuel use and carbon emissions. AI-assisted predictive analytics can help businesses better manage stock levels to avoid overstocking and wasting resources with their demand forecasting. (Beliaev et al., 2023).

1.2 The Rise of E-commerce and its Environmental Implications

The operational environment of consumers and business entities alike has changed due to the boom eCommerce has witnessed in the recent past. This boom propelled the usage of online shopping owing to the increased Internet penetration and the mobile devices in circulation. While eCommerce offers a bulk of advantages, it can also pose detrimental effects towards the environment. The need for eCommerce packages to be shipped over long distances, the wasteful packaging of these parcels, and even the returns users make, significantly enhances the carbon emissions contributed by eCommerce. In addition, the infrastructure for eCommerce including data centers, warehouses, and even the delivery network require energy which further creates a burden on the environment. (Bertram & Chi, 2017)

The increase in delivery vehicles have triggered more emissions which poses a threat to the environment. The surge in demand for same day or next day deliveries is the main reason why there is an increase in the number of delivery vehicles. (Muñoz-Villamizar et al., 2020)

One more notable detrimental effect of e-commerce comes from packaging disposal. Orders placed online are made using a variety of different formats which include cardboard boxes, fillers made of plastic, and bubble wraps that collectively add to waste accumulation. While several companies have been trying to implement sustainable packaging measures such as biodegradable and reusable packaging, very few are fully adopted. (Xie et al., 2021)

1.3 The Role of AI in Green Logistics

AI is a shifting force in the world of logistics providing solutions that amplify productivity and promote sustainability. With the AI algorithms, delivery routes can be optimized in real-time and fuel emissions can be avoided. Demand fluctuations can also be anticipated with the help of predictive analytics maximizing inventory control and eliminating wasted stock. (Deif & Vivek, 2022) With AI powered warehouse automation, operating processes can be simplified, maximizing energy expenditure and minimizing the amount of required space. (Mandal & Archetti, 2023)

2 Literature Review

2.1 Perceived Environmental Benefits

An individual's perception of the benefits of a green initiative's adoption significantly impacts their decisions. Those who believe that services AI-driven green logistics positively impacts the environment tend to adopt such services more frequently. This perception can be influenced by various factors, including an individual's perception of green issues, understanding of the green logistics promise, and company's claim credibility. Many studies have suggested that adoption willingness has a positive relationship with perceived environmental benefits. (Kavas 2020)

Another point of attention is that there is a relationship between visibility of environmental benefits and their value to the consumer. Where the value of green logistics is clear and green technology easy consumable, the knowledge will be valued. The need for effective and open communication of the environmental value of green initiatives is necessary for the general public. (Wu & Zuo, 2023)

Lastly, the social expectations and peer pressure tied to environmental conservation can amplify the already existing market drivers. When green habits are socially accepted or are practiced by people of high status, consumers tend to embrace those habits as well. (Mohammadi et al., 2023) Increasing the sense of community and collective responsibility for environmental stewardship can facilitate the embracing of AI-enabled green logistics. (Sidek et al., 2021)

2.2 AI Awareness in Green Logistics

The consumer recognition of AI's contributions in logistics, especially applications within green logistics, is very essential for its adoption and use. There are many people who do not seem to how how AI is helpful in achieving sustainability in logistics. (Sun et al., 2021) Increasing consumer awareness about the abilities of AI, such as improving delivery routes, increasing fuel efficiency, and waste reduction is very important so as to increase adoption. (Rahman et al., 2023)

Furthermore, the faultiness perceived as having AI can also hinder awareness. The technology may appear difficult to some consumers, which will affect their willingness to accept AI enabled solutions. (Choi, 2023) This hurdle can be overcome by making communication around AI simpler and showing its relevance to green logistics. (Sun et al., 2021)

Moreover, the level of trust in AI systems directly impacts the level of awareness. Users who do not trust AI or who have ethical concerns affecting their willingness to accept modern solutions may not willingly embrace AI enabled green logistics. This can be enhanced by trust through building trust, using transparency and clear communication around the ethics of AI along with its positive effects. (Gao & Wei, 2023)

2.3 Trust in AI-Based Logistics

Trust stands as one of the most vital factors that can determine consumer acceptance and adoption of emerging technologies, especially when it concerns sensitive elements such as logistics. AI-operated systems have to secure consumers' confidence for them to use them. Trust can also be developed in communication that explains how AI works in logistics, the effectiveness of AI algorithms, and even in addressing fears concerning data privacy and security. (Maqbali et al., 2021)

Moreover, their perceived control over AI systems can have a bearing on trust. Concerned consumers who perceive that they possess even a degree of control about how AI makes decisions tend to show some degree of trust. Therefore, articulating the role of AI in logistics and allowing some degree of consumer engagement will promote trust and usage. (Choi, 2023)

2.4 Perceived Ease of Use of AI-Driven Green Logistics

The possible understanding of AI-powered green logistics have substantial effects on how consumers accept them. Solutions that are too complex or hard to use are less likely to be utilized, ultimately affecting adoption rates. Adoption can be positively influenced with the addition of easy to use, straightforward, integration to the put forth e-commerce storefronts. Simplification of selection for green delivery, order tracking, and return management processes helps further enhance the whole experience for the user. (Mucowska, 2021)

In addition, the provision of information and assistance contributes greatly to perceived ease of use. Consumers are likely to be more willing to accept green logistcs when information such as cost and environmental impact is easily accessible. Explaining the role of AI in logistical processes in green logistics would also make the concept simpler and help build trust. (Tan et al., 2020)

In addition, focused personalization and customization can help the product construct appear simpler. The user's experience can be enhanced by perfectly fitting green logistics services to their particular needs and preferences. Further increasing the willingness of consumers entails the provision of more flexible deliveries, personalized suggestions and communication. (Siegfried & Zhang, 2021)

2.5 Price Sensitivity of AI-Driven Green Logistics

Understanding a customer's willingness to pay is important in nurturing environmentally friendly choices among consumers, and is one of the most complex components of their behavior. Even though a significant portion of customers claim to care for the environment, some of them are not ready to spend additional money on green logistics services. The perceived adoption value of green logistics must exceed the outweighed additional cost for adoption to occur. Setting a price, communicating the environmental value earned, and offering discount or loyalty programs can change consumer price sensitivity. (Lazrak & Amrani, 2023)

