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ARTIFICIAL INTELLIGENCE AND BUYING BEHAVIOR: EXPLORING THE BALANCE BETWEEN CONVENIENCE AND PRIVACY IN E-COMMERCE FROM THE PERSPECTIVE OF REGIONALITY

INTELIGÊNCIA ARTIFICIAL E COMPORTAMENTO DE COMPRA: EXPLORANDO O EQUILÍBRIO ENTRE CONVENIÊNCIA E PRIVACIDADE NO COMÉRCIO ELETRÔNICO SOB A PERSPECTIVA DA REGIONALIDADE

INTELIGENCIA ARTIFICIAL Y COMPORTAMIENTO DE COMPRA: EXPLORANDO EL EQUILIBRIO ENTRE CONVENIENCIA Y PRIVACIDAD EN EL COMERCIO ELECTRÓNICO DESDE LA PERSPECTIVA DE LA REGIONALIDAD

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ABSTRACT
Purpose: The study explores how the convenience provided by Artificial Intelligence (AI) in e-commerce affects the purchase intention of Brazilian consumers, considering concerns about data privacy and trust in technology in different regions of Brazil. Methodological Approach: Quantitative-descriptive research was adopted using a cross-sectional survey through an online questionnaire. The analysis of the interrelationships and testing of the hypotheses was carried out through the Structural Equation Modeling technique (PLS-SEM). Findings: The convenience provided by AI has a significant positive impact on purchase intent. Data privacy negatively impacts the perceived desirability of AI. Trust in technology positively influences the desirability of AI. Regional differences have a negative impact on purchase intent. AI Convenience acts as a significant mediator between trust in technology and purchase intent. Limitations of the Research: The sample is predominantly composed of respondents from the city of Uberlândia, limiting the generalization of the results. In addition, the research used a non-probabilistic sampling and an online questionnaire, which can introduce selection biases. Practical Implications: E-commerce businesses should focus on increasing the convenience provided by AI to improve purchase intent. It is crucial to address data privacy concerns and increase trust in technology. Regional adaptations in e-commerce strategies are necessary to better meet the local specificities of consumers.

Keywords: Artificial Intelligence. Buying Behavior. E-commerce. Convenience.Data Privacy. Trust in Technology. Regionalism.

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RESUMO
Objetivo: O estudo explora como a conveniência proporcionada pela Inteligência Artificial (IA) no comércio eletrônico afeta a intenção de compra dos consumidores brasileiros, considerando preocupações com privacidade de dados e confiança na tecnologia em diferentes regiões do Brasil.Abordagem Metodológica: Foi adotada uma pesquisa quantitativa-descritiva, utilizando um survey transversal por meio de questionário online. A análise das inter-relações e o teste das hipóteses foram realizados por meio da técnica de Modelagem de Equações Estruturais (PLS-SEM). Resultados: A conveniência proporcionada pela IA tem um impacto positivo significativo na intenção de compra. A privacidade de dados impacta negativamente a desejabilidade percebida da IA. A confiança na tecnologia influencia positivamente a desejabilidade da IA. As diferenças regionais têm um impacto negativo na intenção de compra. A conveniência da IA atua como um mediador significativo entre a confiança na tecnologia e a intenção de compra. Limitações da Pesquisa: A amostra é composta predominantemente por respondentes da cidade de Uberlândia, limitando a generalização dos resultados. Além disso, a pesquisa utilizou uma amostragem não probabilística e um questionário online, o que pode introduzir vieses de seleção. Implicações práticas: As empresas de comércio eletrônico devem se concentrar em aumentar a conveniência proporcionada pela IA para melhorar a intenção de compra. É crucial abordar as preocupações com a privacidade de dados e aumentar a confiança na tecnologia. Adaptações regionais nas estratégias de comércio eletrônico são necessárias para melhor atender às especificidades locais dos consumidores.

Palavras-chave: Inteligência Artificial. Comportamento de Compra. Comércio eletrônico. Conveniência. Privacidade de Dados. Confiança na Tecnologia. Regionalismo.

