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Logistic Regression In Practice: Determining Impact Resistance Of Polycarbonate Vision Panels With Limited Data Set

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Abstract

International directives require the implementation of safety measures in machine tools to shield operators from hazards like ejected workpieces or tool fragments. A crucial component of these safety measures are polycarbonate vision panels, which allow operators to observe the machining process. The protective performance of these panels is assessed through impact tests using a standardized projectile, in which the so-called impact resistance is determined. The impact resistance is defined as the maximum kinetic projectile energy a safeguard is able to withstand during impact. A novel approach to determine the impact resistance is based on a logistic regression model. In the context of impact testing, this approach has so far proven effective only on a large data set of 104 impact tests. The present study demonstrates how to determine the impact resistance with a small data set of ten impact tests employing a logistic regression approach. The validity of this logistic model was confirmed through additional testing, demonstrating good agreement with experimental results. A further in-depth analysis using the logistic regression model revealed a significant increase in odds, highlighting the sensitivity of impact resistance to even minor variations in projectile energy. These findings suggest the need for a downward adjustment of the standard impact resistance values to maintain a stable safety level for polycarbonate vision panels. This study demonstrates the practical applicability of logistic regression in impact testing, achieving 93 % accuracy in predicting experimental outcomes while substantially reducing the number of required tests. It also outlines potential obstacles in implementation and provides strategies for addressing them. Moreover, this approach offers a more nuanced understanding of the structural behavior of polycarbonate vision panels under impact load and underscores the importance of incorporating odds into the evaluation of the protective performance.

Keywords: safety of machine tools, polycarbonate, impact resistance, logistic regression

1. Introduction

The directive 2006/42/EC (Directive 2006) serves as a pivotal legal framework within the EUROPEAN UNION, establishing the foundation for rigorous safety standards in the design, manufacture and operation of machinery, particularly machine tools. By mandating comprehensive health and safety requirements, the directive not only protects machine operators, but also harmonizes safety standards across member states, thereby ensuring a uniform level of protection and a seamless cross-border market for machinery products (Neudörfer, 2020). Central to achieving this uniformity and high level of safety are harmonized standards, such as ISO 14120 (ISO 14120) and ISO 23125 (ISO 23125). These standards provide detailed specifications and guidelines that align with the overarching objectives of the directive 2006/42/EC (Directive 2006). For the protection of machine tool operators against mechanical hazards ISO-standards (ISO 14120; ISO 23125) mandate the use of safeguards and define testing procedures to demonstrate an adequate level of safety. Those testing procedures involve impact tests with a standardized steel projectile, which are subsequently evaluated according to the aforementioned standards. According to ISO-standards (ISO 14120; ISO 23125) a safeguard passes an impact test if the damage pattern features nothing more than bulging and/or incipient cracks visible only on the impact side of the safeguard. Any other damage pattern, e.g. a continuous crack from the impacted to the averted side of the safeguard or a full penetration, results in a failed test (ISO 14120; ISO 23125). The key parameter to quantify a safeguard's ability to withstand an impact is the so-called impact resistance (IR) Y, which is defined as maximum kinetic projectile energy E_{pr} a safeguard is able to withstand. Given that the IR Y is a quantity that cannot be measured directly, it is generally derived from the analysis of an impact test series.