This makes the relative price of green logistics compared to other options more important in the customer's choice. A significant difference in price may work against the selection of the green option. By exploiting operational efficiencies and economies of scale, it is possible to lessen the cost gap, making green logistics more attractive for consumers who are cost sensitive. (Lee, 2020)

Moreover, how the price data is presented can alter how it is viewed by the customers. Customer focus can be shifted by demonstrating the long-term savings created by green logistics, which include less negative impact on the ecosystem and possible future limitations. Stressing the value of green logistics instead of just the cost can foster acceptance. (Duan, 2019)

2.6 Satisfaction with Green Logistics

Green logistics service satisfaction for consumers is critical for continued loyalty and use. Repeated purchases can be achieved when customers can depend on delivery options and services provided with their orders. Trust can also be built when deliveries purchased are received on time. Customer satisfaction can also be achieved through effective communication, tracking of orders, and easy return policies. (Ejdys & Gulc, 2020)

As noted in literature, the perceived quality of green logistics services renders satisfaction among the users. Customers hope that they will receive at least the same level of quality, if not higher, with the more environment-friendly options. It is vital for green logistics companies to supplement or meet the consumer's expectations in terms of the speed, reliability, and support when delivering satisfaction. (Kwak et al., 2020)

2.7 Sustainable Loyalty in Green Logistics

Sustainable loyalty revolves around the consumer's commitment to businesses that make an effort to act in an environmentally responsible manner over an extended time period. Constructing sustainable loyalty necessitates the use of high-quality green logistics services and cultivating shared values with the consumer towards sustainability. Building sustainable loyalty can be achieved through clear communication about efforts made towards sustainability, involving the consumers, and portraying willingness to protect the environment. (Zhang et al, 2023)

Lastly, loyalty can be further enhanced through the social and emotional ties consumers develop with sustainable brands. Strong and honest relationships with green consumers appeal to their emotions and instill a sense of caring and community among them to promote sustainable loyalty. (Sun et al, 2020). The details of constructs is shown in Table 1.

Table 1. Constructs Derived from the Literature Review

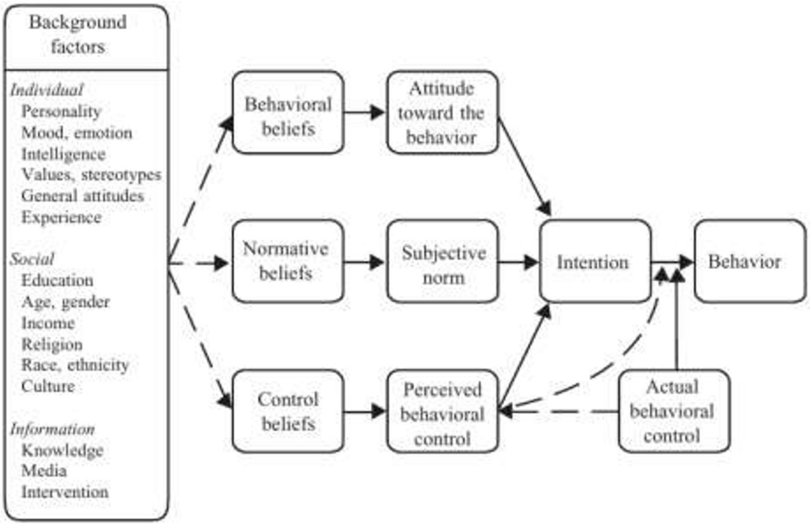
Sr. No.	Construct	Authors
1	**Perceived Environmental Benefits**	Kavas, 2020; Wu & Zuo, 2023; Mohammadi et al., 2023; Sidek et al, 2021
2	**AI Awareness in Green Logistics**	Sun et al., 2021; Rahman et al., 2023; Gao & Wei, 2023
3	**Trust in AI-Based Logistics**	Maqbali et al., 2021; Choi, 2023
4	**Perceived Ease of Use of AI-Driven Green Logistics**	Mucowska, 2021; Tan et al., 2020; Siegfried & Zhang, 2021

3 Theories

3.1 Theory of Planned Behaviour

According to the Theory of Planned Behaviour, an individual's intention to execute a certain action is determined by three factors: attitude, subjective norms, and perceived behavioral control. Evaluating AI-enabled green logistics, a consumer intention would depend upon his or her evaluation of the service which was positive or negative (attitude), the level of social pressure exerted to either use or not use the service (subjective norms), and their ability to access and make use of the service offered (perceived behavioral control. (Liu et al., 2021).

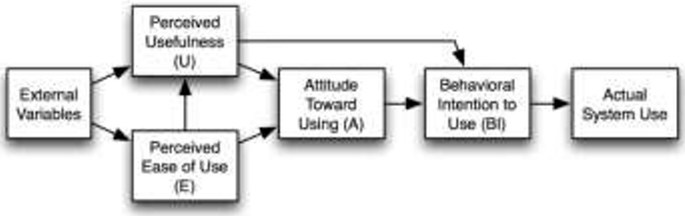
Fig. 1. Adapted from (Ajzen et al., 2005).



3.2 Technology Acceptance Model

The Technology Acceptance Model identifies two main factors affecting the adoption of a new technology: perceived usefulness and perceived ease of use. Perceived usefulness is the belief that a specific technology will improve a person's efficiency or allow them to achieve a particular goal. In green logistics, this is the conviction that AI-driven services will help deliver environmentally friendly protection or more efficient delivery services. All these developments, as mentioned above, pertain to the belief that one can use the technology without much difficulty. These concepts have direct correlation with the "Rure" Framework's perceived environmental benefits and perceived ease of use. (He et al., 2018).