RESUMEN
Objetivo: El estudio explora cómo la conveniencia que ofrece la Inteligencia Artificial (IA) en el comercio electrónico afecta la intención de compra de los consumidores brasileños, considerando las preocupaciones sobre la privacidad de datos y la confianza en la tecnología en diferentes regiones de Brasil. Enfoque metodológico: Se adoptó una investigación cuantitativo-descriptiva mediante una encuesta transversal a través de un cuestionario en línea. El análisis de las interrelaciones y la comprobación de las hipótesis se realizaron mediante la técnica de Modelado de Ecuaciones Estructurales (PLS-SEM). Hallazgos: La conveniencia que ofrece la IA tiene un impacto positivo significativo en la intención de compra. La privacidad de datos impacta negativamente en la percepción de atractivo de la IA. La confianza en la tecnología influye positivamente en su atractivo. Las diferencias regionales tienen un impacto negativo en la intención de compra. La conveniencia de la IA actúa como un mediador significativo entre la confianza en la tecnología y la intención de compra. Limitaciones de la investigación: La muestra está compuesta predominantemente por encuestados de la ciudad de Uberlândia, lo que limita la generalización de los resultados. Además, la investigación empleó un muestreo no probabilístico y un cuestionario en línea, lo cual puede introducir sesgos de selección. Implicaciones prácticas: Las empresas de comercio electrónico deben centrarse en aumentar la comodidad que ofrece la IA para mejorar la intención de compra. Es crucial abordar las preocupaciones sobre la privacidad de los datos y aumentar la confianza en la tecnología. Es necesario adaptar las estrategias de comercio electrónico a las necesidades regionales para satisfacer mejor las particularidades locales de los consumidores.

Palabras clave: Inteligencia Artificial. Comportamiento de compra. Comercio electrónico. Comodidad. Privacidad de datos. Confianza en la tecnología. Regionalismo.

INTRODUCTION

The exponential growth in Internet use continues to exert a significant influence on global dynamics, reconfiguring interactions, communications, and transactions between people. According to the Digital 2023: Global Panorama report, prepared by , more than 5.6 billion individuals around the world now have access to the Internet, reaching about 71% of the global population. Hootsuite & We Are Social (2023)

In the Brazilian scenario, the increase in online connectivity is remarkable. The ICT Domiciles survey, conducted by the Internet Steering Committee in Brazil, reveals that, in 2023, approximately 84.1% of Brazilian households had access to the internet, representing a growth of 12.7 percentage points in the last five years. (CTIC.BR, 2023)

In Brazil, the preference for online shopping over physical stores reaches approximately 61% of the population, driving the growth of e-commerce. This sector, according to "The Global Payments Report 2023", is projected to expand by 11% by 2026, reaching the expressive figure of US$ 78 billion. For companies operating in this segment, providing a fluid shopping experience, from website navigation to customer support and the checkout process, becomes imperative for success. (WorldPay - FIS, 2023) (Pay Retailers, 2023)

On a global scale, more than half of small businesses report earning up to 50% of their revenues through online sales, with 37% of them reaching the 51% to 100% mark on these channels. In Brazil, the situation is even more prominent: 52% of companies reach up to half of their revenue online, while a surprising 48% exceed this mark. This outperformance compared to countries such as the US, Colombia and Spain highlights Brazil as a leader in e-commerce adoption among small businesses. (GS1 Brazil, 2023)

The revolution in e-commerce platforms, driven by the implementation of recommendation systems based on Artificial Intelligence (AI), redefines the shopping experience, personalizing it and increasing consumer engagement Powered by machine learning algorithms, these systems analyze browsing and purchasing behavior, personal preferences, and market trends to suggest relevant products to users, optimizing conversion rates and customer lifetime value. Studies show the positive impact of these technologies, associating platforms that apply AI recommendations with a significant increase in return on investment (ROI) and customer convenience and satisfaction. (Jannach & Adomavicius, 2016). (Sarwar et al., 2000)

Data privacy concerns in e-commerce become increasingly central in the information age, with consumers demanding transparency and security. Companies now not only comply with stringent regulations, such as the General Data Protection Law, but also adopt data protection practices that foster customer trust and establish lasting relationships based on integrity. Recent studies indicate that trust in the security of personal data exerts a direct influence on users' purchasing decisions, making privacy a strategic imperative for online stores. (Chamber of Deputies, 2018) (Anic et al., 2019)

User trust in technology plays a crucial role in the success of e-commerce platforms, serving as a key pillar for customer adoption and loyalty in the digital environment. Secure devices, intuitive interface, and robust fraud protection systems create an environment of perceived security that encourages consumers to transact online with greater peace of mind. Empirical evidence indicates that greater trust in technology is associated with an increase in purchase intent and customer satisfaction, which is directly reflected in overall performance. (Corbitt et al., 2003) (Escobar-Rodríguez & Bonsón-Fernández, 2017)

In summary, the current e-commerce landscape reveals a global reality in constant evolution, marked by the exponential growth of internet access and the significant preference of consumers for online transactions. In this context, the transformative role of Artificial Intelligence (AI) in offering convenience stands out, redefining the shopping experience and driving consumer engagement. Given this conjuncture, the relevant research problem arises: **How does the convenience offered by Artificial Intelligence in e-commerce affect purchase intention, taking into account concerns about data privacy, the level of trust in technology, and the regional behavior of Brazilians?** This study thus seeks to explore and understand the complex interactions between the key elements of the current digital landscape, aiming to offer valuable insights to improve the academic and practical understanding of these phenomena in the context of e-commerce.