A classical procedure for deriving the IR Y is the bisection method. This method starts by establishing a broad interval where the IR Y is presumed to exist, and then progressively narrows this range to a sufficiently small interval by additional impact tests (Landi et al., 2022; Uhlmann et al., 2021). A critical characteristic of the bisection method is its reliance on the two last impact tests used to define the narrow interval. Assessing whether the two last impact tests results are representative for the entire test series or whether they merely represent outliers, is impossible due to the limited number of tests. Addressing this limitation Uhlmann et al. (Uhlmann et al., 2017, 2022) employed a normal distribution to model an impact test series, which permits a reliable statistical evaluation of the results. However, fitting a normal distribution to the results of an impact test series has drawbacks of its own, as it requires extensive data preparation. According to Uhlmann et al. (Uhlmann et al., 2023) this process of data preparation can significantly influence the results of the normal distribution fitting. Thus, they suggested the use of a logistic regression model and demonstrated the same accuracy in predicting the IR Y for both distributions. A notable advantage of the logistic regression model is its capacity for direct application to impact test results without the need for preliminary data preparation, rendering it a more efficient and practical choice for modeling purposes (Uhlmann et al., 2023). However, a data set of $n_{pc} = 104$ impact tests was analyzed in their investigation. The number of impact tests n_{pc} is notably large, considering that a typical data set for assessing the IR Y with the bisection method generally includes $4 \leq n_{pc} \leq 6$ impact tests (Landi et al., 2022, Uhlmann et al., 2022).

The present paper is motivated by the substantial discrepancy on number of impact tests n_{pc}, aiming to demonstrate the determination of IR Y using a total number of $n_{pc} = 10$ impact tests. Moreover, the accuracy of the logistic regression approach is validated through a goodness-of-fit (GOF) examination and additional impact tests. A subsequent analysis of odds O and odds rations O_r provide further insights into the safety performance of the safeguards.

2. Experimental and mathematical methods

2.1. Impact test facility

This study focuses on impact tests carried out on square Exolon GP clear 099 polycarbonate (PC) vision panels with a width of $w_{pc} = 500$ mm and a thickness of $t_{pc} = 12$ mm. PC is a common material for vision panels in machine tools, making the comprehension of its structural response under impact load crucially important (Neudörfer, 2020). All impact tests were conducted at the Institute for Machine Tools and Factory Management (IWF) of TU Berlin, as illustrated in Figure 1(a). The velocity of the projectile v_{pr} is controlled by the acceleration length l_a of the projectile and the pressure p in the pressure tank. The projectile's velocity v_{pr} between the barrel's exit and the PC-vision panel is measured by a light barrier. The impact test facility is equipped with two high-speed cameras to capture the impact. The PC-vision panel itself is fastened to a frame using screw clamps, with an overlapping width of $w_o = 25$ mm, as depicted in Figure 1(b). This frame in turn is secured to the test sample mount using additional screw clamps.

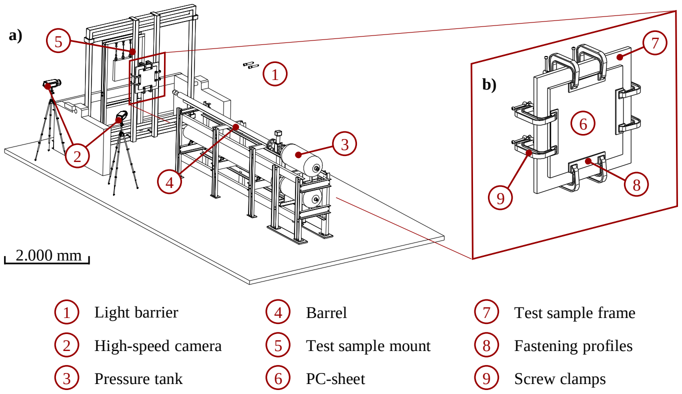

Fig. 1. Impact test facility: (a) Isometric view of entire test facility; (b) Detailed view of the PC-vision panels mounting conditions.