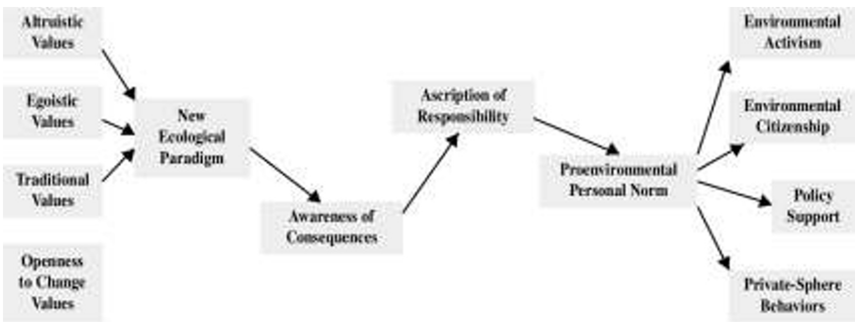
Figure 2. Adapted from (Davis, Fred., 1985)



3.3 Value Belief Norm Theory

As the Value Belief Norm Theory suggests, one's pro-environmental behavior stems from their values, beliefs, and personal norms. Within this construct of the theory, a value is defined as a protective belief or principle that needs to be defended and held dearly. A belief is paradigm associated with the specific interpretation of the responsibility one has towards the environment, such as believing that carbon emissions could be reduced through the use of green logistics. Personal norms are self-imposed expectations to act in accordance with one's values and beliefs. All these constructs fit well with the Rure Framework underneath the perceived environmental benefits, AI awareness and sustainable loyalty. (Zhang et al., 2020).

Figure 3. Adapted from (Stern, et al., 1999)

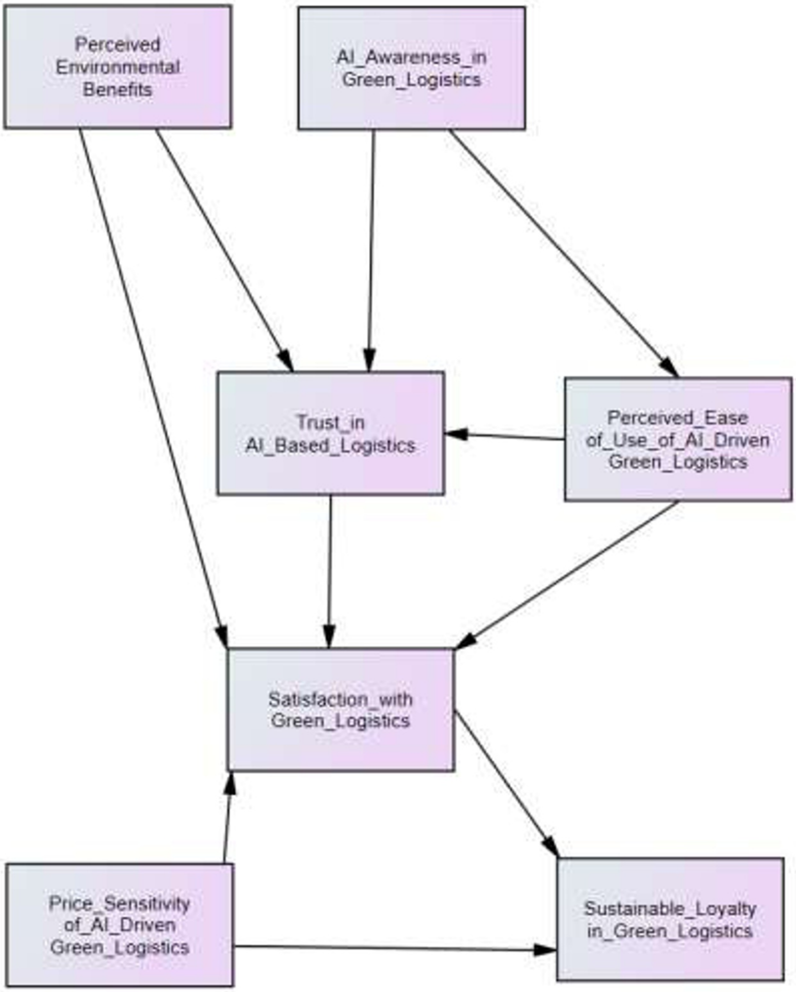


4 The Proposed Rure Framework

This newly Development Rure Framework (Figure 4) seeks to provide a model for analyzing consumer behavior regarding the adoption of green AI logistics in an online shopping environment. It comprises seven elements: Perceived Environmental Benefits, AI Awareness in Green Logistics, Trust in AI Based Logistics, Perceived Ease of

Use of AI Driven Green Logistics, Price Sensitivity of AI Driven Green Logistics, Satisfaction with Green Logistics, and Sustainable Loyalty in Green Logistics. To appreciate the factors that affect consumer trust and satisfaction towards loyalty with sustainable solutions for logistics, the relationships between these constructs are analyzed. In particular, the construct Perceived Environmental Benefits and the construct AI Awareness in Green Logistics are two example antecedents that have a direct effect on Trust in AI Based Logistics. In addition, consumers' confidence in the system is shaped. (Wang & Zhao, 2023)

Figure 4. The "Rure" Framework



The formulated model handles the Price Sensitivity Motivator alongside other Trust in AI Based Logistics to Satisfaction with Green Logistics to underline its all-embracing nature. It is consumer satisfaction that is highlighted as important for nurturing long-term loyalty to brands that practice AI powered sustainable logistics solutions. The explanatory power of the provided framework stems from combining consumer satisfaction and the models with traditional econometric techniques, such as Regression Analysis, ANOVA, and Structural Equation Modelling (SEM) through Likert scale questions. This brand-new model provides a starting point, which can be developed further, for the evaluation of the relationship of environmental concerns, trust, easiness of use, satisfaction, and loyalty in green AI powered logistics. (Gansser & Reich, 2021)

The framework also aids in exploring sustainable logistics in e-commerce by concentrating on other significant factors like consumer perceptions, trust, usability, price sensitivity, satisfaction and loyalty. (Sur, 2014)

4.1 Research Objectives

To investigate the factors influencing Indian e-commerce consumers' adoption of AI-driven green logistics services, based on the Rure Framework (Perceived Environmental Benefits, AI Awareness, Trust, Perceived Ease of Use, Price Sensitivity, Satisfaction, and Sustainable Loyalty), and to analyze the interrelationships among these factors.