THEORETICAL FOUNDATION AND RESEARCH HYPOTHESES

PURCHASE INTENT

Intention, as a psychological construct, refers to an individual's predisposition or propensity to perform a future action, as discussed by . He emphasized the importance of intention as an essential element in the process of forming behaviors, highlighting its influence on the actions and decisions of individuals based on their goals and expectations. Their contributions to the understanding of the relationship between intentions and behaviors offered subsidies on the decision-making processes of individuals. Katona (1953)

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Moving on to purchase intent, this specific concept focuses on the consumer's predisposition to purchase a particular product or service. Seminal authors established the theoretical basis for understanding purchase intention, emphasizing the importance of attitudes and social norms in the formation of this intention. The expansion of these concepts by the Unified Model of Acceptance and Use of Technology (UTAUT) contextualizes the purchase intention in the context of the purchase on digital technology platforms, highlighting factors such as perceived utility, ease of use and performance expectations as key determinants of this behavior. These theoretical contributions have been essential to understand and predict consumer behavior in the context of purchase decisions, strengthening the relationship between intentions and actions in the sphere of e-commerce. Fishbein & Ajzen (1977) Venkatesh et al. (2003)

AI CONVENIENCE

Convenience is a core construct that describes the ease and efficiency provided by a given process, product, or service, allowing individuals to perform tasks with less effort and greater agility. In line with the perspective of this research, it introduced the idea of convenience in its Technology Acceptance Model, emphasizing the importance of perceived usability and usefulness to influence the acceptance and adoption of technologies. This aspect of convenience ranges from simplicity in interaction to saving time and resources in carrying out various activities, contributing significantly to the effectiveness and satisfaction of users in relation to a given system or context. Venkatesh et al. (2003)
The convenience provided by artificial intelligence (AI) in e-commerce transforms the online shopping experience by personalizing recommendations, automating customer service, and optimizing inventory management. highlight that AI analyzes large volumes of data to provide more relevant and efficient interactions, saving time and improving customer satisfaction. Virtual assistants and chatbots offer instant and seamless support, while recommendation algorithms make searches more accurate. These facilities increase purchase intent, as described by , which relates utility and ease of use to increased transaction intent. Brynjolfsson & McAfee (2014) Venkatesh et al. (2003)
Thus, the first research hypothesis is defined:

H1: The convenience provided by Artificial Intelligence in e-commerce has an impact on the purchase intention of Brazilian consumers.

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DATA PRIVACY

Data privacy is an essential construct that addresses the protection and control of individuals' personal information in the midst of technological advancements. Concern about data privacy dates back to debates that predate the digital age, with researchers as highlighting the importance of safeguarding privacy in the face of the increasing collection and use of personal information. Sensitivity towards privacy in the digital context was further amplified by in their study on understanding online privacy, highlighting the importance of privacy views and privacy guidelines as a standard. These contributions highlight the need for policies and mechanisms to protect individuals' data, promoting transparency and security in the management of personal data. Westin (1968) Barth et al. (2023)

In the realm of e-commerce, data privacy plays a crucial role in consumer trust and technology adoption. indicated that the perception of privacy threats can significantly influence consumers' attitudes and behaviors towards online businesses. The protection of users' personal data has become a central concern, where transparency in data collection and use practices, along with robust cybersecurity measures, are key to building a relationship of trust between businesses and consumers. This attention to data privacy not only reflects ethical and legal concerns but also directly influences consumers' purchasing decisions and engagement on e-commerce platforms. Culnan & Bies (2003)

Thus, the second research hypothesis is defined:

H2: The concern with data privacy impacts the convenience of AI in the online shopping journey.

CONFIDENCE IN TECHNOLOGY

Trust is a multidimensional construct that implies belief in the trustworthiness, integrity, and competence of an entity or individual. They describe trust as the willingness of one party to be vulnerable to the actions of another party, based on the expectation that the second party will perform an action that is important to the first, regardless of the ability to monitor or control that other party. complement this definition, considering trust as a psychological state that comprises the intention to accept vulnerability based on positive expectations of the intentions or behaviors of the other. Mayer et al. (1995) Rousseau et al. (1998)

When it comes to technology, trust takes on an essential dimension for the acceptance and use of technological innovations. explore this construct, highlighting that initial trust in technology is formed from the perception of attributes such as perceived utility, ease of use, and benevolence. This perspective is reinforced by the Unified Technology Acceptance and Use Model (UTAUT) of , which emphasizes trust as a crucial factor for the adoption and continued use of new technologies. Trust in technology is particularly relevant in the context of emerging systems such as artificial intelligence and e-commerce, directly affecting users' interaction and dependence on these systems. McKnight et al. (2002) Venkatesh et al. (2003)

The combination of these perspectives illustrates how trust, both in individuals and in technologies, is critical to the formation of positive expectations and the willingness to accept vulnerabilities, allowing for greater engagement and efficient use of modern technologies.