2.2 Logistic regression

Logistic regression has evolved as a statistical tool for analyzing the relationship between a binary outcome variable Y_d and an explanatory variable x. In logistic regression this relationship is described by a quantity called conditional mean $E(Y_d|x)$, which represents the expected outcome variable Y_d given a certain value of the explanatory variable x (Hosmer et al., 2013). The logistic regression model reads as shown in (1).

$$E(Y_d\,|\,x) \;=\; \pi(x) \;=\; \frac{e^{\beta_0+\beta_1 x}}{1-\; e^{\beta_0+\beta_1 x}}$$

Note, that the quantity $\pi(x) = E(Y_d|x)$ has been introduced in (1) for the sake of simplifying the notation. In the logistic regression model, the explanatory variable x is weighted by unknown parameters β_0 and β_1, which in turn are associated to the mean $\bar{x}$ and the standard deviation (STD) s of the logistic regression model, see (1).

$$\begin{aligned}\beta_0 &= -\bar{x}/s\\ \beta_1 &= 1/s\end{aligned} \tag{1}$$

Similar to linear regression these parameters must be estimated. Within the context of logistic regression this is generally accomplished by means of a likelihood estimation (Stoltzfus, 2011), which yields values that maximize the probability P of obtaining the observed data (Hosmer et al., 2013). Given a set of n independent observations, each defined by $i = 1, 2, \ldots, n$ independent variables x_i and binary outcome variables y_i the maximum likelihood function l yields (2) (Hosmer et al., 2013).

$$l(\beta_0, \beta_1) \;=\; \prod_{i=1}^{n} \pi(x_i)^{y_i}[1 \;-\; \pi(x_i)]^{1-y_i}. \tag{2}$$

However, in logistic regression it is mathematical beneficial to work with a log-likelihood function L, instead of the maximum likelihood function l (Hosmer et al., 2013), which is defined as shown in (3).

$$L(\beta_0, \beta_1) \;=\; ln[l(\beta_0, \beta_1)] \;=\; \sum_{i=1}^{n}\{y_i\, ln[\pi(x_i)] \;+\; (1 \;-\; y_i) ln[1 \;-\; \pi(x_i)]\} \tag{3}$$

The solution of (3) is typically computed numerically (Hosmer et al., 2013) and was performed in case of the present study using the PYTHON module STATSMODELS.

3. Logistic regression for impact tests

3.1. Experimental design

The successful application of logistic regression requires a well-planned experimental design, in particular when dealing with limited data sets. The primary objective of this study is to determine the IR Y using a small data set of n_{pc} = 10 impact tests. A major challenge posed by such compact data sets is ensuring that each test adds significant value to the logistic regression model. Logistic regression as being a predictive analysis requires a conclusive and representative range of data to adequately model the relationship between the explanatory variable x and the outcome variable Y_d. Gathering representative data from impact tests is especially demanding, since it requires approximative knowledge about the IR Y prior to the impact tests. An inadequately chosen interval for the explanatory variable x could result in an over-representation of one outcome in the outcome variable Y_d. For impact tests explanatory variable x represents the kinetic projectile energy E_{pr}, whereas the outcome variable Y_d describes the probability of observing a failed impact tests P according to ISO 23125 (ISO 23125). If, for instance, the n_{pc} = 10 tests are placed in an interval of projectile energies E_{pr} where only failed impact tests are observed, little information can be drawn from these test results and more importantly, this data cannot be represented by a logistic regression model. Thus, the interval of projectile energies E_{pr} must feature a balanced quantity of both passed and failed impact tests.

Equally important is the distribution of individual impact tests within the selected interval. A well-distributed set of tests throughout the interval ensures a more comprehensive understanding of the IR Y across different scenarios. In contrast, a poorly distributed set of tests may lead to numerical issues, like complete separation. Generally speaking complete separation describes the case in which the outcome variables Y can be divided by a vector – or in case of only one explanatory variable x – a line α and only one of the two possible outcomes can be found on each side of this line (Albert et al., 1984). As a consequence, the maximum likelihood estimator become unbiased, resulting in infinite parameter estimates, or in other words unreliable results (Mansournia et al., 2018). An illustration of a complete separation for impact tests is shown in Figure 2 alongside with a logistic regression model of well-distributed impact test data. Note, that the experimental results are categorized as either zero or one, whereas one represents a failed impact test according to ISO-standards (ISO 23125) and vice versa.