5 Research Gap and Need for Study

Sustainable Logistics and AI Adoption: Understanding Consumer Behavior in Online Shopping, identifies a growing gap within the evolution of AI-enabled green logistics powered workflows. There is a rising interest in sustainable logistics and a tremendous opportunity for AI powered workflows to supercharge the processes. However, little has been done in an effort to evaluate how consumers interact with the aforementioned practices. The existing research has predominantly focused on the use of AI technologies in logistics or consumer attitude towards sustainability. There are frameworks that attempt to assess adoption of green logistics by the consumers utilizing e-commerce, but most are incomplete. This study attempts to solve these gaps through the introduction of the Rure Framework, which is driven by key parameters – environmental benefits, AI understanding, trust, ease of use, price sensitivity, satisfaction, and sustainable loyalty. This research aims to offer greater perspective on consumer behavior of green AI-enabled logistics and foster the creation of sound strategies for the implementation of the technology. (Yuan et al., 2023)

6 Scope of the Study

This research focuses on a specific aspect of consumer behavior: the adoption of AI-powered green logistics by online shoppers. It studies the interrelationship of the seven constructs of the Rure Framework, which are: perceived environmental benefits, AI awareness, trust, perceived ease of use, price sensitivity, satisfaction, and sustainable loyalty. This research's goal is to evaluate how these aspects assist in consumer decision making when it comes to the selection of green logistics alternatives provided by e-commerce sites. It has a focus on the consumer and the factors that enable or impede this behavior. (Gupta & Singh, 2020)

7 Research Methodology

This research uses a quantitative approach with structural equation modeling analysis to study the relationships between different components within the Rure Framework. E-commerce users who have experienced green logistics will be offline surveyed using structured questionnaires with a Likert scale. The analysis will begin with confirmatory factor analysis of the measurement model's validity, and then perform structural equation modeling to test the proposed relationships between the constructs. Later, regression analysis will be performed to determine the impact of several factors on consumers' acceptance of AI-powered green logistics. The SEM analysis will be conducted in IBM SPSS AMOS v26, and IBM SPSS Statistics v26 for the regression analysis. (Al-Nuaimi et al., 2021).

In the selection of participants who have experience in green logistics services in online shopping, non-probability sampling, especially purposive sampling, will be used. The minimum sample size of 400 participants will be chosen in accordance with SEM analysis requirements to ensure sufficient statistical measures can be taken. Beyond identifying the relevant the Rure Framework and its application within e-commerce towards sustainability, the combination of quantitative research with statistical techniques will allow for a thorough explanation of the proposed Rure framework and sustainable e-commerce practices. (Lie et al., 2021).

For this study, the target population is e-commerce consumers from eight states in India (as shown in, chosen to capture the variety of the nation's geography and culture. Two states from the northern, southern, eastern and western zones were selected based on the availability of internet facilities and online shopping activities. This selection purposefully attempts to ensure that the sample consists of users who likely come across eco-friendly logistics services within the country so as to assess their purchasing behavior in the different regions. The data collected from these states will give an understanding of the demographics that determine the usage of AI based green logistics in India's online shopping. (Bala et al., 2021).

Table 2. Target Cities of Sample Collection

Region	State	Data Collection Location
North	Uttar Pradesh	Lucknow, Kanpur
	Delhi	Delhi, New Delhi
South	Karnataka	Bangalore, Mysore
	Tamil Nadu	Chennai, Coimbatore
East	West Bengal	Kolkata, Asansol
	Bihar	Patna, Gaya
West	Maharashtra	Mumbai, Pune
	Gujarat	Ahmedabad, Surat

8 Findings

The demographics details of sample is shown in Table 3.

Table 3. Demographics

Demographics (N=454)			
Sr. No.	**Demographic Parameter**	**Frequency**	**Percent**
1	**Gender**		
	Male	237	52.2%
	Female	217	47.8%
	Total	**454**	**100.0%**
2	**Age**		
	18-28	133	29.3%
	29-38	149	32.8%
	39-48	131	28.9%
	49-58	26	5.7%
	Above 58	15	3.3%
	Total	**454**	**100.0%**

3	**Marital Status**		
	Married	267	58.8%
	Unmarried	187	41.2%
	Total	**454**	**100.0%**
4	**Education**		
	No formal education	5	1.1%
	Up to higher secondary	40	8.8%
	Diploma	204	44.9%
	Graduation	205	45.2%
	Total	**454**	**100.0%**
5	**Occupation**		
	Student	80	17.6%
	Home Maker	30	6.6%
	Self Employed	135	29.7%
	Salaried	193	42.5%
	Retired	16	3.5%
	Total	**454**	**100.0%**
6	**Annual Family Income**		
	Below 2,00,000	95	20.9%
	2,00,001 – 4,00,000	115	25.3%
	4,00,001 – 6,00,000	71	15.6%
	6,00,001 – 8,00,000	72	15.9%
	8,00,000 and above	101	22.2%
	Total	**454**	**100.0%**
7	**Household Size**		
	1-2	121	26.7%
	3-4	113	24.9%
	5-6	94	20.7%
	More than 6	126	27.8%
	Total	**454**	**100.0%**

