

ARTIFICIAL INTELLIGENCE IN THE JUDICIARY IN BRAZIL: AN ANALYSIS THROUGH THE TECHNOLOGY ACCEPTANCE MODEL (TAM)

INTELIGÊNCIA ARTIFICIAL NO PODER JUDICIÁRIO NO BRASIL: UMA
ANÁLISE PELO MODELO DE ACEITAÇÃO TECNOLÓGICA (TAM)

Ciências Humanas • 26/10/2026

REGISTRO DOI: [10.70773/revistatopicos/792899041](https://doi.org/10.70773/revistatopicos/792899041)

Felipe Nery da Silva¹

Robert Armando Espejo²

ABSTRACT

Artificial Intelligence (AI) is viewed as a promising response to delays and overload in the Brazilian Judiciary, but its effective adoption depends on users' acceptance. This study applies the Technology Acceptance Model (TAM) to examine factors influencing AI acceptance among personnel of the Judiciary of Mato Grosso do Sul (PJMS). Based on a quantitative survey of 507 respondents, analyzed through Structural Equation Modeling, the results confirmed the model's validity in the judicial context, with satisfactory fit indices. All hypothesized paths were statistically significant, especially perceived ease of use on perceived usefulness and perceived usefulness on attitude toward use. The findings show that training is the main challenge and a strategic priority for safe and responsible AI implementation.

Keywords: Artificial Intelligence; Judiciary of Mato Grosso do Sul; Technology Acceptance Model (TAM).

RESUMO

A Inteligência Artificial (IA) apresenta-se como uma solução promissora para enfrentar a morosidade e a sobrecarga do Poder Judiciário brasileiro, embora sua efetiva adoção dependa da aceitação pelos usuários. Este estudo aplica o Modelo de Aceitação de Tecnologia (Technology Acceptance Model – TAM) para examinar os fatores que influenciam a aceitação da IA entre os integrantes do Poder Judiciário de Mato Grosso do Sul (PJMS). Com base em uma pesquisa quantitativa realizada com 507 respondentes, cujos dados foram analisados mediante Modelagem de Equações Estruturais, os resultados confirmaram a validade do modelo no contexto judicial, com índices de ajuste satisfatórios. Todas as relações hipotetizadas apresentaram significância estatística, destacando-se, especialmente, a influência da facilidade de uso percebida sobre a

utilidade percebida e desta sobre a atitude em relação ao uso. Os resultados evidenciam que a capacitação constitui o principal desafio e uma prioridade estratégica para a implementação segura e responsável da Inteligência Artificial.

Palavras-chave: Inteligência Artificial; Poder Judiciário de Mato Grosso do Sul; Modelo de Aceitação de Tecnologia (TAM).

1. INTRODUCTION

Numerous technological advances have been incorporated into society over the past decades and support scholars' perception that the next Industrial Revolution—the fourth—has already begun (Cabral; Santiago, 2022). Among these innovations, Artificial Intelligence (AI) emerges as a prominent strategic resource for increasing productivity and reducing operational costs (Schmidt et al., 2025).

Driven by recent progress in solving complex tasks that previously depended almost exclusively on human intelligence (Steffen, 2023), this tool has been presenting new opportunities for optimization across various fields (Xu et al., 2021), including the judicial sphere, where it is expected to assist in addressing historical challenges such as procedural delay and workload overload (Ribeiro; Carneiro, 2025).

Interest in this technology appears to be intensifying within the Brazilian Judiciary. The most recent survey conducted by the National Council of Justice (2025) reveals that, in the base year 2024 alone, 98 new AI projects were developed in courts and councils, totaling 178 active initiatives when also considering solutions conceived in previous years but currently at different stages of

production. According to the report, in 2023 there were 140 registered AI projects, and in 2022, 111 projects.

The expansion of this portfolio reflects the adoption of an institutional strategy deemed indispensable to confront the mismatch between the explosive number of judicial demands and the Judiciary's capacity to process them (Berzagui; Silva, 2022; Brito; Fernandes, 2020). Artificial Intelligence—and its ability to process large volumes of data—is thus perceived as an operational lifeline in the face of the phenomenon of “hyper-judicialization” and the crisis of effectiveness that threaten the functionality of the justice system (Tauk; Salomão, 2023).

The slowness of Brazilian justice is, in fact, not a recent phenomenon. Experts point to various causes for its occurrence and persistence, ranging from excessive litigation (low filing costs, a culture of judicialization, excessive procedural appeals) to structural and normative obstacles (a large number of lawyers per capita, the impossibility of greater delegation of routine procedural acts), among other factors (Castelliano, Guimaraes and Gomes, 2024).

This scenario is reflected in the numbers. The most recent “Justice in Numbers” report issued by the National Council of Justice (2025) indicates that, at the end of 2024, approximately 80.6 million cases were pending resolution in the country, which also recorded the highest number in the historical series of new filings, totaling 39.4 million new cases, compared to 36.9 million in the previous year, representing a 6.7% increase in litigation, exceeding the estimated population growth of 4.68% between 2023 and 2024 (Barbosa, 2024).