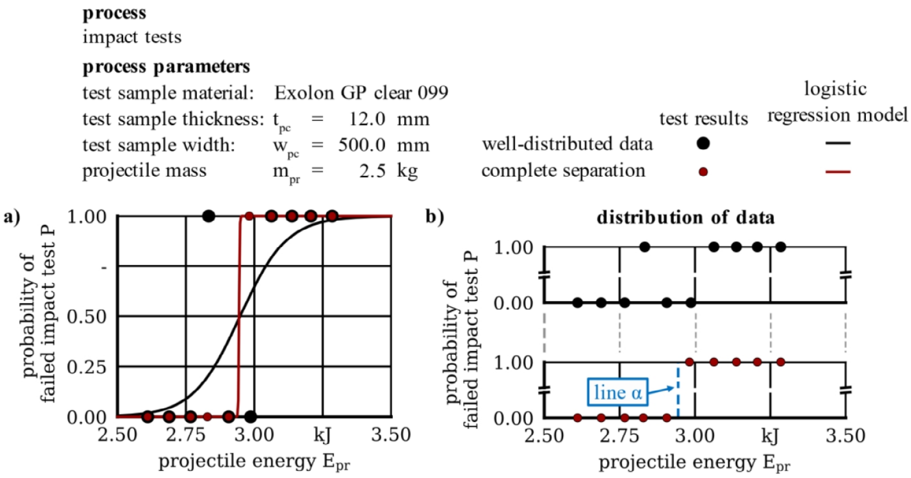

Fig. 2. Example illustrating the effect of complete separation;
(a) logistic regression model; (b) detailed presentation of the test data distribution.

On this account, it can be concluded that the success of logistic regression analysis applied to impact tests heavily depends on two key factors:

- a well-suited interval of projectile energies E_{kin} that consists of a balanced quantity of passed and failed impact tests as well as
- well-distributed impact test results within the interval, to avoid complete separation.

Meeting both conditions is challenging without prior knowledge of the impact test outcome. However, the ballistic limit velocity (BLV) v_{bl} serve as estimate for the upper limit of this interval. The BLV v_{bl} is another quantitative metric for the safety performance of safeguards based on the work of Recht and Ipson (Recht et al., 1963). It is defined as minimum projectile velocity v_{pr} that is required to completely perforate a safeguard and emerge from it with a projectile velocity of v_{pr} = 0 m/s (Ben-Dor et al., 2006). Hence, safeguards subjected to an impact with BLV v_{bl} feature by definition damage patterns considered as failed test according to ISO-standards (ISO 23125). Since the BLV v_{bl} and its corresponding ballistic limit projectile energy $E_{pr,bl}$ represents the minimum projectile energy E_{pr} required to obtain a complete perforation, both quantities provide a reasonable estimate for the upper interval limit.

In addition to estimating the upper interval limit, it is equally important to approximate the lower interval limit. In this context, the studies conducted by Landi et al. (Landi et al., 2022) and Uhlmann et al. (Uhlmann et al., 2021) provide essential insight. Their investigation into the relationship between IR Y and the ballistic limit projectile velocity $E_{pr,bl}$ resulted in the derivation of an approximation formula, in which a so-called reduction coefficient $c_{R,E}$ was introduced that establishes a link between the IR Y and ballistic limit projectile velocity $E_{pr,bl}$, as shown in (4).

$$Y = \frac{E_{pr,bl}}{c_{R,E}} \tag{4}$$

Both investigations found slightly different values for the reduction coefficient $c_{R,E}$, but observed a strong dependence on the dimensions of the impacted safeguard. Since Uhlmann et al. (Uhlmann et al., 2021) utilized PC-vision panel dimensions identical to those in the present study, their results are adopted as a basis for approximating the lower interval limit. The interval for the impact tests is defined as shown in (5).

$$6.2 \text{ kJ} \leq E_{pr} \leq 7.6 \text{ kJ} \tag{5}$$

To avoid accuracy problems due to complete separation, the majority of the impact tests were performed in the middle of the interval, with fewer tests at the limits. Figure 3 and Table 1 show the impact test results together with the logistic regression model and its corresponding model parameters.