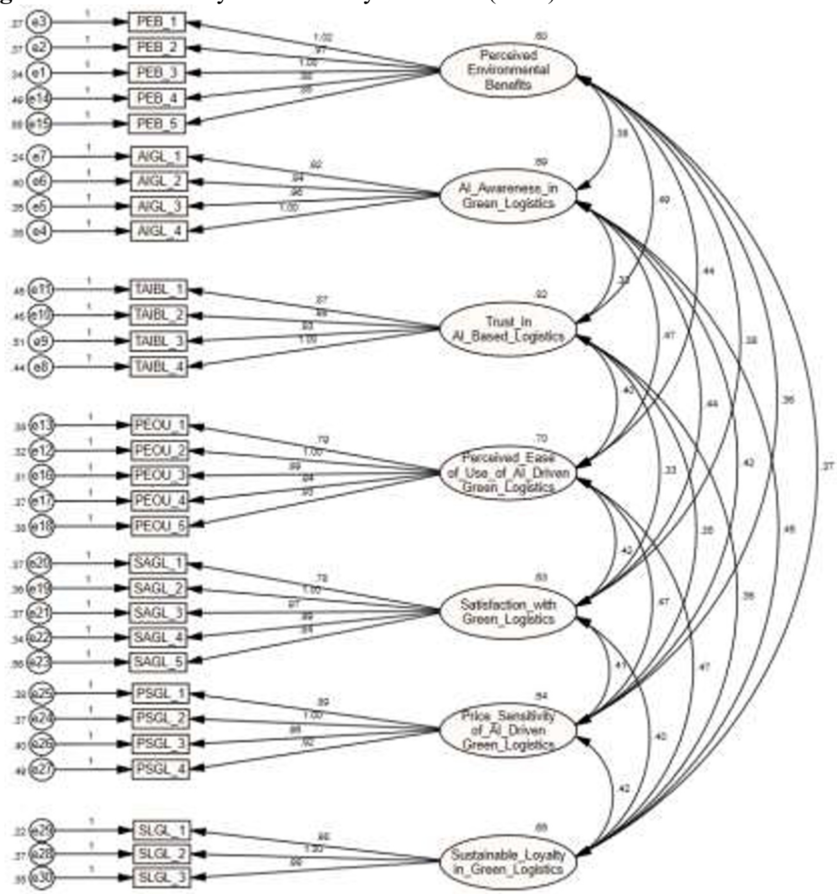
Analyzing the demographic breakdown of survey participants (N = 454), several characteristics of the respondents are worth noting. The sample consists of 52.2% males and 47.8% females, revealing a reasonable balance among genders. This balance suggests that both men and women are interested in the adoption of AI-powered green logistics in online shopping. The respondents concentrated in the age group 18-48 years is significant – 29.3% aged 18-28, 32.8% aged 29-38, and 28.9% aged 39-48. This age bracket is critical as they are more advanced in e-commerce and use of modern age consumption sustainably. This group is also most likely to be digitally active and responsive to new technology and eco-friendly initiatives. (Ghosh, 2020)

9 Data Analysis

9.1 Measurement Model

The confirmatory factor analysis is shown in Figure 5.

Figure 5. Confirmatory Factor Analysis Model (CFA)



Confirmatory Factor Analysis (CFA) was performed to validate and check the reliability of each component within the Rure Framework. Figure 5 CFA model shows the relation between all the observed variables (survey items) and their corresponding latent constructs (for example perceived environmental benefits, AI awareness, trust). The results generated from this analysis ensure that the measurement tools developed to construct the items are useful and valid for testing the proposed concepts in the hypothesis through Structural Equation Modelling. (El-Den et al., 2020)

9.2 Reliability & Validity (Convergent Validity Assessment)

The Table 4 shows the measures (AVE & CR) for convergent validity. The convergent validity measured through Average Variance Extracted (AVE) and Composite Reliability (CR) offers strong support for the measurement model being employed.

Table 4. Convergent Validity

Factors	Estimate	AVE	CR
Price_Sensitivity_of_AI_Driven_Green_Logistics	0.755	0.584	0.848
	0.798		
	0.774		
	0.727		
Perceived_Environmental_Benefits	0.788	0.558	0.862
	0.777		
	0.796		
	0.700		
	0.663		
AI_Awareness_in_Green_Logistics	0.841	0.655	0.884
	0.775		
	0.805		
	0.815		
Trust_in_AI_Based_Logistics	0.765	0.614	0.864
	0.798		
	0.762		
	0.808		
	0.729	0.630	0.895

Perceived_Ease_of_Use_of_AI_Driven_Green_Logistics	0.829		
	0.828		
	0.793		
	0.785		
Satisfaction_with_Green_Logistics	0.713	0.569	0.868
	0.798		
	0.785		
	0.802		
	0.662		
Sustainable_Loyalty_in_Green_Logistics	0.860	0.674	0.861
	0.800		
	0.802		

All of the seven constructs comprising the Rure Framework models possessed AVE values greater than the set at 0.50, meaning that each construct is accounted for more than half of the variance of the observed variables. This allows an assumption of good convergent validity, which indicates that items within each separate construct are correlating to one single underlying factor. Moreover, all CR values tend to exceed 0.70 as is very commonly accepted as the standard reliability. This indicates that there is high internal consistency among the items comprising each construct, which serves as further evidence for convergent validity. By combining the evidence of AVE and CR values above the recommended thresholds, the measurement model is claimed to have the constructs properly measured, thus fulfilling the requirements for further scrutiny. (Carlson & Herdman, 2010)

9.3 Quality Measurement (Discriminant Validity Assessment)

The measurement model confirms discriminant validity which was measured through the Heterotrait-Monotrait Ratio of Correlations criterion. The Table 5 shows the HTMT measures for convergent validity.

Table 5. Discriminant Validity

Factors	**Price_Sensitivity_of_AI_Driven_Green**	**Perceived_Environmental_Benefits**	**AI_Awareness_in_Green_Logistics**	**Trust_in_AI_Based_Logistics**	**Perceived_Ease_of_Use_of_AI_Driven_Green_Logistics**	**Satisfaction_with_Green_Logistics**	**Sustainable_Loyalty_in_Green_Logistics**

	_Logistics						
Price_Sensitivity_of_AI_Driven_Green_Logistics	**0.764**						
Perceived_Environmental_Benefits	0.575	**0.747**					
AI_Awareness_in_Green_Logistics	0.623	0.597	**0.809**				
Trust_in_AI_Based_Logistics	0.482	0.699	0.433	**0.784**			
Perceived_Ease_of_Use_of_AI_Driven_Green_Logistics	0.703	0.686	0.679	0.526	**0.794**		
Satisfaction_with_Green_Logistics	0.640	0.614	0.664	0.460	0.632	**0.754**	
Sustainable_Loyalty_in_Green_Logistics	0.652	0.589	0.672	0.492	0.690	0.629	**0.821**

The HTMT values in the Table provided all fall below the conservative threshold of 0.85 which confirms that the constructs within the Rure Framework are different from one another. This means that every construct is indeed measuring a separate facet of the issue and that there is no significant overlap or blurred boundaries between them. Increased validity on the measurement model has been achieved with confirmation of discriminant validity, and firmly, that the constructs are indeed separate and independently contribute to the understanding of AI-driven green logistics adoption. (Oršič et al., 2019)

9.4 Model Fit (Goodness-Of-Fit Indices)

The goodness-of-fit indices presented in Table 6 show that the Rure Framework fits with the data exceptionally well, demonstrating that the Framework is robust and valid.