H3: Trust in technology impacts the convenience of AI in the online shopping journey.

REGIONALISM

Regionalism, as a concept, refers to the appreciation and preservation of the distinct cultural, economic, and social identities of each geographic region. He is considered a seminal author in the discussion of regionalism, highlighting the importance of local differences in the formation of regional identities and in the definition of policies and practices that take into account the specificities of each locality. Regionalism promotes the diversity and autonomy of regions, recognizing their particularities and strengthening relations between communities in an increasingly globalized world. Haas (1958)

Considering the crucial role of regionalism in e-commerce, it is critical for businesses to understand and direct their strategies according to regional nuances and expectations. It highlights the importance of personalizing and adapting online services according to local characteristics, including preferred payment methods, language, social contexts and specific cultural values. By considering regionalism, businesses can build stronger relationships with customers, promote greater engagement, and strengthen brand trust, creating more relevant and authentic shopping experiences for consumers in different parts of the world. The understanding of the influence of regionalism and the diversity of behavior as a function of the geography of the consumer broadens the understanding of the research theme. Gong (2009) (Klein, 1999)

H4: Regional differences impact purchase intention.

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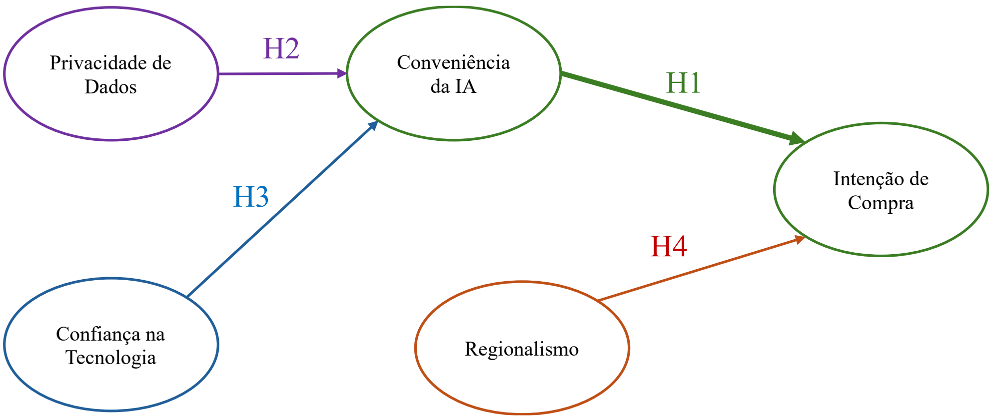
The diagram of the model proposed for the research is described in **Figure 1**. This study was based on several theories established to better understand the motivations and behavior of consumers when buying products in e-commerce.

Figure 1 - Diagram of the model proposed for the research



Source: Produced by the authors

RESEARCH METHOD

The study adopted a quantitative-descriptive research approach, using a cross-sectional survey through an online form. The verification of the interrelations inherent to the theoretical model considered, as well as the testing of the proposed hypotheses, was carried out through the technique of Structural Equation Modeling. (Creswell, 2007) (Hair, 2009)

The survey was conducted with e-commerce users who have already used platforms with recommendation systems based on Artificial Intelligence (AI) and who voluntarily accessed the link shared on social networks. This was a non-probabilistic quantitative survey and respondents were encouraged to share the survey link with their contacts. (Cochran, 1977)

DATA COLLECTION AND PROCESSING TOOL

To achieve the objectives established in this study, an online questionnaire was developed as a data collection instrument. The answers obtained through this survey were used to understand the relationships between the constructs analyzed in this research. (Fowler Jr, 2013) (Hair, 2009)

To measure the constructs, a continuous interval distribution scale was adopted, considering that the intervals between the positions are equal, according to the requirement

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established by structural equation modeling. The scale of each construct was established in accordance with previously validated scales. Likert (1932) (Hair, 2009) (Wakita et al., 2012)

For each construct, an existing and proven scale was established for its measurement. For the Convenience of AI, a scale was used as established by , in relation to Purchase Intention, the scale defined by , for Data Privacy, the scale proposed by , for the Trust in Technology construct, the scale proposed by was considered, and for the Regionalism Construct, geographic questions of the respondents were included to be used as moderators of Purchase Intention. Wagner et al. (2009) Voorhees (2006) Okazaki et al. (2009) Schlosser et al. (2006)

Demographic and social issues were incorporated into the data collection form to characterize the profile of the interviewees in the survey. To ensure the validity and reliability of the questionnaire, a pre-validation process was carried out involving a professor with a PhD in Administration to ensure clarity, relevance and alignment with the research objectives. (Malhotra et al., 2017)

Table 1 below presents a structured view of the main theoretical references that guide this research. Each theory brings unique approaches to different aspects of consumer decision-making, such as concerns, motivations, perspectives, and the impact of regionality. By incorporating these theories into this research, we sought to gain a comprehensive understanding of the factors that influence consumer behavior in online shopping.