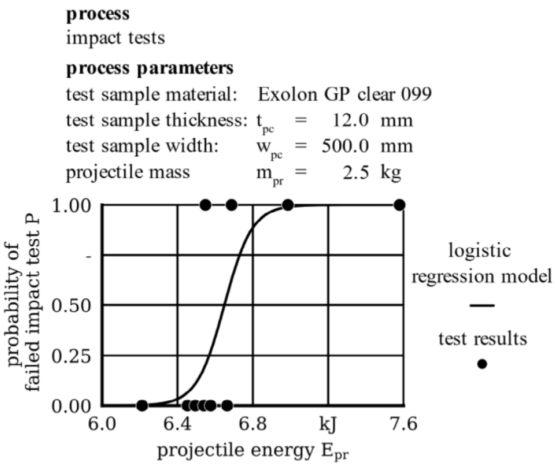

Fig. 3. Experimental impact test results and logistic regression model.

Table 1. Results of the logistic regression.

Parameter of logistic regression model	value
Mean $\bar{x}$ in kJ	6.6
STD s in kJ	$7.3 \cdot 10^{-3}$

An examination of the data presented in Figure 3 reveals that the key criteria essential for a successful application of the logistic regression were fulfilled in the test series. The results exhibit a balance of both passed and failed impact tests. More importantly, the concentration of impact tests towards the middle of the test interval effectively prevented the occurrence of complete separation on the logistic regression model. Nevertheless, a thorough assessment of the model's accuracy is crucial, given the novelty of this approach in the context of impact tests and the limited size of the data set the logistic regression model is based on.

3.2. Model validation

The validation of the logistic regression model is accomplished by an inspection of the model's GOF. For a small data set of $n_{pc} = 10$ impact tests the pseudo R^2-value according to McFadden (McFadden, 1977) is an appropriate choice. It should be noted, that the pseudo R^2-value works differently than the similar coefficient of determination in linear regression R^2_{lin}. In logistic regression values ranging from $0.2 \leq R^2 \leq 0.4$ indicate a good model fit (McFadden, 1977). With a pseudo R^2-value of $R^2 = 0.47$ the present model fits the data very well. Although, the pseudo R^2-value offers a statistical measure of the model's capacity to predict the experimental data, it does not evaluate the physical plausibility of these predictions.

To assess the model's capability to generate physically plausible predictions, additional impact tests were carried out across three distinct ranges. These ranges were defined to anticipate a low, medium and high probability of encountering a failed impact test P, as predicted by the logistic regression model. For each range $n_{pc,v} = 5$ additional impact tests were conducted. To provide a quantitative basis for evaluating the accuracy of the logistic regression model, the number of anticipated failed impact tests $n_{fail,e}$ was calculated, according to (6).

$$n_{fail,e} = P \cdot n_{pc,v} \tag{6}$$

Table 2 shows the detailed description of the expected probabilities P, the corresponding projectile energies E_{pr} and the expected number $n_{fail,e}$ of failed impact tests. Note, that the results for the expected number $n_{fail,e}$ has been rounded to the nearest whole number.

Table 2. Specifications of ranges defined for logistic regression model validation.

Property	Range I	Range II	Range III
Expected probability of failed impact tests P	$0.01\ \% \leq P \leq 5.00\ \%$	$30.00\ \% \leq P \leq 70.00\ \%$	$95.00\ \% \leq P \leq 99.99\ \%$
Projectile energy E_{pr}	$5.97\ \text{kJ} \leq E_{pr} \leq 6.43\ \text{kJ}$	$6.59\ \text{kJ} \leq E_{pr} \leq 6.71\ \text{kJ}$	$6.86\ \text{kJ} \leq E_{pr} \leq 7.67\ \text{kJ}$
Expected number n_{fail} of failed impact tests	$n_{fail,e} < 1$	$2 \leq n_{fail,e} \leq 4$	$n_{fail,e} \geq 5$

The results of the additional impact tests are shown in Figure 4.