Table 6. Results

Measure	Model Fit	Threshold
Chi-square	656.105	
CMIN/DF	1.709	< 3 great; < 5 acceptable
CFI	.966	> .90 good; > .95 great
NFI	.923	> .90 good; > .95 great
IFI	.967	> .90 good; > .95 great
TLI	.962	> .90 good; > .95 great
SRMR	.0393	< .08
RMSEA	.040	< .08

This is further supported by the model's strong Chi-square value of 656.105. With a CMIN/DF ratio of 1.709, which is significantly lower than the ideal 3, indicates strong alignment with the hypothesized relationships. Moreover, the values of CFI (0.966), NFI (0.923), IFI (0.967), and TLI (0.962) not only exceed the minimum threshold of 0.90, but also the more challenging one of 0.95, demonstrating outstanding model fit. These results reinforce the fact that the framework is theoretically sound and empirically valid, serving as the foundation for further AI-driven green logistics adoption. (Alavi et al., 2020)

Moreover, the low values of SRMR (0.0393) and RMSEA (0.040) signify minimum residual differences and mark the observed data as perfectly fitting the model. These results further emphasize the frameworks' ability to capture and contain the underlying factors structural relationships through model precision and clarity. Overall, these results and other indices capture the fact that the Rure Framework is practically credible and applicable for rigorous investigations AI driven green logistics, making it an unmatched tool for consumer behavior understanding in the sustainable logistics context. (Talouki et al., 2021)

9.5 Structural Equation Modelling (Path Analysis)

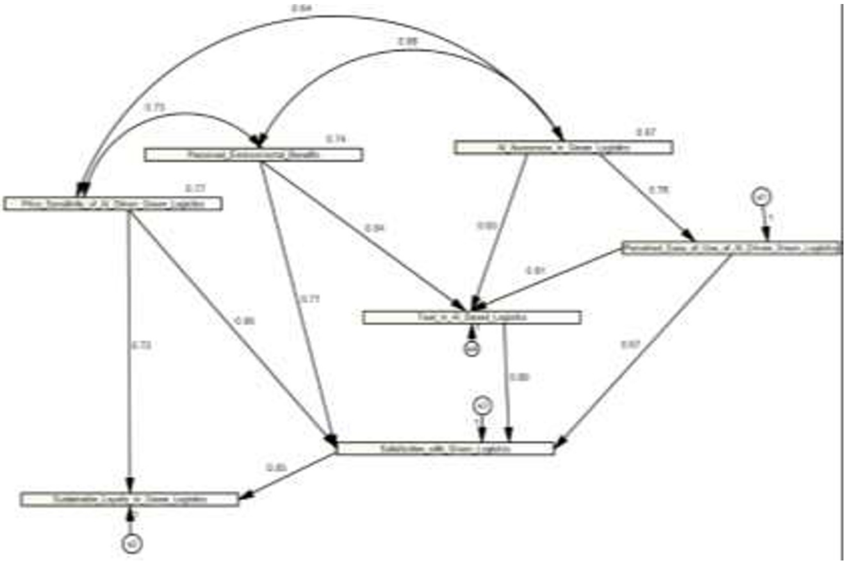


Figure 6. Imputed Path Analysis Model

Figure 6 displays a path analysis model that captures the structural interrelationships among the core components of the Rure Framework. One of the most complex interactions models provided in this study incorporates the understanding and behaviors of the consumers towards AI-enabled green logistics solutions while participating in e-commerce. As described in the prior section, the model fit indices which were reported are quite robust and add to the confidence and the utility of the framework aimed at comprehensively understanding sustainable logistics from a consumer's behavior perspective and strategic actions. The purpose of this path analysis is to impute the relationships and construct a comprehensive visual presentation of the factors that assist in the effective adoption and implementation of AI-driven green logistics solutions, which in turn increases the productivity of researchers and business/learn practitioners. (Hao et al., 2020). Summary results for path analysis is shown in Table 7.

Table 7. Path Analysis Summary

Sr. No.	Path	Effect	Beta Co-efficient	p-value
1	Perceived Environmental Benefits → Trust in AI Based Logistics	Direct	0.84	<0.001

2	Perceived Environmental Benefits → Satisfaction with Green Logistics	Direct	0.71	<0.001
3	AI Awareness in Green Logistics → Trust in AI Based Logistics	Direct	0.63	<0.001
4	AI Awareness in Green Logistics → Perceived Ease of Use of AI Driven Green Logistics	Direct	0.76	<0.001
5	Trust in AI Based Logistics → Satisfaction with Green Logistics	Direct	0.89	<0.001
6	Perceived Ease of Use of AI Driven Green Logistics → Trust in AI Based Logistics	Direct	0.81	<0.001
7	Perceived Ease of Use of AI Driven Green Logistics → Satisfaction with Green Logistics	Direct	0.67	<0.001
8	Satisfaction with Green Logistics → Sustainable Loyalty in Green Logistics	Direct	0.85	<0.001
9	Price Sensitivity of AI Driven Green Logistics → Sustainable Loyalty in Green Logistics	Direct	0.72	<0.001
10	Price Sensitivity of AI Driven Green Logistics → Satisfaction with Green Logistics	Direct	0.86	<0.001

9.6 Regression Analysis

H1

- **Null - - Hypothesis H0:** Perceived Environmental Benefits does not influence Trust in AI Based Logistics.
- **Alternative - - Hypothesis H1:** Perceived Environmental Benefits does influence Trust in AI Based Logistics.

As the regression analysis shows, there is a correlation that exists between Trust in AI Based Logistics and the Perceived Environmental Benefits with an R-square value of 0.837. This means that Trust in AI Based Logistics is explained by Perceived Environmental Benefits by 83.7 percent. The ANOVA results show that this model is statistically significant ($F = 2321.006$, $p < 0.001$), which further proves that the predictor variable adds value to the model. The Perceived Environmental Benefits also showed a high standard coefficient ($\beta = 0.915$) and significant relationship ($p < 0.001$).

