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Research Article

Assessment of Critical Factors in home injuries

Rodrigo Luz Santos[a], Adonias Magdiel Silva Ferreira[a], Cristiano Hora Fontes[a], Jorge Laureano Moya Rodríguez[a*]

[a]Universidade Federal da Bahia, Escola Politécnica, Programa de Engenharia Industrial, Salvador, BA, Brasil

*jorgemoyar@gmail.com

Abstract

Paper aims: The aim of this paper is to develop a model to evaluate the risk of home injuries by identifying and evaluating the different variables involved in domestic accidents.

Originality: This work evaluated critical factors that increase the risk of domestic accidents through an approach based on structural equation modeling, the results of which and sample planning were supported by statistical indicators.

Research method: The method applied a survey, using the Google Forms tool and the data obtained were analyzed using Structural Equation Modeling (SEM) based on Partial Least Squares (PLS). Five hypotheses were tested.

Main findings: The proposed model identifies critical factors associated with the risk of domestic accidents. This represents a relevant contribution to the broad area of safe consumption and national bodies dedicated to this topic.

Implications for theory and practice: The modeling carried out has the potential for theoretical and practical contributions: identification of critical variables; improvement of theoretical models; proposing public policies; implementing targeted interventions; improving the safety of consumer products; education and awareness; improvement of domestic and consumer accident monitoring systems.

Keywords

Home injuries. Domestic accidents. Risks. Structural equation modeling (SEM).

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1. Introduction

Accidents are unplanned, unexpected and preventable events which can result in injury and damage (Aydin, 2016; Yapici et al., 2019; Maia & Martins, 2022). The Global Burden of Disease estimated that 973 million people made use of health services due to injuries and 4.8 million people died. Injuries account for 10.1% of the global burden of disease (Zhou & Shen, 2024).

The indicator DALY (Disability-Adjusted Life Year) shows that the rates of disability-adjusted life years in the age group from 50 to 79 years worldwide were higher in high-income regions, being more frequent in men (Haagsma, Graetz et al., 2016, Yapici et al., 2019). Old people face domestic accidents more often than other age groups because they spend most of their time at home.

The number of accidents which occur in the home are a growing concern that affects thousands of people every year across Canada (Khudadad et al., 2024). These authors analyzed three determinants of accident occurrence: situational vulnerability, economic dependence, and residential instability. The work highlights that understanding socioeconomic disparities within neighborhoods can help identify vulnerable populations and prioritize the implementation of public policies.

Domestic accidents can be further classified as intentional and unintentional (Shaban et al., 2023). Intentional domestic accidents are related to cases of murder, suicide, domestic violence, sexual assault, hate crimes, and accidents involving firearms. On the other hand, unintentional domestic accidents represent the main cause of death and disability. Every year, more than five million people worldwide die from injuries caused by accidents and tens of millions of people are treated in emergency centers due to drowning, falls, violence, electrocution, bites, etc., which entails a high cost of physical and mental rehabilitation (Al Sulaie, 2024). Worldwide, accidents rank as the fourth most common cause of mortality (AL-Abedi et al., 2023)

Domestic accidents are defined as those that occur inside or around (garden or garage) the house (Backett, 1965; Khan et al., 2019a) and represent the second most frequent type of accident, comprising 18% to 25% of the total (Aydin, 2016). On the other hand, domestic accidents constitute 82% of accidents among the elderly. In addition to the specific features of the elderly, the home environment can also contribute to the occurrence of accidents (Zorlu, 2017). Although domestic accidents have a high impact associated with their frequency, there is no general method in the literature to evaluate the critical variables that influence the occurrence of these accidents, which therefore constitutes a scientific and social problem to be resolved. Therefore, the following question guides this work: What are the critical factors that increase the potential for domestic accidents among the elderly and how can these factors be assessed and mitigated using an approach based on structural equation modeling?

Consumer accidents are caused by non-compliance of the product or service with technical standards and regulations, provision of incomplete information by the manufacturer and improper use of the product or service (Instituto Nacional de Metrologia, Qualidade e Tecnologia, 2016). Inappropriate functions are often assigned to equipment, resulting in the mistaken assessment of human abilities and limitations or misleading the operator (Carpes Junior & Sell 2004). This work is based on the hypothesis that domestic accidents among the elderly are significantly influenced by a combination of individual factors (such as physical and cognitive limitations), features of the home environment (such as inadequate furniture arrangement and lack of safety adaptations) and the non-compliance of consumer products. Structural equation modeling can identify and quantify the impact of these factors, providing a basis for targeted interventions that can reduce the occurrence of domestic accidents. The identification of critical factors associated with the risk of domestic accidents, based on data and information and supported by consistent statistical indicators, is an important contribution especially to the area of safe consumption involving accidents caused by end-use products and services.

2. Literature review

Risk is an incident associated with an unexpected and unwanted result ((Ritchie & Jiang, 2019), (Chua et al., 2020)). In developing countries, the level of monitoring of domestic accidents is still incipient (Ribeiro et al., 2019) although it has a significant impact on the public health system, especially in rural areas (Sudhir et al., 2014). Domestic accidents are one of the top five causes of death in industrialized and developing countries (Galal, 1999, Al Rumhi et al., 2020).

Falls in the elderly are caused by difficulty in maintaining an adequate position (sitting, leaning or crooked) and represent a serious public health problem due to the associated morbidity and mortality. (Torres et al., 2022) identified five profiles of adults for assessing home accidents: i) younger elderly people who were at risk and fell from a height; ii) younger elderly people with specific health problems who fell downstairs; iii) independent elderly people who fell due to loss of balance; iv) dependent elderly people who fell during low-intensity activities and v) very elderly.

Fractures were more frequent among individuals in the first profile. The results highlight the diversity of circumstances in which elderly people fall. A greater understanding of these circumstances is necessary to implement specific prevention actions (Torres et al., 2022).

(Banerjee et al., 2022) categorized the mechanisms of 'in-home' injuries and compare their outcomes with 'outside home injuries'. Applying multivariate regression analysis, the authors showed that in children and the elderly, injuries at home are associated with a higher mortality rate. (Stalin et al., 2015) analyzed the occurrence of home accidents, identifying the factors associated with home injuries and its economic and health system impacts. The authors conducted a study in a semi-urban area and applied a structured survey in 3947 participants. The variables involved socio-demography, housing conditions, epidemiological factors, medical and economic consequences of domestic accidents. Falls were the most common type of domestic accident.

(Paliwal et al., 2014) developed an investigation in a hospital to understand the etiologic factors and pattern of burns caused using liquefied petroleum gas (LPG) among health service users. The authors considered the age, gender, mode of injury, burn mechanism, place of incidence, extent of burn and inhalation injury of the victims. The most common cause of these accidents was the gas leak from LPG cooking system components. (Sadeghi-Bazargani & Mohammadi, 2013) also developed a study to map out epidemiological features of unintentional burn injuries among Iranian victims using data from the national injury registry. (Ferrante et al.,

2013) considered four different patterns of hurt associated with domestic accidents (falls, bumps, cut and burns) and identified seven profiles of people exposed to such accidents.

A recent systematic literature review involved the meta-analysis of 20 other references related to risk analysis in domestic accidents (Gheshlaghi et al., 2023). Adopting a 95% confidence level, the authors identified the association of domestic accidents with falls, knives or cuts, suffocation, burns and poisoning in 15%, 24%, 1%, 31% and 7% of the cases analyzed, respectively.