Table 1 – Structured view of the research

Construct	Applicable Theory	Key Authors of the Theory Cited in the Text	Author of the Construct Measurement Scale
AI convenience	Technology Acceptance Model (TAM) - Davis et al. (1989)	Venkatesh et al., (2003), Brynjolfsson & McAfee (2014)	Translated and adapted from Wagner et al. (2009)
Purchase Intent	Theory of Planned Behavior (BPD) - Ajzen (1991)	Katona (1953), Fishbein & Ajzen (1977), Venkatesh et al. (2003)	Translated and adapted from Voorhees (2006)
Data Privacy	Data Privacy Theory - Westin (1968)	Barth et al. (2023), Culnan & Bies (2003)	Translated and adapted from Okazaki et al. (2009)
Confidence in Technology	Unified Technology Acceptance and Use Model (UTAUT) - Venkatesh et al. (2003)	Mayer et al. (1995), Rousseau et al. (1998), McKnight et al. (2002),	Translated and adapted from Schlosser et al. (2006)
Regionalism	Theory of Regionalism – Haas (1958)	Gong (2009), Klein (1999)	The city where the respondent lives was used to moderate the

			Purchase Intention in the analyses

Source: Produced by the authors

The questionnaire was distributed digitally through social networks, with 190 respondents. Among these, 175 had already made purchases in e-commerces with recommendations through AI, which was the focus of the survey. Of the valid results, 21 questionnaires were not completely completed, representing 12% of the valid sample. These were excluded from the analysis, following the practice of "listwise deletion". (Hair, 2009)

The survey sample resulted in 154 valid records, which is considered adequate for structural equation modeling (SEM-PLS). Second, to ensure an adequate estimate of the model parameters, the common recommendation is to have a sample size of at least 10 times the number of indicators of the largest formative construct. In the case of this survey, there are 7 indicators, which requires 70 valid records for a consistent analysis. Therefore, the sample obtained exceeds the minimum requirement by more than double, ensuring the robustness of the analysis. Henseler et al. (2015)

STRUCTURAL MODELING

For the research, the PLS-SEM (Partial Least Squares-Structural Equation Modeling) approach was used, in order to analyze the relationships between the variables simultaneously and the inference of the cause and effect relationships between the established variables of interest. (Hair, 2009)

The latent variables considered in the study were: **AI Convenience**, **Purchase Intention**, **Data Privacy**, **Trust in Technology,** and **Regionalism**. A reflexive measurement approach was adopted, since these variables are seen as manifestations of an underlying construct that influences or causes the observed measurements. (Byrne, 2013)

After the configuration of the structural model in the SmartPLS-4 software, the questions of the collection form were associated with the constructs in a reflexive way, according to the theoretical recommendation for the measurement of these constructs. In this way, questions Q5, Q6, Q7, Q8, and Q9 were connected to AI Convenience; Q10 and Q11 to Purchase Intention; Q12, Q13, Q14 and Q15 to Data Privacy; Q16, Q17, Q18, Q19, Q20 and Q21 to Confidence in Technology; and question Q25 to the construct Regionalism.

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SURVEY RESULTS

As shown in **Table 2**, the analyzed sample has a profile composed mostly of well-educated individuals, with high income and a balanced distribution between genders and predominantly residents of Uberlândia. Most participants have completed graduate studies (55.84%), followed by those with complete higher education (18.18%) and incomplete graduate studies (18.18%). In terms of place of residence, most respondents live in Uberlândia (67.53%), while the others are distributed in other locations (32.47%).

As for the average monthly income, more than half of the participants (55.84%) have an income above R$ 10,000.00, with a smaller distribution among the lower income brackets. The sample is composed of 54.55% men and 45.45% women. Regarding age, the highest age recorded is 70 years old and the lowest is 23 years old, with a mean age of 54 years and a median of 45 years.