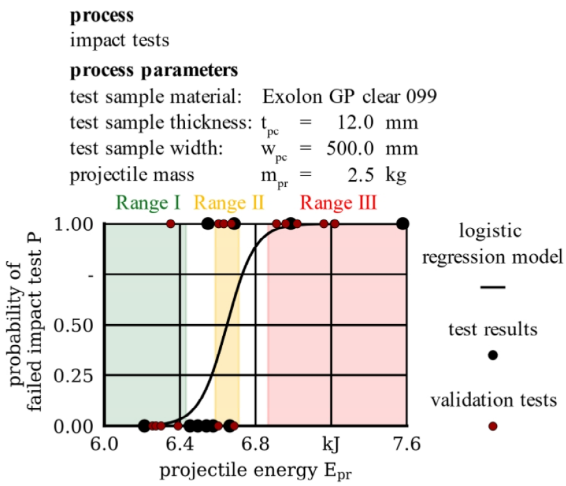

Fig. 4. Experimental impact test results alongside validation and logistic regression model.

All additional impact tests for validation purposes were placed successfully in the designated range. When comparing the expected number of failed impact tests $n_{fail,e}$ from Table 2 with the actual validation results in Figure 4 an overall good accuracy of the logistic regression model can be observed. However, for Range I $n_{fail,e} < 1$ failed impact tests were expected, when $n_{fail} = 1$ failed impact tests were in fact observed in the tests. This allows for two possible explanations:

1. The model's predictions for Range I are inaccurate or
2. The model is accurate and the unexpected observation of $n_{fail} = 1$ impact tests is merely a consequence of the fact, that the probability P of finding such a behavior is low, but not zero.

What speaks in favor of the second argument is the model's capacity to predict the outcome in Range II and III precisely. With $2 \leq n_{fail,e} \leq 4$ predicted and $n_{fail} = 3$ observed failed impact tests in Range II, the results demonstrate precisely the behavior anticipated. The same is true for Range III, where the number of experimentally observed failed impact tests n_{fail} matches perfectly the prediction of $n_{fail,e} \geq 5$ failed tests. Given the symmetry of the logistic regression model around the mean $\bar{x}$ at a probability of $P = 0.5$, the likelihood of the model to accurately predict outcomes for Ranges II and III while exhibiting reduced precision on Range I is minimal. However, such a scenario cannot be conclusively dismissed without further testing. Despite the observed discrepancies in predictive accuracy for Range I, the overall alignment of the model's predictions with experimental outcomes in Ranges II and III underscores its robust predictive capabilities. Consequently, the model is considered valid for modelling the impact test series. Nevertheless, the two failed tests in Range I highlight the stochastic character of a PC-vision panels response under impact load.

4. Analysis of safety performance

With the demonstrated capabilities of the model, it is now feasible to analyze the safety performance of the investigated PC-vision panel. This analysis includes utilizing the logistic regression model to derive a probabilistic value for the IR Y, whereas the IR Y in context of a logistic regression is defined according to (7).

$$Y := \pi\,(x = 0.01) = 6.3 \text{ kJ} \tag{7}$$

Besides an evaluation of the mere safety performance the application of odds *O* and odds ration O_r allow for an in-depth understanding of the evolving probabilities associated with observing failed impact tests ***P***. The quantity in (8) is called odds *O* (Montgomery et al., 2014).

$$O(x) = \frac{\pi(x)}{1 - \pi(x)} = e^{\beta_0 + \beta_1 x} \tag{8}$$

In general, the odds *O* allows to quantify the strength of the association between the explanatory variable x and the outcome variable Y_d. In terms of impact tests, they can be interpreted as increase in the probability of observing a failed impact test ***P***. For instance, if the odds are $O = 2$ for a specific projectile energy E_{pr}, this indicates that observing a failed impact test is twice as probable as seeing a passed impact test at that particular projectile energy E_{pr}. Figure 5 shows the odds *O* for the PC-vision panels investigated in this study.