The joint influence of factors related to lifestyle, health and housing are decisive in the occurrence of domestic accidents among the elderly. It was found that the kitchen was the place where 33% of accidents occurred. Falls were responsible for 86% of accidents and 33% of accidents were the immediate consequence of sudden nausea. Poor lighting in the home, depression, physical activities and cleaning activities are the main causes of domestic accidents (Camilloni et al., 2011). (Jeon et al., 2022) analyzed the effects of age on hospital mortality among patients who suffered traumatic brain injuries related to falls at home in relation to specific locations in the home (bedroom, living room, kitchen, bathroom, stairs and external spaces). Elderly people over 85 years of age have the highest frequency of deaths due to traumatic brain injuries related to falls at home (Jeon et al., 2022).

There is no evidence of an integral analysis of home injuries considering different types of variables and using structural equation modeling. The literature suggests that the occurrence of domestic accidents in the elderly is influenced by a combination of individual, environmental and consumer product compliance factors (Table 1).

Table 1. Factors influencing the occurrence of domestic accidents in the elderly.

Factors	References
Individual factors:	(Torres et al., 2022);
• Elderly people are more prone to domestic accidents due to physical and cognitive limitations, which intensify with aging.	
·	(Jeon et al., 2022);
• The use of certain medicines/drugs can affect balance and coordination, increasing the risk of falls and other accidents.	(Ribeiro et al., 2019);
·	(Ferrante et al., 2013)
• Studies indicate that gender influences the probability and type of domestic accidents.	
Home environment: • Poor lighting is an important factor that contributes to falls and other types of accidents.	(Camilloni et al., 2011);
• Inadequate arrangement of furniture, lack of handrails and other safety adaptations are determining factors in the occurrence of accidents.	(Sudhir et al., 2014);
• Certain rooms, such as the living room, are more prone to accidents due to the frequency of use and the arrangement of furniture.	(Jeon et al., 2022)
Consumer product compliance	(Henderson Junior et al., 2020; Maier et al., 2024; Vincoli, 2024)
• Improper use of consumer products can lead to serious accidents such as burns.	
• Products that do not meet safety standards increase the risk of accidents.	

This work was carried out in order to evaluate critical factors which can enhance domestic accidents in general, identifying the variables associated with risk. A survey was applied using the Google Forms tool and the data obtained were analyzed using Structural Equation Modeling (SEM) based on Partial Least Squares (PLS). Five hypotheses were tested. The results show that age, use of drugs and medications, as well as gender, are the most relevant factors related to the occurrence of home injuries.

3. Materials and methods

The general procedure adopted throughout the work is shown in Figure 1.

Structural equations allow the specification of complex interrelationships between observed and latent variables. The Partial Least Squares method, commonly referred to as PLS structural equation modeling (PLS-SEM) or PLS path modeling (Tenenhaus et al., 2005; Cepeda-Carrión et al., 2022; Saftari & Sinta, 2022) is widely adopted for identifying models based on structural equations (Khan et al., 2019b; Hwang et al., 2020). This method has recently gained massive dissemination in business research and other sectors areas of knowledge such as agriculture, ecology, environmental sciences, geography and psychology (Sarstedt, 2019).

The PLS-SEM requires the specification of the structural model and measurement model. The structural model represents the structural paths between the constructs, while the measurement model represents the

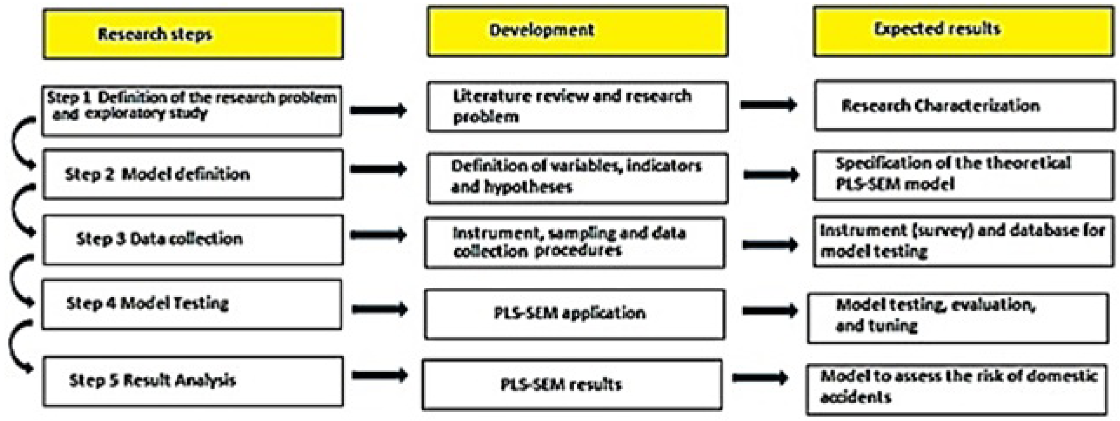

Figure 1. Work stages.

relationships between each construct and its associated indicators. Structural Equation Modeling (SEM) allows both the definition of latent variables measured indirectly through observed variables and also the estimation of the measurement error associated with the latter (Marôco, 2010, Hair Junior et al., 2017a, b).

Latent variables are classified into two types: exogenous and endogenous. The first, called independent or predictive variables, constitute those that are not influenced or are not affected by other model variables. The latter, also called dependent, represent those that are influenced by other variables considered in the model (De Souza Bido & Da Silva, 2019).

SEM can be organized according to the relational structure between variables into two sub models: measurement and structural. Measurement theory specifies how latent variables are measured, making use of confirmatory factor analysis. In a model based on structural equations, the latent variables are interrelated, and their location is obtained from the expert's knowledge through regression and path analysis. The predictive performance of the model and the consistency of the relationships between the latent variables are verified (Hair Junior et al., 2017a, b; Krajangsri & Pongpeng, 2017). The path model is capable of graphically illustrating the assumptions and relationships between the variables to be evaluated by PLS-SEM.

Two equations represent the measurement model (Krajangsri & Pongpeng, 2017) :

$$x = \lambda_x \xi + \delta \tag{1}$$

$$y = \lambda_y \eta + \epsilon \tag{2}$$

where x and y are the observed variables, ξ is the vector of exogenous latent variables, η is the vector of endogenous latent variables, δ and ϵ are the vectors with the measurement errors of the exogenous and endogenous variables, respectively. λ_x and λ_y are the matrices of model coefficients (parameters).

Measurement models can be specified reflectively or formatively. In a reflective measurement model, indicators are seen as imperfect reflections of the underlying construct (MacKenzie et al., 2011; Kono & Sato 2022; Yildiz, 2023]). A reflective measurement model is given by:

$$Z = C\gamma + \epsilon \tag{3}$$

Where Z is a vector of all indicators, C is a charge matrix relating indicators to latent variables and ε is the perturbation term. When viewed in a path model, a reflective measurement model has direct construct relationships with its indicators. On the other hand, a formative measurement model combines indicators to model the construct (MacKenzie et al., 2011):

$$\gamma = H\gamma + \theta \tag{4}$$

where H is the matrix of weights of the regressions of each latent variable in its associated indicators, θ is the perturbation term which, if null, making the formative model equivalent to a weighted composite of indicators

(Sarstedt & Cheah, 2019). A formative measurement model has direct relationships from a set of indicators to a given construct.

Other authors affirm that the structural model can be expressed by (Krajangsri & Pongpeng, 2017):

$$\eta = \beta\eta + \Gamma\xi + \zeta \tag{5}$$

ζ is the vector of latent errors, β and Γ are coefficient matrices.

According to (Sarstedt & Cheah, 2019) the structural model is formally defined as:

$$\gamma = B\gamma + \zeta \tag{6}$$

where γ is a vector of all latent variables, B is a matrix of path coefficients and ζ is the perturbation term related to the dependent latent variables.