H2

- **Null - - Hypothesis H0:** Perceived Environmental Benefits does not influence Satisfaction with Green Logistics.
- **Alternative - - Hypothesis H1:** Perceived Environmental Benefits does influence Satisfaction with Green Logistics.

The regression analysis reveals a significant relationship between the Perceived Environmental Benefits and the Satisfaction with Green Logistics, with the R-square value standing at 0.729, meaning that 72.9 % of the change in Satisfaction with Green Logistics is caused by Perceived Environmental Benefits. The ANOVA also endorses the null hypothesis of the model $F = 1165.514$, $p < 0.001$, which implies the model is valid, and the predictor variable does provide a sufficient explanation for the variations observed in the dependent variable. The relationship is also in agreement with the coefficient analysis, where the standardized coefficient was high ($\beta = 0.854$), and the p-value was significantly low ($p < 0.001$).

H3

- **Null - - Hypothesis H0:** AI Awareness in Green Logistics does not influence Trust in AI Based Logistics.
- **Alternative - - Hypothesis H1:** AI Awareness in Green Logistics does influence Trust in AI Based Logistics.

The regression results are indicative of a significant relationship between AI Awareness in Green Logistics and Trust in AI Based Logistics as depicted by the R-square value of 0.648. This means that 64.8% of the variance Trust in AI Based Logistics is affected by AI Awareness in Green Logistics. The ANOVA results also substantiate the model ($F = 656.147$, $p < 0.001$), suggesting that AI Awareness in Green Logistics has a positive predictive value for Trust in AI Based Logistics. The analysis of coefficients also complied with this finding, reaching standardized coefficient of β = 0.805, while achieving a statistically significant p-value ($p < 0.001$).

H4

- **Null - - Hypothesis H0:** AI Awareness in Green Logistics does not influence Perceived Ease of Use of AI Driven Green Logistics.
- **Alternative - - Hypothesis H1:** AI Awareness in Green Logistics does influence Perceived Ease of Use of AI Driven Green Logistics.

The regression analysis suggests a relationship between AI Awareness in Green Logistics and Perceived Ease of Use of AI-Driven Green Logistics as shown by the R-square statistic of 0.774, which indicates that a variance of 77.4% in Perceived Ease of Use is explained by AI Awareness in Green Logistics. The ANOVA results show great significance of the overall model ($F = 960.980$, $p < 0.001$), which strengthens this relationship. The coefficient analysis confirms this impact too with a standardized coefficient of β = 0.880 and an equally significant p-value ($p < 0.001$).

H5

- **Null - - Hypothesis H0:** Trust in AI Based Logistics does not influence Satisfaction with Green Logistics.
- **Alternative - - Hypothesis H1:** Trust in AI Based Logistics does influence Satisfaction with Green Logistics.

The regression analysis proves that there exists a statistically significant correlation between Trust in AI-Based Logistics and your Satisfaction with the service provided in Green Logistics. The model explains 89.6% of the variance in Satisfaction with Green Logistics ($R^2 = 0.896$). Thus, the model has a high level of explanatory power. ANOVA has determined the significance of the model ($F = 5162.526$, $p = 0.001$), which indicates that Trust in AI-Based Logistics has a major determinant influence on satisfaction level. In the remainder, the analysis confirms this, too, with a coefficient of β = 0.946 and p value less than 0.001.

H6

- **Null - - Hypothesis H0:** Perceived Ease of Use of AI Driven Green Logistics does not influence Trust in AI Based Logistics.
- **Alternative - - Hypothesis H1:** Perceived Ease of Use of AI Driven Green Logistics does influence Trust in AI Based Logistics.

The relationship between AI-Driven Green Logistics and Trust in AI Logistics was found to be strong and statistically significant, as demonstrated by the regression analysis. This model already explained 82.4% of the variance in Trust in AI Based Logistics ($R^2 = 0.824$), which indicates remarkable accuracy. The results of the ANOVA test demonstrated the general significance of the model ($F = 1295.502$, $p < 0.001$), indicating that Perceived Ease of Use does significantly impact trust in AI based logistics. This is further proven in the coefficient analysis with p_value < 0.001 and β = 0.908.

H7

- **Null - - Hypothesis H0:** Perceived Ease of Use of AI Driven Green Logistics does not influence Satisfaction with Green Logistics.
- **Alternative - - Hypothesis H1:** Perceived Ease of Use of AI Driven Green Logistics does influence Satisfaction with Green Logistics.

The regression shows a notable relationship between the satisfaction score with the perceived ease of use AI-Driven Green Logistics, one important thing that stands out here is that the model explains 68.8% of the variance in Satisfaction with Green Logistics ($R^2 = 0.688$ which means that it has pretty optimistic explanatory power as well. The results of the ANOVA confirm the statistical validity of the model $F = 994.247$, $p < 0.001$) which pretty convincingly shows that Perceived Ease of Use is an important determinant of satisfaction. The findings of the coefficient analysis serve to strengthen this point with the results of a standardized coefficient of $\beta = 0.830$ and a p-value which is highly significant ($p < 0.001$).

H8

- **Null - - Hypothesis H0:** Satisfaction with Green Logistics does not influence Sustainable Loyalty in Green Logistics.
- **Alternative - - Hypothesis H1:** Satisfaction with Green Logistics does influence Sustainable Loyalty in Green Logistics.

The regression suggests that Satisfaction with Green Logistics has significance in enhancing Sustainable Loyalty. The model explains 86.1% of the variance in Sustainable Loyalty ($R^2 = 0.861$), indicating a very high degree of accuracy. The ANOVA test also validates the model ($F = 2050.739$, $p < 0.001$), which complements the findings. A depth analysis reveals yet another explained relationship with a standardized coefficient of $\beta = 0.928$ and $p < 0.001$.

H9

- **Null - - Hypothesis H0:** Price Sensitivity of AI Driven Green Logistics does not influence Sustainable Loyalty in Green Logistics.
- **Alternative - - Hypothesis H1:** Price Sensitivity of AI Driven Green Logistics does influence Sustainable Loyalty in Green Logistics.