Table 2 – Respondents' profile

Variable	***n***	**%**
Educational Level		
Incomplete high school	2	1.30%
Incomplete higher education	10	6.49%
Complete Higher Education	28	18.18%
Incomplete graduate studies	28	18.18%
Complete postgraduate	86	55.84%
Place of Residence		
Uberlândia	104	67,53%
Other	50	32,47%
Average Monthly Income		

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Less than R$ 1,000.00	2	1.30%
$ 1.000,00 - R$ 2.499,99	10	6.49%
R$ 2.500,00 - R$ 4.999,99	28	18.18%
R$ 5.000,00 - R$ 9.999,99	28	18.18%
Above R$ 10,000.00	86	55.84%
Gender		
Male	84	54.55%
Female	70	45.45%
Age		
Age: 70 years old		
Minor: 23 years old		
Average Age: 54 years old		
Median Age: 45 years		

Source: Produced by the authors

EVALUATION OF THE MEASUREMENT MODEL

The results shown in **Table 3** indicate that all constructs (Trust in Technology, AI Convenience, Purchase Intention, and Data Privacy) have high internal consistency and reliability, as evidenced by the high values of Cronbach's Alpha and Composite Reliability with values greater than 0.7. In addition, the Extracted Mean Variance (AVE) for all constructs is above the acceptable limit of 0.5, indicating that a significant proportion of the variance of the indicators is explained by the respective constructs. Therefore, the constructs used in the model are valid and reliable for analysis.

DISCRIMINANT VALIDITY

The discriminant validity of the model was evaluated using two main criteria: the Fornell-Larcker criterion and the Heterotrait-Monotrait ratio (HTMT). According to the Fornell-Larcker criterion, the Extracted Mean Variance (AVE) of each construct must be greater than the square correlation between the construct and any other construct in the model. This indicates that each construct shares more variance with its own indicators than with other constructs, confirming discriminant validity. In addition, all HTMT values are lower than 0.85, which reinforces the discriminant validity between the constructs, since values below 0.85 indicate good discriminant validity.

RELATIONSHIPS BETWEEN CONSTRUCTS

Path Coefficients indicate the strength and direction of the relationships between the constructs in the model. The relationship between Trust in Technology and AI Convenience has a coefficient of 0.413, suggesting a moderate direct relationship. The relationship between AI Convenience and Purchase Intent is very strong, with a coefficient of 0.842, indicating that AI Convenience is a strong predictor of Purchase Intent. On the other hand, the relationship between Data Privacy and AI Convenience is negative (-0.117), suggesting that privacy concerns may reduce AI's perception of convenience. The relationship between Regionalism and Purchase Intent is also negative (-0.131), indicating that regionalism can have an adverse impact on purchase intent.

Specific indirect effects show how one construct influences another through a mediator. For example, Trust in Technology influences Purchase Intent through AI Convenience with a knock-on effect of 0.348. Similarly, Data Privacy negatively influences Purchase Intent through AI Convenience, with a knock-on effect of -0.098. These results highlight the importance of AI Convenience as a significant mediator in the model.

QUALITY OF MODEL FIT

The quality of the model's fit was evaluated using the R^2 (Coefficient of Determination) and the SRMR (Standardized Root Mean Square Residual). The R^2 for AI Convenience is 0.208, indicating that 20.8% of the variance in AI Convenience is explained by the model. For Purchase Intention, the R^2 is 0.715, meaning that 71.5% of the variance in Purchase Intention is explained by the model, demonstrating strong explanatory power.

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The SRMR of the saturated model is 0.079 and the estimated model is 0.081, both below 0.08, which indicates a good fit of the model.

These results confirm that the model has good fit quality, with a significant amount of variance explained in endogenous variables and SRMR values that indicate a good fit of the model. The explained variance ratio (R^2) is especially high for Purchase Intention, demonstrating that the model's constructs are good predictors of this variable. In addition, the absence of significant collinearity problems is confirmed by VIF values below 5.

COLLINEARITY

Collinearity in the model was evaluated using the VIF (Variance Inflation Factor). All VIF values are less than 5, indicating that there are no significant collinearity problems between the indicators. VIF values below 5 suggest that the indicators are not highly correlated, which is desirable to ensure the accuracy of the path coefficient estimates in the model.

The results shown in **Table 3** indicate that the model has high reliability and validity, as evidenced by the high values of Cronbach's Alpha, Composite Reliability and AVE. Discriminant validity is confirmed by the Fornell-Larcker and HTMT criteria. The path coefficients show significant relationships between the constructs, and the R^2 indicates a good explanatory power of the model. The fit of the model is considered good based on the SRMR values, and there are no significant collinearity issues. Therefore, the model is valid and reliable for analysis.