There are two types of SEM: covariance-based (CB-SEM) and partial least squares (PLS-SEM). CB-SEM is used to confirm or reject theories and PLS-SEM to develop theories by maximizing the variance of endogenous constructs (Rigdon et al., 2017; Dash & Paul, 2021; Cepeda-Carrión et al., 2022). The latter one, adopted in this work, has been most used for three reasons, namely, data distribution (normal behavior is not required), small sample size and use of formative and reflective indicators (Hair et al., 2012, Hair Junior et al., 2014; Cepeda-Carrión et al., 2022).

Model estimation in PLS-SEM – as implemented in SmartPLS – is based on the extension of Wold's original PLS algorithm (Wold, 1985) proposed by Lohmöller in 1989 (Lohmöller, 2013), which comprises two stages. The first step involves a four-step algorithm to estimate the weights of each measurement model. The weights correspond to zero-order correlations between a latent variable and each of its indicators (Mode A) or are obtained through regression between a variable and its indicators (Mode B). After convergence, the weights are used to compute the scores of the latent variables as linear combinations of their indicators. The second step uses the latent variable scores as input into a series of common least squares regressions to estimate the model parameters, both measurement and structural (e.g., loadings, weights, and path coefficients). PLS-SEM follows a composite-based method for SEM in which the algorithm uses weighted mixtures of indicators to represent the latent variables in the statistical model (Rigdon et al., 2017), whatever measurement models are specified (reflexively or formatively) (Sarstedt & Cheah, 2019).

Several extensions of Lohmöller's PLS-SEM algorithm (Lohmöller, 2013) have been proposed to allow categorical variable handling to test the one-dimensionality of measurement models or adjust original estimates to accommodate common factor models. Further extensions have been proposed in the context of latent class analysis, a class of methods designed to identify and treat unobserved heterogeneity (Henseler, 2017; Rigdon et al., 2017; Shmueli et al., 2019; Sarstedt et al., 2020; Kock, 2021).

When using PLS-SEM, it is necessary to follow a multi-step process involving the specification of the internal and external models, evaluation of the external model and evaluation of the internal model (De Souza Bido & Da Silva, 2019).

3.1. Model evaluation

Model evaluation in PLS-SEM follows a two-step procedure: The first one involves the measurement model and is based on different sets of metrics which depend on the type of model adopted. In the case of reflective measurement models, the metrics comprise the indicator and construct reliability, convergent validity and discriminant validity (Table 2). Formative measurement models need to be evaluated for convergent validity, multicollinearity, and the significance and relevance of indicator weights (Hair et al., 2012; Hair Junior et al., 2017a; Shmueli et al., 2019; Sarstedt et al., 2021). The second step involves the structural model and focuses on the significance and relevance of the path coefficients and the explanatory power of the model (i.e. the R^2) as well as its predictive power, e.g. using PLSpredict (Shmueli et al., 2016; Shmueli et al., 2019; Cho et al., 2022). Model-fit testing using metrics such as Standardized Root Mean Square Residuals (SRMR) or exact-fit tests (Lohmöller, 2013; Henseler, 2017) should be considered with extreme caution due to their conceptual shortcomings in the context of PLS-SEM (Hair Junior et al., 2017b). Instead, researchers should focus on evaluating the predictive model by testing different configurations (Sharma et al., 2021; Sarstedt et al., 2022).

Once the measurement and structural models are specified, the next step is to run the PLS-SEM algorithm. Initially, the reliability and validity of measurement model are evaluated based on the results and, at this moment, it is considered that the relationships of the structural model are accurately represented. It is important to emphasize that depending on the measurement approach, reflective or formative, the evaluation measures are different. Table 2 shows the criteria (and indicators) adopted in the reflective approach (Eg & Zeller, 1991).

Table 2. Summary of measures of evaluation of reflective indicators (measurement model).

Purpose	Indicator/Procedure	Criterion	References
Indicator	Factor loading*	> 0.708	(Eg & Zeller 1991; Roberts & Priest, 2006; Chin & Dibbern, 2010)
Convergent validity	Average variance extracted (AVE)	AVE > 0.5	(Hair et al., 2012; Purwanto & Sudargini 2021)
Internal consistency	Cronbach's alpha (AC)	AC > 0.5	
	Composite Reliability (CC)	CC > 0.7	
	Rho_A	Rho_A > 0.7	
Discriminant validity	Cross loading	Factorial load	(Nasution et al., 1981; Fornell & Larcker, 1981; Chin, 1998; Rasoolimanesh, 2022)
	Fornell and Larcker criterion	$(AVE)^2$	(Afthanorhan et al., 2021; Fornell & Larcker, 1981; Rasoolimanesh 2022)
	Heterorait-Monotrait ratio	HTMT	(De Souza Bido & Da Silva 2019)

*This criterion can be analyzed depending on the problem.

The average variance extracted (AVE) corresponds to the portion of data existing in the variables that is explained by each of the respective latent variables in their sets of variables. This means saying how much, on average, the variables are positively correlated with their latent variables (Ringle et al., 2014; Tripathi & Dhir, 2022). According to the Fornell and Larcker criteria (Fornell & Larcker, 1981), AVE values must be greater than 0.5. (Cohen, 1988; Vallejos, 2022).

According to (Bayaga & Kyobe 2022; Hair Junior et al., 2017b, 2021), Cronbach's alpha values, Rho_A, and the composite reliability between 0.60 to 0.70 are considered adequate in exploratory research, values between 0.7 and 0.9 are considered satisfactory in more advanced research phases and values above 0.9 are not desirable, as they indicate that the latent variables are measuring the same phenomenon.

Furthermore, Cronbach's alpha is sensitive to the number of items and generally tends to underestimate the reliability of internal consistency. Rho_A returns an average value between Cronbach's alpha and composite reliability. Thus, due to the limitations of Cronbach's alpha, it is technically more appropriate to use composite reliability (Hair Junior et al., 2021).

Discriminant validity is understood as an indicator that measures the independence of a latent variable in relation to another (Ringle et al., 2014; Hair Junior et al., 2021), and can be assessed by observing cross-loads (Chin 1998; Rönkkö & Cho, 2022) or by Fornell and Larcker criteria (Henseler et al., 2015; Ab Hamid et al., 2022). In the case of cross-loading, discriminant validity is adequate when the highest loading of the observed variables is in their respective latent variables. The Fornell and Larcker criterion indicates whether a construct presents more variation with its associated indicators than with any other construct (Hair Junior et al., 2021). The assessment of the hypothetical relationships within the structural model is evaluated according to Table 3.

Table 3. Summary of structural model assessment measures.

Objetive	Indicator/procedure	References
Collinearity	Collinearity (VIF)	(Cohen, 1988)
To evaluate the portion of the variance of the endogenous variables that is explained by the structural model	Determination of the Pearson R^2 correlation coefficient	(Ebrahimi et al., 2021; Suleiman & Abdulkadir 2022)
To evaluate how useful each construct is to fit the model	Effect size or Cohen's criteria (f^2)	(Villalva, 2021)
To evaluate the accuracy of the fitted model	Predictive validity or Stone-Geisser indicator or cross-validity redundancy (Q^2)	(Russo & Stol, 2021; Sulaiman et al., 2021)
To evaluate causal relationships	Path coefficient	(Hair et al., 2012; Kock 2021)

In order to assess collinearity, each set of predictive constructs must be examined separately for each subpart of the model. Tolerance values below 0.20 (variance inflation factor -VIF) or above 5 in the predictive constructs are classified as a critical level of collinearity (Hair Junior et al., 2021).

Pearson's coefficients of determination are then evaluated (R^2). According to (Ringle et al., 2014, Hair Junior et al., 2021), the R^2 evaluates the amount of variance of the endogenous variables that is explained by all the linked exogenous variables, representing a measure of the predictive power within the sample.