The outcome of the regression analysis showcases the notable effect of the Price Sensitivity of AI-Driven Green Logistics on Sustainable Loyalty within Green Logistics. This model has significant predictive power as the Adjusted R Square value indicates that 73.7% of the variance in Sustainable Loyalty is accounted for by the model ($R^2 = 0.737$). The statistical significance of the results was further corroborated by ANOVA test, the results were as follows – $F = 1231.858$ with $p < 0.001$, which confirms the model's goodness-of-fit.

H10

- **Null - - Hypothesis H0:** Price Sensitivity of AI Driven Green Logistics does not influence Satisfaction with Green Logistics.
- **Alternative - - Hypothesis H1:** Price Sensitivity of AI Driven Green Logistics does influence Satisfaction with Green Logistics.

For H10, the regression analysis results suggest that Price Sensitivity of AI-Driven Green Logistics has a significant influence on Satisfaction with Green Logistics. R square value of the model indicates that 87.6% of the variation in Satisfaction with Green Logistics is explained by the model. The data supports the hypothesis as the ANOVA test confirms that the model is statistically significant ($F = 2228.635$, $p < 0.001$).

9.7 Hypotheses Summary

Summary of hypothesis test results are shown in Table 8.

Table 8. Hypotheses Summary

Sr. No.	Hypotheses	Test	Results	Significance
1	H_01	Structural Equation Modelling and Regression Analysis	$R^2 = 0.837$, $F(1, 452) = 2321.006$, $p < 0.001$	Rejected
2	H_02		$R^2 = 0.729$, $F(1, 452) = 1165.514$, $p < 0.001$	Rejected
3	H_03		$R^2 = 0.648$, $F(1, 452) = 656.147$, $p < 0.001$	Rejected
4	H_04		$R^2 = 0.774$, $F(1, 452) =$	Rejected

			960.980, $p < 0.001$	
5	H_05		$R^2 = 0.896$, $F(1, 452) = 5162.526$, $p < 0.001$	Rejected
6	H_06		$R^2 = 0.824$, $F(1, 452) = 1295.502$, $p < 0.001$	Rejected
7	H_07		$R^2 = 0.688$, $F(1, 452) = 994.247$, $p < 0.001$	Rejected
8	H_08		$R^2 = 0.861$, $F(1, 452) = 2050.739$, $p < 0.001$	Rejected
9	H_09		$R^2 = 0.737$, $F(1, 452) = 1231.858$, $p < 0.001$	Rejected
10	H_010		$R^2 = 0.876$, $F(1, 452) = 2228.635$, $p < 0.001$	Rejected

10 Implications

Summary implications is shown in Table 9.

Table 9. Implications

Theoretical Implications	Practical Implications	Managerial Implications
1. The research deepens the Technology Acceptance Model (TAM) by adding AI-enabled logistics and sustainability as important factors for technology adoption by consumers.	1. Forms purposeful strategies for e-commerce businesses to instill trust in consumers concerning AI green logistics.	1. Aids managers create customer-friendly sustainability policies by measuring the impact of trust, ease of adoption, and perceived environmental good on adoption levels.
2. Fulfills the VBN Theory by explaining the link between perceived environmental impacts and attitude towards AI-enabled green logistics.	2. Allows logistic service providers to redesign AI-assisted green practices based on the needs and expectations of the customers.	2. Prospective investment in artificial intelligence technologies by the companies is guided, with emphasis on effective and sustainable logistics operations.
3. Supports TPB by showing that confidence in AI-enabled logistics services changes the consumer attitude towards the use of green logistics practices.	3. Aids in developing adequate policies to promote AI enabled sustainability in logistics and transportation.	3. Helps managers foster greater AI communication and accountability, thus improving customer trust in sustainable logistics services.
4. Introduces the previously unexplored Rure	4. Helps e-commerce enterprises to stand out in	4. Facilitates the application of artificial intelligence for cost efficient

Framework as a new approach aimed at explaining consumer adoption of AI-enabled green logistics..	the competitive marketplace with the assistance of sustainable and green AI logistics.	and environmentally friendly logistics services in AI enabled supply chain management.

11 Discussion & Conclusion

The outcomes of this study shed light on the diverse determinants concerning the adoption of AI-enabled green logistics services by Indian e-commerce consumers as captured within the Rure Framework. The research proves the hypothesis that consumers adopt the services because they are satisfied with the Perceived Environmental Benefits, AI Awareness, Trust, Perceived Ease of Use, Price Sensitivity, Satisfaction and Sustainable Loyalty. The study results demonstrate that belief in AI-driven logistics systems is a foremost factor for customer satisfaction, which highly promotes sustainable loyalty. Moreover, the more user-friendly AI powered green logistics services are, the more trust and satisfaction users have, which suggests that there is growing need for companies to make AI powered green logistics system more transparent and user friendly. Price sensitivity has also been revealed as a major driver affecting satisfaction and lasting loyalty with these green systems, thus emphasizing the importance for the claiming of cost optimization and value for money communication within the context of AI enabled sustainable logistics. (Liu et al., 2021)

Also, this research adds to the body of work by proposing the novel Rure Framework, which combines several behavioral, technological, and economical approaches to study the interrelations of consumer perceptions and adoption intentions. This means that companies can appropriately shift their strategy towards increasing AI understanding, stressing pro-environmental AID efforts, and enhancing trust for consumer acceptance. (Talouki et al., 2021)

12 Limitations and Future Scope for the Study

This study is thorough in its coverage, but has gaps that can be covered by future research. The consideration of ethnic Indian e-commerce consumers does not allow for external validity in other cultures or markets. Subsequent studies could further analyze AI-powered green logistics adoption for cross-culture comparisons. Moreover, the tendency to underestimate undesirable outcomes may be due to self-reported data, hence future research should seek to incorporate behavioral data in a mixed methods approach. (Demir et al., 2022)

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The data supporting the findings of this study are available from the corresponding author upon reasonable request.

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Authors have no competing interests to declare that are relevant to the content of this article.

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