Table 3 – Model synthesis

Indicator	Confidence in Technology	AI convenience	Purchase Intent	Data Privacy	Justification
Cronbach's alpha (α)	0.856	0.916	0.885	0.882	Good internal consistency (α > 0.7)
Composite Reliability (ρa)	0.865	0.923	0.887	0.898	High reliability (ρa > 0.7)
Composite Reliability (ρc)	0.891	0.937	0.945	0.918	High reliability (ρc > 0.7)
Extracted Mean Variance (AVE)	0.578	0.749	0.896	0.738	Convergent validity (AVE > 0.5)
Fornell-Larcker	Raisin	Raisin	Raisin	Raisin	Discriminant validity
HTMT	< 0.85	< 0.85	< 0.85	< 0.85	Good discriminant validity

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					(HTMT < 0.85)
Path Coefficients	0.413	0.842	-0.117	-0.131	Strength and direction of relations
R^2 (AI Convenience)	0.208				20.8% of variance explained
R^2 (Purchase Intent)	0.715				71.5% of variance explained
SRMR (Saturated)	0.079				Good model fit (SRMR < 0.08)
SRMR (Estimated)	0.081				Good model fit (SRMR < 0.08)
VIF	< 5	< 5	< 5	< 5	No significant collinearity issues (VIF < 5)

Source: Survey data

MODEL NODE DIAGRAM SYNTHESIS

The node diagram of the PLS-SEM model highlighted in **Figure 2** depicts the relationships between the constructs and the indicators, as well as the interrelationships between the constructs themselves. In the model in question, four main paths were identified: Trust in Technology -> AI Convenience (0.413), AI Convenience -> Purchase Intent (0.842), Data Privacy -> AI Convenience (-0.117), and Regionalism -> Purchase Intent (-0.131). These path coefficients indicate the strength and direction of the relationships between the constructs. Positive values indicate a direct relationship, while negative values indicate an inverse relationship.

Figure 2 - Diagram of the model proposed for the research

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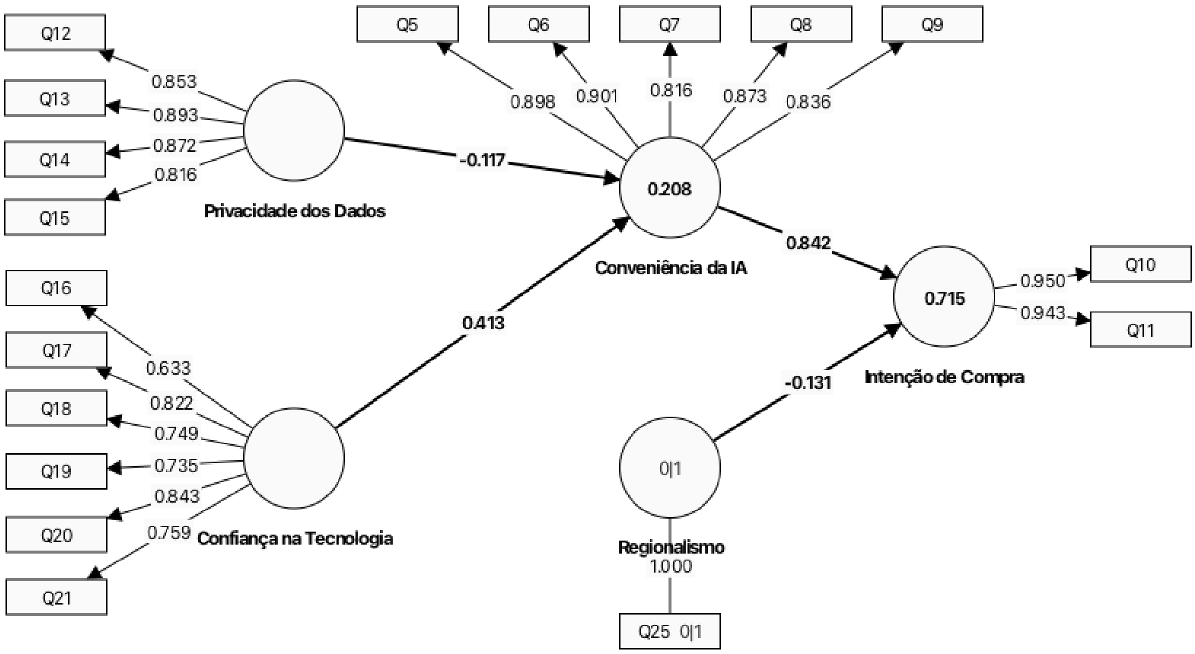

Source: Survey data

Indirect effects are also significant, as seen in the influence of Trust in Technology on Purchase Intent through AI Convenience (0.348) and the negative influence of Data Privacy on Purchase Intent through AI Convenience (-0.098). These results highlight the importance of AI Convenience as a significant mediator in the model. The analysis of path coefficients and indirect effects helps to better understand how the different constructs interrelate and influence the endogenous variables in the model.