According to (Cohen, 1988), in the area of social and behavioral sciences, he suggests the classification of small effect for R^2= 2%, medium effect for R^2= 13% and large effect for R^2 = 26%. This convention is adopted in this paper.

The effect size or Cohen's indicator (f^2) aims to evaluate the contribution of an exogenous construct to the value of R^2 in the endogenous latent variable. The guidelines are that values of 0.02, 0.15, and 0.35, respectively, represent small, medium, and large effects of the exogenous latent variable (Cohen, 1988; Hair Junior et al., 2021). The Stone-Geisser value (Q^2) evaluates how close the model is to what was expected of it, that is, the predictive relevance of the trajectory model for a given dependent construct (Ringle et al., 2014; Hair Junior et al., 2021). To do so, it uses the ``Blindfolding'' technique of sample reuse that systematically omits data points and provides a prognosis of their original values (Chin, 1998). The value of Q^2 can be calculated using two approaches (Hair Junior et al., 2021): cross-validation of construct redundancy and cross-validation of construct commonality. The first is based on the trajectory model estimates of the structural model and of the measurement model. The second uses only the estimated scores for the target endogenous construct.

3.2. Research framework

This study comprises the development of a predictive model to assess the level of risk associated with domestic accidents and the validation of this model through a questionnaire applied to the population. The variables associated with each construct are shown in Table 4. Figure 2 shows the paths between attributes and the accident risk.

Table 4. Attribute structure for domestic accident risk assessment.

Constructs	Indicator variables and description
Risk of accident (RA)	RA1: Accident risk culture
	RA2: Information about the risk of an accident
	RA3: Perception of accident risk
	RA4: Economic effects of accidents
	RA5: Possibility to avoid the accident
	RA6: Social effects of accidents
Age (I)	I1: Age is of great importance in the occurrence of accidents
	I2: Children are more likely to have accidents
	I3: The elderly are more likely to have accidents
	I4: Elderly people who live alone are more likely to have an accident
Educational level (NE)	NE1: The level of education influences the occurrence of accidents
	NE2: People with a low level of education are more prone to accidents
	NE3: People with a high level of education are less likely to have accidents
	NE4: The highest number of accidents occurs with people with a medium level of education
Social Composition (CS)	CS1: The Social Composition has great influence on the occurrence of accidents
	CS2: In cities, accidents are more common.
	CS3: In rural areas the number of accidents is lower
	CS4: The number of family members influences the occurrence of accidents
	CS5: Housing conditions influence domestic accidents
Gender	G1: Gender influences domestic accidents
	G2: Accidents among housewives are more frequent
	G3: Domestic accidents in men are uncommon
	G4: Accidents in adolescent women are frequent
Consumption of drugs and medication	DR1: Drug consumption has an influence on the occurrence of accidents
	DR2: The consumption of psychotropic drugs has an influence on the occurrence of accidents
	DR3: People who consume medicine have a higher risk of accidents
	DR4: Elderly people take more medication

3.3. Hypotheses

Five hypotheses were developed (Table 5), which relate the accident risk constructs identified in the literature with their effect.

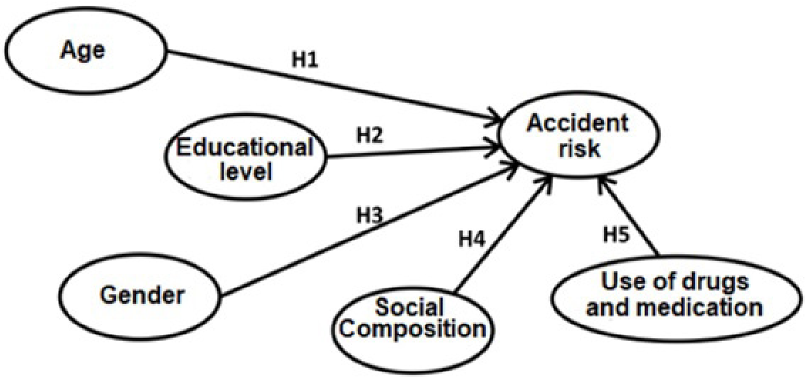

Figure 2. Preliminary model to assess accident risk.

Table 5. Framework of hypotheses.

H1	Age has a great influence on the risk of an accident	(Backett, 1965; Bhanderi & Choudhary, 2008; Moore, 2009; Woolcott et al., 2009; Camilloni et al., 2011; Sudhir et al., 2014; Nour et al., 2018; Soumyashree et al., 2018; Khan et al., 2019a; Morgan et al., 2019; Ribeiro et al., 2019; Bressan et al., 2021; Kalvandi et al., 2021)
H2	Educational level has a great influence on the risk of an accident	(Backett, 1965; Bhanderi & Choudhary, 2008; Moore, 2009; Arulogun et al., 2013; Lafta et al., 2014; Sudhir et al., 2014; Akturk & Erci, 2016; Silva et al., 2016; El Seifi et al., 2018; Soumyashree et al., 2018; Khan et al., 2019b; Kalvandi et al., 2021)
H3	Gender has an influence on the risk of an accident	(Backett 1965; Bhanderi & Choudhary, 2008; Moore, 2009; Soumyashree et al., 2018; López-Soto et al., 2019; Rehman et al., 2020; Suteja et al., 2021)
H4	Social composition has a great influence on accident risk (urban or rural), number of family members, etc.	(Backett 1965; Bhanderi & Choudhary, 2008; Moore, 2009; Sudhir et al., 2014; Soumyashree et al., 2018; López-Soto et al., 2019; Ribeiro et al., 2019; Bressan et al., 2021; Kalvandi et al., 2021)
H5	The use of medication has a great influence on the risk of an accident.	(Backett, 1965; Teculescu, 2007; Khlat et al., 2008; Camilloni et al., 2011; Sudhir et al., 2014; Khan et al., 2019b; Zaara et al., 2022)

3.4. Data collection and the instrument

Data collection was carried out through the Google Forms platform. This enabled the definition of multiple-choice questions, the use of the Likert scale and the online distribution of the form via email, social networks and websites, among others. An online cross-questionnaire (five-point Likert scale) was applied considering the effect of 5 input factors (age, education, social composition, gender, drug use) on the risk of accidents. The answer alternatives include: “completely disagree”, “disagree”, “I do not agree nor disagree”, “partially agree” and “completely agree”. The survey was developed following predefined phases, according to (Gil, 2002): (a) specification of objectives; (b) operationalization of concepts and variables; (c) elaboration of the data collection instrument; (d) instrument pre-test; (e) sample selection; (f) data collection and verification; (g) data analysis and interpretation; (h) presentation of results.

The questionnaire (Appendix 1) is divided into a cover letter, registration data and questions which measure the model’s constructs.

These data were properly processed according to the requirements of the model and SmartPLS SEM. SmartPLS software was used for structural equation modeling based on partial least squares, providing additional tools for correlation analysis between latent variables and validation of the structural model through different indicators (e.g., Average Variance Extracted, Composite Reliability and Variance Inflation Factor). Hypothesis tests were also carried out to evaluate the effect of exogenous variables on the endogenous variable.

The exogenous variables (age, education, drug and medication consumption, gender and social composition) and the endogenous variable (risk of domestic accidents) were defined based on the literature review. A pre-test of the questionnaire was carried out with a small group of participants to assess the clarity and compliance of the questions in relation to the objectives. In a later stage, the same questionnaire was applied to an audience made up of a universe of economically active consumers with a complete higher education level. The questionnaire items were designed to evaluate the perception of the responding group, taking as references the hypotheses defined for the study.