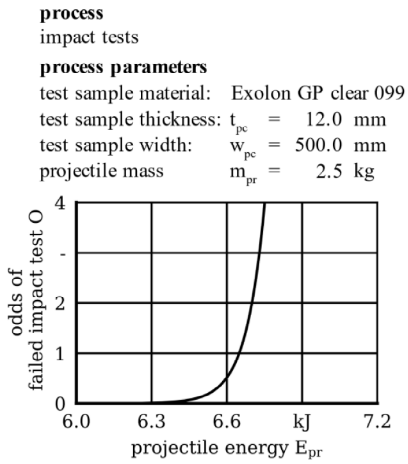

Fig. 5. Odds O of observing a failed impact test.

From examining Figure 5 the pronounced exponential increase off odds *O* for a growing projectile energy E_{pr} is evident. This is also illustrated by the odds ratio, defined as $O_r = e^{\beta_1}$. The current logistic regression model has an odds ratio of $O_r = 80.1 \cdot 10^4$ kJ $^{-1}$, or expressed in joules $O_r = 1.01$ J $^{-1}$. This means that with every $E_{pr} = 1$ J increase in projectile energy the odds *O* of a failed impact test increase by a factor of 1.01, which underscores the significant sensitivity of impact test results to even minor variations in projectile energy E_{pr}.

The analysis of odds *O* and odds ratios O_r within the logistic regression framework enables a critical re-evaluation of the current procedure for assessing the safety performance of PC-vision panels. To date, the evaluation of PC-vision panels' safety performance has been focused entirely on their IR Y. However, the odds *O* found in this study suggest that while IR Y is indeed safe in probabilistic terms, it simultaneously is an "unstable" safety level.

Notably, a slight increase in the projectile energy E_{pr} by only 5 % above the IR of Y = 6.3 kJ already increases the probability of a failed impact test to P = 42.4 %. This significant susceptibility to slight variations in projectile energy E_{pr} strongly suggests the need for a reassessment of the IR Y threshold. In light of these findings, and considering the implications of the odds O, it appears prudent to further reduce the IR Y to a level where minor fluctuations do not precipitate hazardous outcomes. Although the precise reduction factor for the IR Y of PC-vision panels may depend on their specific dimensions and remains yet to be determined, the findings of this study indicate that a 5 % decrease in projectile energy E_{pr} consistently leads to a safer threshold. A 5 % reduction of IR Y thus yields a compensated IR of Y_c = 5.9 kJ. This observation suggests the necessity of incorporating odds O in the determination of IR Y, to ensure enhanced safety.

5. Conclusion

The primary aim of this study was to demonstrate the application of logistic regression in the context of impact tests, utilizing a small dataset of only n_{pc} = 10 impact tests. The validity of the logistic regression model was assessed through GOF metrics and supplementary validation tests. These additional tests are in good agreement with the model's predictions, affirming its reliability. However, they also highlight the inherent probabilistic nature of the response of PC-vision panels under impact load.

A deeper analysis of the safety performance of the panels on basis of the logistic regression model, indicates that relying solely on the evaluation of IR Y could lead to potentially unsafe conclusions. The model's odds O suggest that even minor fluctuations in projectile energy E_{pr} significantly increase the likelihood of hazardous outcomes in impact tests. Consequently, this study proposes a further reduction of the IR Y by 5 %. This investigation underscores that valuable insights can be drawn from a small dataset of n_{pc} = 10 impact tests, thereby highlighting the efficacy and potential of the logistic regression approach in evaluating the safety performance of PC-vision panels.

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