DISCUSSION OF THE RESULTS

The research carried out on the influence of Artificial Intelligence on the buying behavior of Brazilian consumers in e-commerce addresses crucial aspects such as convenience, data privacy, trust in technology and regionalism. Based on a quantitative-descriptive approach, using the Structural Equation Modeling (PLS-SEM) technique, the study tested four main hypotheses. The results revealed significant relationships between the constructs studied, showing how the convenience provided by AI, privacy concerns, trust in technology, and regional differences impact consumers' purchase intention.

The node diagram of the PLS-SEM model describes the relationships between the constructs and the indicators, as well as the interrelationships between the constructs themselves. In the model in question, four main paths were identified: Trust in Technology -> AI Convenience (0.413), AI Convenience -> Purchase Intent (0.842), Data Privacy -> AI

Convenience (-0.117), and Regionalism -> Purchase Intent (-0.131). These path coefficients indicate the strength and direction of the relationships between the constructs. Positive values indicate a direct relationship, while negative values indicate an inverse relationship.

The first hypothesis (H1) suggests that the convenience provided by Artificial Intelligence in e-commerce has an impact on the purchase intention of Brazilian consumers. This hypothesis was accepted because the path coefficient between AI Convenience and Purchase Intent is 0.842, indicating a very strong and positive relationship. This result is in line with the theoretical framework of Venkatesh et al. (2003) , which relates utility and ease of use with the increase of transaction intentions. they also highlight that AI improves customer satisfaction, which corroborates the acceptance of this hypothesis. Brynjolfsson & McAfee (2014)

The second hypothesis (H2) states that the concern with data privacy impacts the convenience of AI in the online shopping journey. This hypothesis was also accepted, as the path coefficient between Data Privacy and AI Convenience is -0.117, indicating a negative relationship. This result suggests that privacy concerns reduce AI's perception of convenience, as discussed by which they indicate that the perception of privacy threats can significantly influence consumer attitudes. Culnan & Bies (2003)

The third hypothesis (H3) proposes that trust in technology impacts the convenience of AI in the online shopping journey. This hypothesis was accepted, since the path coefficient between Trust in Technology and AI Convenience is 0.413, indicating a moderate direct relationship. This result is in accordance with the theoretical framework of and , which highlight trust as a crucial factor for the acceptance and continued use of new technologies. McKnight et al. (2002) Venkatesh et al. (2003)

The fourth hypothesis (H4) suggests that regional differences impact purchase intention. This hypothesis was accepted, because the path coefficient between Regionalism and Purchase Intention is -0.131, indicating a negative relationship. This result suggests that regionalism can adversely impact purchase intention, as discussed by and , who emphasize the importance of personalizing and adapting online services according to local characteristics. Gong (2009) Klein (1999)

Considering the variable Q25, which deals with the respondent's city of origin, where 1 represents Uberlândia and 2 represents the other cities, it is possible to conclude that the respondents from Uberlândia, who constitute the majority of the sample (67.53%), may have significantly influenced the general results of the survey. The predominance of

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respondents from Uberlândia suggests that the perceptions and behaviors observed in the study may strongly reflect the characteristics and preferences of this specific city. Therefore, when interpreting the results, it is important to consider that the conclusions about AI desirability, data privacy, trust in technology, and regionalism may be particularly representative of the behavior of consumers in this city.

CONCLUSIONS

The results of this survey highlight the importance of the convenience provided by Artificial Intelligence (AI) in e-commerce, evidencing its significant impact on the purchase intention of Brazilian consumers. By analyzing the interrelationships between convenience, data privacy, trust in technology, and regionalism, the study reveals that AI not only facilitates the purchase journey but also acts as a critical mediator between trust in technology and the purchase decision. Concern about data privacy, on the other hand, remains a challenge, reducing AI's perception of convenience. In addition, regional differences play a crucial role, indicating the need for e-commerce strategies that are more tailored to local specificities.

For future research, some suggestions can be considered to overcome the identified limitations and explore new areas of investigation. First, it is recommended to use a more diverse and representative sample, including respondents from different regions of Brazil to improve the generalization of the results. Adopting a probability sampling method can also help reduce selection biases and increase sample representativeness.

Another suggestion is to conduct longitudinal studies to track changes in consumer perceptions and behaviors over time. This can provide deeper insights into evolving attitudes towards AI, data privacy, and trust in technology.

In addition, future research can explore in greater detail the interactions between different variables, such as moderation and mediation effects, to better understand the complex dynamics that influence purchase intent in e-commerce. The inclusion of new variables, such as previous experience with AI and the level of digital literacy, can also enrich the analysis.

Finally, it is important to consider conducting complementary qualitative studies, such as in-depth interviews and focus groups, to explore consumer perceptions and sentiments in a more detailed manner. These qualitative methods can provide a richer and more

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contextualized understanding of the factors that influence purchasing behavior in the context of e-commerce.

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