Using the G*Power 3.0.10 software (Hair Junior et al., 2014, 2021; Hair Junior et al., 2017a) for sample planning, a sample size of 92 was obtained considering $f^2 = 0.15, \beta = 0.80, \alpha = 0.05$ and 5 predictors. Since the survey had a sample of 117 respondents, it is possible to show that the significance was around 0.016 which implies a higher level of reliability than that predicted by the significance initially established. Effect size (f^2) assesses the "usefulness" of each construct for model adjustment. Values of 0.02, 0.15 and 0.35 are considered small, medium and large, respectively. Additionally, low test power contributes to false negatives, while a high level of significance contributes to an increase in false positives.

When the emphasis is on the explorations instead off confirmations, PLS-SEM does not require a big sample size nor a specific assumption about the distribution of the data (Hair Junior et al., 2021).

Other researchers use an online calculator recommended for SEM in general (Sopper, 2023) . When using this software, the sample size is higher than when it used the G*power, and the advantages of the PLS SEM cannot be used.

For the multiple regression statistical test, the type of priori power analysis was defined. In the input parameters, the size of the f^2 effect (0.15), the probability of error (0.05), the statistical power (0.80), the degree of freedom (5) and the number of predictors (5) were determined. When using the PLS-SEM, greater statistical power means a greater probability of identifying significant causal relationships (Sarstedt & Mooi, 2014; Hair et al., 2019). The values used are conventional in the literature and recommended by (Cohen, 2013; Hair Junior et al., 2021; Privitera, 2022).

In the classification by (Cohen, 1988, 2013), the size of the f^2 effect has 3 levels: small = 0.02, represents 2% of the variance of the dependent variable; mean = 0.15, represents 15% of the variance of the dependent variable; and large = 0.35, represents 26% of the variance of the dependent variable.

Figure 3 shows the G*Power® software screen with the calculation of the minimum sample size. A sample size with 92 individuals was required. Two hundred e-mails were sent with a return of 117 respondents (58.5%). A minimum number of 92 observations would be necessary to achieve a statistical power of 80% and R^2 values of at least 0.1 with a probability of error of 5% (Mayr et al., 2007; Hair Junior et al., 2021).

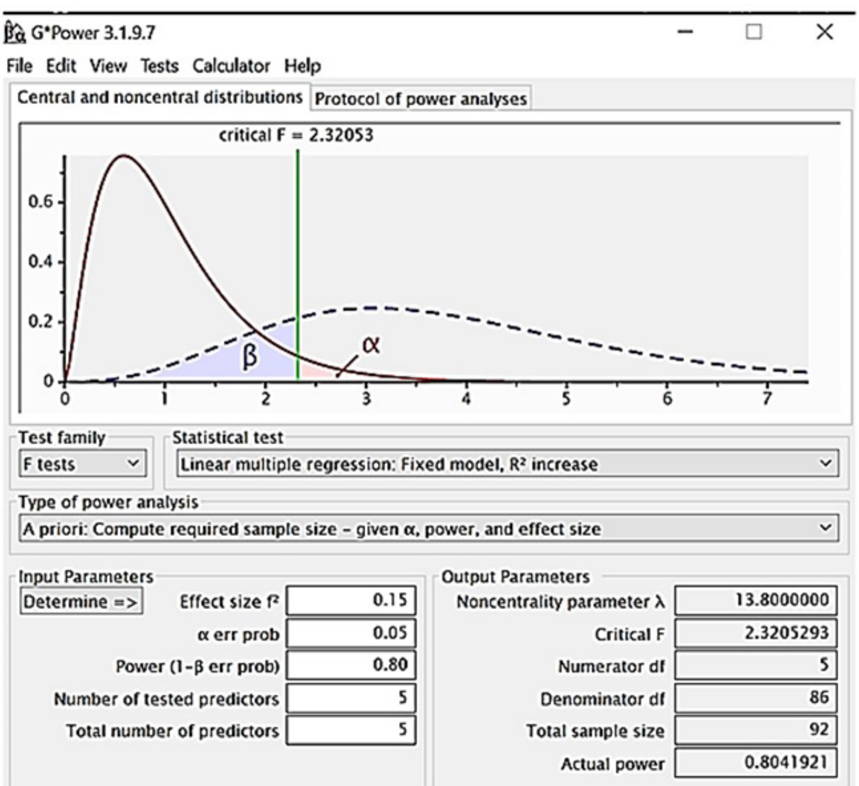

Figure 3. Screen of the G*Power® software with the calculation of the minimum sample size.

4. Analysis of results and discussion

The model presented in Figure 2 was proposed after an exploratory analysis. Subsequently, the model was tested to validate the significance and quality of the forecast. First, the data used to test the model were analyzed observing the features of the sample, such as validity and reliability. Model specification and results of both measurement and structural models were carried out.

The modeling comprised two stages: the first involved the measurement model in which different statistics were verified (Table 2) to assess the consistency of the definition of the variables observed as an effect of the respective correlated factors. The second stage identified a structural model capable of describing the interaction between the factors. Statistics (Table 3) assess the importance of these interactions. Inferences for the statistics obtained in these steps can be obtained using two methods: Jacknife or bootstrapping (Hair et al., 2012; Purwanto & Sudargini, 2021). The bootstrapping method was adopted to enable inferential analyses of the statistics of the measurement model and the structural model.

The following configurations were adopted in the bootstrap approach: number of subsamples of 5x103 to guarantee the stability of the results; no sign change, in which the results are presented as they are, featuring a conservative estimate; complete bootstrap, with generation of all available results; bootstrap corrected and accelerated as a confidence interval method because it is the most stable and does not require excessive computational resources; two-tailed test; significance level of 0.1 for being an exploratory study. For blindfolding, the default omission distance 7 was adopted.

4.1. Measurement model

The first aspect to be observed in relation to the measurement model is the convergent validities, obtained by the observations of the Average Variance Extracted (AVE) which corresponds to the portion of data existing in the variables that is explained by each of the respective latent variables. According to the Fornell and Larcker criteria (Fornell & Larcker, 1981), AVE values greater than 0.5 ensure that the model converged to a satisfactory result. The analysis of Table 6 and Figure 4 shows that only the latent variables educational level and social composition did not present an AVE value greater than 0.5. (Ringle et al., 2014) recommend the elimination of observed variables with lower factor loadings (correlations) to increase the AVE value. AVE values greater than 0.5 (Table 6) show the reliability of the construct and its quality.

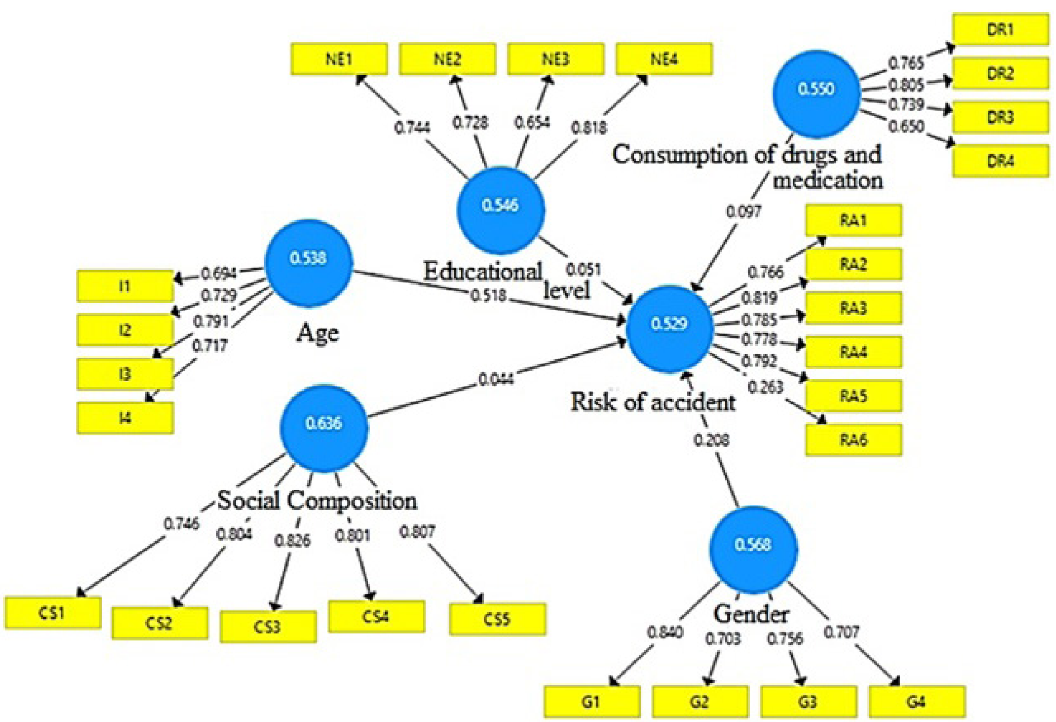

Figure 4. Average variance extracted (AVE) from the model.

Table 6. SEM model quality values.

Variable	Cronbach's alpha	rho_A	Composite reliability	Average Variance Extracted (AVE)
Social Composition	0.857	0.865	0.897	0.636
Gender	0.752	0.773	0.839	0.568
Age	0.713	0.718	0.823	0.538
Educational level	0.722	0.742	0.827	0.546
Risk of accident	0.802	0.848	0.862	0.529
Consumption of drugs and medication	0.732	0.749	0.829	0.550

Table 6 shows that all latent variables presented an AVE value greater than 0.5, Cronbach's alpha, composite reliability and rho_A greater than 0.7, so that the validity of the model and the reliability are assured (Wong 2013; Ringle et al., 2014; Bongso & Hartoyo, 2022; Siraphatthada et al., 2022). Internal consistency (Cronbach's alpha), Rho_A and composite reliability values show that the sample is free of bias and that the responses are reliable.

Discriminant validity assesses whether the phenomena captured by the construct are not represented in other constructs of the model (Ringle et al., 2014). Discriminant validity can be verified from cross-loads, using the Fornell and Larcker criterion (Fornell & Larcker, 1981) or the Heterotrait-Monotrait Ratio (HTMT) criterion (Hair Junior et al., 2014, 2021; Hair Junior et al., 2017a). Table 7 shows that the composite reliability values are satisfactory, and the model reliability is valid. The model's discriminant validity was assessed by observing cross-loads and the Fornell and Larcker criterion (Fornell and Larcker 1981).

Table 7. Discriminant validity - result of the Fornell-Larcker criterion.

Latent Variable	Social Composition	Gender	Age	Educational level	Risk of accident	Consumption of drugs and medication
Social Composition	**0.797**					
Gender	0.419	**0.753**				
Age	0.513	0.664	**0.734**			
Educational level	0.495	0.624	0.515	**0.739**		
Risk of accident	0.457	0.613	0.721	0.506	**0.728**	
Consumption of drugs and medication	0.359	0.111	0.170	0.378	0.243	**0.742**

Another criterion to validate the model is the existence of cross-loads. Table 8 presents the indicators and factor loadings. Table 8 shows that there is discriminant validity as the factor loadings of the indicators are higher in their constructs than in the others (Chin, 1998). Although some variables present high correlations in other constructs, this phenomenon is justified. Latent variables are population-level concepts, and these concepts were measured by individuals from the same population. Therefore, individual perception is more homogeneous than in the studies involving different organizations or different organizational levels (De Souza Bido & Da Silva, 2019).

Table 8 shows that the factor loadings of the variables observed in the latent variables are greater than others. Therefore, according to this criterion, it can be considered that the model has discriminant validity. The Fornell-Larcker criterion (Table 7) shows that the model has discriminant validity since the square roots of the AVEs are greater than the correlations between the constructs. If this criterion was not satisfied, it would be necessary to remove new observed variables. Ensuring discriminant validity completes the adjustments and validation of the measurement model.

4.2. Evaluation of the structural model

Table 9 presents the collinearity analysis and the VIF values do not show collinearity since they are below the limit of 5. Thus, collinearity between constructs is not a critical aspect in the structural model.

The path coefficients which represent the hypothetical relationships between the constructs were analyzed (Hair Junior et al., 2021). All path coefficients are positive (Table 10) and two of them have a low value (hypotheses 2 and 4). The *p values* of these hypotheses are not admissible, and these are not supported. Hypothesis 5 also has unacceptable *T test* and *p values* but it was maintained in the model which is justified by its content validity.

Table 8. Cross Loads

Variable	Social Composition	Consumption of drugs and medication	Gender	Age	Educational level	Risk of accident
CS1	**0.746**	0.181	0.391	0.351	0.415	0.291
CS2	**0.804**	0.265	0.302	0.428	0.340	0.404
CS3	**0.826**	0.324	0.288	0.404	0.464	0.345
CS4	**0.801**	0.266	0.347	0.434	0.366	0.413
CS5	**0.807**	0.390	0.358	0.414	0.412	0.343
DR1	0.349	**0.765**	0.050	0.188	0.213	0.214
DR2	0.222	**0.805**	0.124	0.136	0.255	0.193
DR3	0.210	**0.739**	0.086	0.117	0.374	0.174
DR4	0.289	**0.650**	0.073	0.021	0.322	0.119
G1	0.396	0.074	**0.840**	0.602	0.452	0.575
G2	0.342	0.165	**0.703**	0.472	0.412	0.491
G3	0.260	0.072	**0.756**	0.454	0.559	0.369
G4	0.218	0.000	**0.707**	0.439	0.504	0.348
I1	0.476	0.230	0.553	**0.694**	0.390	0.517
I2	0.285	0.044	0.594	**0.729**	0.306	0.528
I3	0.332	0.153	0.460	**0.791**	0.434	0.582
I4	0.424	0.068	0.335	**0.717**	0.378	0.484
NE1	0.400	0.284	0.502	0.342	**0.744**	0.380
NE2	0.401	0.226	0.611	0.416	**0.728**	0.343
NE3	0.351	0.403	0.277	0.352	**0.654**	0.296
NE4	0.331	0.243	0.445	0.416	**0.818**	0.452
RA1	0.363	0.228	0.472	0.596	0.395	**0.766**
RA2	0.314	0.234	0.469	0.511	0.408	**0.819**
RA3	0.353	0.144	0.459	0.604	0.317	**0.785**
RA4	0.378	0.245	0.560	0.521	0.567	**0.778**
RA5	0.318	0.045	0.444	0.630	0.280	**0.792**
RA6	0.333	0.260	0.183	0.107	0.209	**0.263**

Table 9. Collinearity analysis

Indicator	VIF	Indicator	VIF
CS1	1.816	I1	1.352
CS2	1.938	I2	1.395
CS3	2.418	I3	1.678
CS4	2.023	I4	1.576
CS5	2.023	NE1	1.384
DR1	1.403	NE2	1.394
DR2	1.578	NE3	1.297
DR3	1.581	NE4	1.523
DR4	1.457	RA1	3.118
G1	1.619	RA2	3.477
G2	1.362	RA3	2.059
G3	2.463	RA4	1.729
G4	2.335	RA5	2.038
		RA6	1.182

A new model (adjusted model) was identified considering only the hypotheses H1, H3 and H5 (Figure 5), and the same validation procedure was applied (Tables 11-13). Table 11 shows that all latent variables presented an AVE value greater than 0.5 and composite reliability Cronbach's alpha and rho_A greater than 0.7. Table 12 shows that the 3 hypotheses (H1. H3 and H5) are supported.

The adjusted model also fulfils the Fornell-Larcker criteria (see Table 14)

The discriminant validity according to the cross-load criterion is achieved (Table 14). The indicator load must be the largest on the measured variable and not on another.

Table 10. Supported and unsupported hypotheses.

	Hypotheses		Path coefficient	Standard deviation	T test**	P value*	Decision	f²(size effect)
H1	Age →	Risk of accident	0.518	0.086	5.993	0.000	Supported	0.306
H2	Educational Level →	Risk of accident	0.051	0.099	0.517	0.605	Not supported	0.003
H3	Gender →	Risk of accident	0.208	0.096	2.170	0.030	Supported	0.044
H4	Social Composition	Risk of accident	0.044	0.092	0.474	0.635	Not supported	0.003
H5	Consumption of drugs and medication →	Risk of accident	0.097	0.078	1.245	0.214	Not supported	0.017

*$p<0.1$; **Ttest>1.65.

Table 11. Reliability and validity of the adjusted model construct.

Variable	Cronbach's alpha	rho_A	Composite reliability	Average Variance Extracted (AVE)
Gender	0.752	0.773	0.839	0.568
Age	0.713	0.718	0.823	0.538
Risk of accident	0.802	0.849	0.862	0.529
Consumption of drugs and medication	0.732	0.750	0.829	0.550

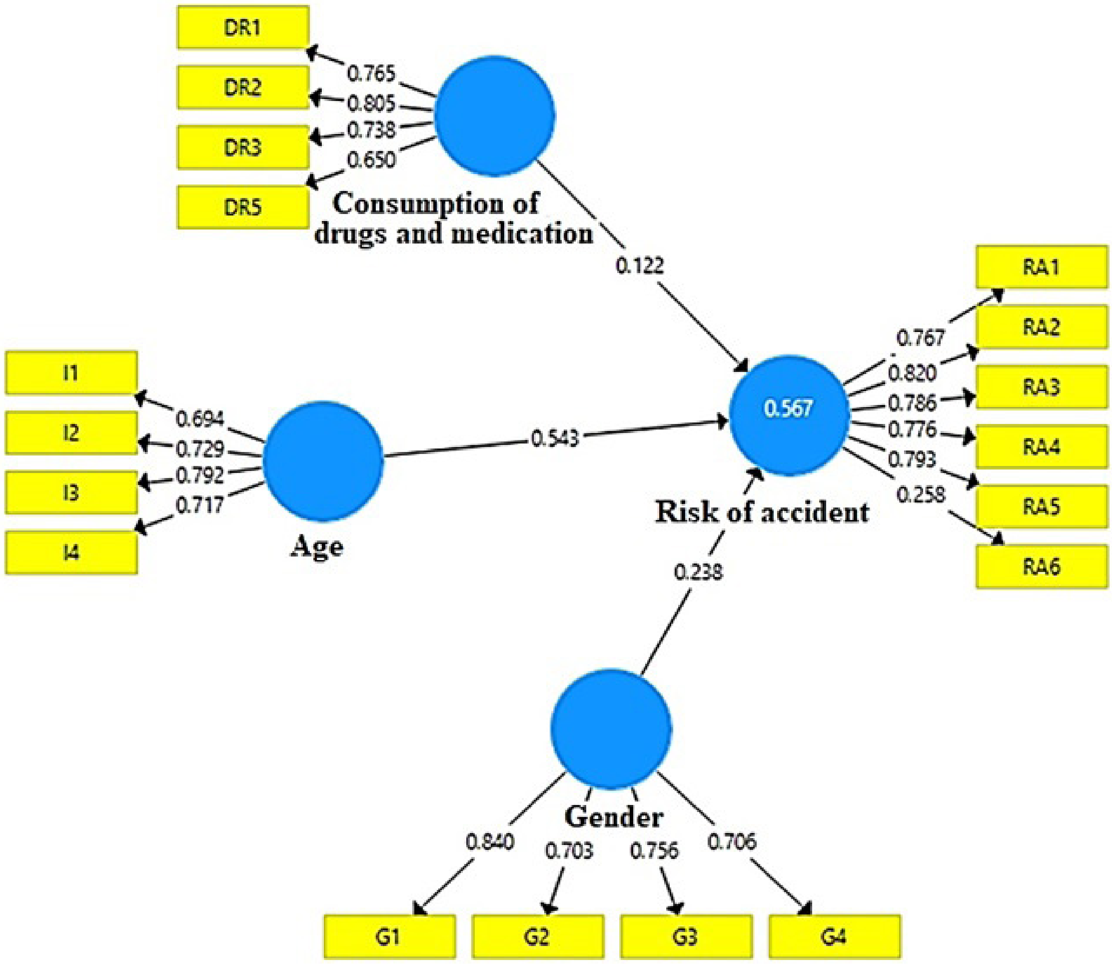

Figure 5. Adjusted model.

Table 12. Supported and unsupported hypotheses of the fitted model.

Hypotheses			Path coefficient	Standard deviation	T test**	P value*	Decision	f²(size effect)
H1	Age →	Risk of accident	0.543	0.082	2.789	0.005	Supported	0.375
H3	Gender →	Risk of accident	0.238	0.085	6.657	0.000	Supported	0.073
H5	Consumption of drugs and medication →	Risk of accident	0.122	0.067	1.823	0.069	Supported	0.034

*$p<0.1$; **Ttest>1.65.

Table 13. Discriminant validity of the adjusted model according to the Fornell-Larcker criterion.

Variable	Gender	Age	Risk of accident	Consumption of drugs and medication
Gender	**0.753**			
Age	0.664	**0.734**		
Risk of accident	0.612	0.722	**0.728**	
Consumption of drugs and medication	0.111	0.170	0.241	**0.742**

Table 14. Discriminant validity of the adjusted model according to the cross-loads criterion.

Variable	Consumption of drugs and medication	Gender	Age	Risk of accident
DR1	**0.765**	0.050	0.188	0.213
DR2	**0.805**	0.124	0.136	0.192
DR3	**0.738**	0.086	0.117	0.173
DR5	**0.650**	0.073	0.021	0.118
G1	0.074	**0.840**	0.602	0.575
G2	0.165	**0.703**	0.472	0.491
G3	0.072	**0.756**	0.454	0.369
G4	0.000	**0.706**	0.439	0.347
I1	0.230	0.553	**0.694**	0.518
I2	0.044	0.594	**0.729**	0.528
I3	0.153	0.460	**0.792**	0.583
I4	0.068	0.335	**0.717**	0.484
RA1	0.228	0.472	0.596	**0.767**
RA2	0.234	0.469	0.511	**0.820**
RA3	0.144	0.459	0.604	**0.786**
RA4	0.245	0.560	0.521	**0.776**
RA5	0.046	0.444	0.630	**0.793**
RA6	0.260	0.183	0.107	**0.258**

Table 15. Discriminant validity of the adjusted model according to the Heterotrait-Monotrait Ratio (HTMT) criterion.

Variable	Gender	Age	Risk of accident	Consumption of drugs and medication
Gender				
Age	0.884			
Risk of accident	0.751	0.815		
Consumption of drugs and medication	0.186	0.252	0.352	

Table 15 shows discriminant validity according to the (HTMT) criterion.

Three criteria (Fornell – Larcker coefficient. cross loads and HTMT) presented indicators within the expected range (see Tables 14 and 15).

Table 16 shows the collinearity of the adjusted model. ensuring that all values are less than 5 which show that the model does not have problems of collinearity.

Table 16. Collinearity analysis of the adjusted model (VIF)

Indicator	VIF	Indicator	VIF
DR1	1.403	I2	1.395
DR2	1.578	I3	1.678
DR3	1.581	I4	1.576
DR5	1.457	RA1	3.118
G1	1.619	RA2	3.477
G2	1.362	RA3	2.059
G3	2.463	RA4	1.729
G4	2.335	RA5	2.038
I1	1.352	RA6	1.182

Another important aspect to evaluate is the cross-validation of construct redundancy (Hair Junior et al., 2021), see Table 17.

Table 17. Cross-validation of construct redundancy.

Variable	SSO	SSE	Q^2 (=1-SSE/SSO)
Gender	388.000	388.000	
Age	388.000	388.000	
Risk of accident	582.000	419.696	0.279
Consumption of drugs and medication	388.000	388.000	

According to (Hair Junior et al., 2021) the value of Q^2 can be calculated through cross-validation of construct redundancy. The cross-validation of construct redundancy was addressed in view of the inclusion of the structural model. The Q^2 value was 0.279 for the risk of accidents. demonstrating that the model is accurate.

The fit of the model was then evaluated (see Table 18)

Table 18. Model fit.

Criterion	Saturated Model	Estimated Model
SRMR (Standardized Residual Root Mean Square)	0.108	0.108
d_ULS (Euclidean distance squared)	2.006	2.006
d_G (Geodetic Distance)	0.875	0.875
Chi-Square (Chi-quadrado Test)	431.748	431.748
NFI (Normed fit index or the Bontler and Bonett index)	0.529	0.529

The SRMR measures the difference between the observed correlation matrix and the model's implicit correlation matrix. By convention, the model has a good fit when the SRMR takes on values less than 0.08 (Hu & Bentler, 1998). Other authors accept a value lower than 0.10. In this case the values are very near 0.10.

The d_ULS and d_G values are obtained from the Bootstrapping procedure. Differences between correlation matrices need not be significant ($p > 0.05$) for the model to have a good fit. The Chi-square test measures the model's degrees of freedom. The normalized fit index (NFI) is not a recommended measure for complex models.

The RMS_theta is a measure used only in pure reflective models and measures the degree of correlation of the external model residuals. Values close to 0 indicate a good model fit. In this case the RMS_theta was 0.146.

From the previous analysis it can be concluded that the model has a good fit. On the other hand, the R2 value of the RA variable (risk of accident) is 0.567. This means that 56.7% of the variance in the AR variable was explained by the model.

Regarding the measurement model, Tables 6, 7 and 8 evaluate the performance of the construct in relation to the definition of the observed variables. Regarding the structural model, Tables 9, 10 and 11 evaluate the performance of the construct in relation to the definition of the established factors or latent variables. The results presented in Tables 12 to 18 assess the adjustment and quality of the model. The inferential analysis of these statistics confirms the observed variables and the factors (latent variables) that should be part of the constitution of the final model and, therefore, are respectively called critical observed variables and critical factors. This procedure is consistent with the main objective of the study, which consists of identifying the critical factors that increase the risk of domestic accidents.

5. Conclusions

This paper analyzed the risk or possibility of occurrence of domestic accidents (endogenous variable) in Brazilian society considering how this parameter varies according to age, educational level, consumption of drugs and medication, gender and social composition (exogenous variables).

The results showed that age is the variable that most influences the possibility of an accident. followed by gender and consumption of drugs and medication.

The identification of critical factors associated with the risk of domestic accidents provides a better understanding of how these variables interrelate and increase vulnerability to accidents. The indicators show the effectiveness of a predictive and robust model, based on structural equations, capable of studying the influence of multiple factors on the endogenous variable (risk of domestic accidents).

It is therefore possible to state that the proposed model provides important information to assess the possibility of an accident occurring, considering that the variables used indicate that the predictive power of the model is satisfactory.

The results can guide the development of public policies aimed at preventing domestic accidents. Governments and healthcare organizations can use these insights to create more effective awareness programs and regulations that focus on the most impactful variables such as age and use of medication.

The identification of critical factors associated with the risk of domestic accidents, especially those related to consumer accidents caused by end-use products and services, is a relevant contribution to Brazilian society, considering that there are public policies aimed at this issue, especially those related to the actions of the National Consumer Secretariat. This organization was created on May 28, 2012, and is part of the Ministry of Justice and Public Security (MJSP). Its responsibilities are established in the Consumer Protection Code and focus on the planning, preparation, coordination and execution of the National Consumer Relations Policy. Combating consumer accidents strengthens the national product safety policy, which is a strategic issue for the Brazilian State, and the National Consumer Secretariat plays a fundamental role in preserving the life, health and safety of consumers.

Product safety is part of the international agenda and the number of consumer accidents in relation to the international scenario is monitored. The Safe Consumption and Health Coordination has a dialogue with international organizations (Organization for Economic Cooperation and Development) and national organizations (Safe Consumption and Health Network) and these entities have been promoting research on this topic. In turn, the Safe Consumption and Health Network is an initiative designed to promote the protection of consumer rights through monitoring the safety of consumer products and services at a national and hemispheric level.

Modeling based on structural equations can also be considered as a data-driven (information) approach. The size and representativeness of the sample (data collection was carried out through an online survey) are limiting factors and may exclude information related to other segments of the population. Furthermore, the information collected through the questionnaire is self-declared, which may introduce biases, including aspects of a social-cultural nature.

Some factors which can increase the risk of domestic accidents, such as structural conditions of homes, arrangements and models of furniture and utensils, local health and safety policies and regional climate differences, were not considered in the model. The research was cross-sectional, capturing data at a given moment in time. This limits the ability to establish causality or observe changes in accident patterns over time.

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Appendix 1. Questionnaire (instrument).

Age												
Question	Assessment					Weight					Total	Weighted value
	1	2	3	4	5	1	2	3	4	5		
Age plays a major role in the occurrence of accidents												
Children are more likely to have accidents												
Elderly people are more likely to have accidents												
Elderly people who live alone are more likely to have an accident												
Subtotal												
Total												
Level of education												
	1	2	3	4	5	1	2	3	4	5	Total	Weighted value
The level of education influences the occurrence of accidents												
People with low levels of education are more prone to accidents												
People with a high level of education are less prone to accidents												
The highest number of accidents occurs among people with a medium level of education												
Subtotal												
Total												
Social Composition												
	1	2	3	4	5	1	2	3	4	5	Total	Weighted value
Social composition has a great influence on the occurrence of accidents												
Accidents are more common in cities.												
In rural areas the number of accidents is lower												
The number of family members influences the occurrence of accidents												
Housing conditions influence domestic accidents												
Subtotal												
Total												
Gender												
	1	2	3	4	5	1	2	3	4	5	Total	Weighted value
Gender influences domestic accidents											0	0
Accidents among housewives are more frequent											0	0
Domestic accidents in men are uncommon											0	0
Accidents among teenage women are frequent											0	0
Subtotal												
Total												
Drug and medicine use												
	1	2	3	4	5	1	2	3	4	5	Total	Weighted value
Drug use influences the occurrence of accidents												
The consumption of psychotropic drugs influences the occurrence of accidents												
People who take medication have a higher risk of accidents												
Subtotal												
Total												
Accident risk												
	1	2	3	4	5	1	2	3	4	5	Total	Total
There is a culture about the risk of accident												
There is information about the risk of accidents												
People are aware of the risk of accidents												
Subtotal												
Total												

The scale goes from 1 to 5 where: You must mark the value 1 in place of X. 1- Completely disagree; 2-Disagree; 3- Neither agree nor disagree; 4- Partially agree; 5- Totally agree.