Paradoxically, the report also indicates that the Brazilian Judiciary, even considering the decline in 2020 due to the COVID-19 pandemic, has accumulated an expressive 88.2% increase in productivity over the past 15 years and, even so, it is estimated that, in a hypothetical scenario without new filings, it would require 1 year and 10 months to eliminate the backlog if the current processing capacity of judges and court staff were maintained (National Council of Justice, 2025).

This picture reveals the exhaustion of the national justice system. It is no “secret that the Brazilian Judiciary faces a workload far beyond its operational capacity” (Martini, Prado and Paula, 2024, p. 143), generating considerable dissatisfaction among litigants (Gomes, Ferreira and Andrade, 2022), who are unable to obtain their rights within a reasonable time frame relative to their practical utility, and contributing to the overload of legal professionals (Ribeiro; Lima, 2022).

Nevertheless, despite the growing interest and although specialized literature (Berzagui; Da Silva, 2022; Valle et al., 2023; Brito; Fernandes, 2020; Jiya; Samaila; Surajo, 2023, among others) has identified that Artificial Intelligence may be used in the Judiciary to increase efficiency by reducing the time and cost of case processing, the effective incorporation of these solutions into institutional routines does not arise automatically from their technical availability or projected benefits (Guitton et al., 2025; Jankovski et al., 2025).

The present study therefore aims to analyze the factors that influence the acceptance of Artificial Intelligence by the personnel of the Court of Justice of Mato Grosso do Sul (TJMS)³, in order to identify challenges that may limit the effective use of this tool to improve judicial services. To this end, it is grounded in the

Technology Acceptance Model (TAM), developed by Davis (1989), which explains users' behavioral intention based on two central constructs: perceived usefulness—that is, the degree to which the user believes that the technology improves job performance—and perceived ease of use, related to the level of effort required to use the system (Nguyen; Do; Wu, 2021).

Based on this problem, the research seeks to answer the following central question: **Which factors influence the acceptance of Artificial Intelligence by the personnel (judges and court staff) of the Court of Justice of Mato Grosso do Sul, considering the elements of the Technology Acceptance Model (TAM)?**

From this main research question, the following sub-questions are derived: **a)** Do TJMS personnel perceive Artificial Intelligence as useful for improving their professional performance? **b)** Does perceived ease of use influence their willingness to use the tool in daily activities? **c)** What are the main challenges, in the perception of TJMS personnel, for the adoption of AI technology?

2. TECHNOLOGY ACCEPTANCE MODEL – TAM

As previously mentioned, TAM was proposed by Davis (1989) based on the Theory of Reasoned Action (TRA) developed by Fishbein and Ajzen. Its objective is to identify and explain the determining factors of technology acceptance and use, considering specific beliefs about usefulness and ease of use. Unlike other models, such as UTAUT (Venkatesh et al., 2003), TAM focuses on two central constructs: Perceived Usefulness (PU) and Perceived Ease of Use (PEOU), establishing a direct relationship between the user's perception of the technology and their willingness to use it.

The traditional TAM model is composed of five main constructs. Perceived Usefulness (PU) corresponds to the degree to which a user believes that using the technology will improve job performance (Davis, 1989). Perceived Ease of Use (PEOU) refers to the degree to which a user believes that using the technology will be free of effort (Davis, 1989). Attitude Toward Use (ATT) represents the favorable or unfavorable evaluation that an individual holds regarding the use of the technology, directly influencing their willingness to adopt it. Behavioral Intention to Use (BI), in turn, expresses the probability that the individual will actually use the technology at a future moment and is considered a strong predictor of actual behavior.

Finally, Actual Use (UR) refers to the frequency and the effective manner in which the technology is used, representing the practical materialization of the perceptions and intentions previously formed within the model. In the context of the TJMS study, these constructs were evaluated through a structured questionnaire, encompassing perceptions regarding the application of artificial intelligence in the judicial environment.

TAM establishes a set of causal relationships describing how users' perceptions and beliefs influence their behavior. PEOU exerts a direct influence on PU, since systems perceived as easier to use tend to be considered more useful. Both PU and PEOU affect BI, with PU usually presenting a greater direct impact on intention to use. In some formulations of the model, ATT acts as a mediator between PU and BI, reinforcing the effect of perceived usefulness on behavioral intention. BI, in turn, is the main predictor of UR, translating declared intention into effective behavior. This theoretical structure has been validated in multiple contexts, including the educational

environment (Masrom, 2007; Scherer, Siddiq and Tondeur, 2019), mobile services (Lu, Yu and Liu, 2009), green technology practices (Akman; Mishra, 2015), and review and meta-analysis studies (King; He, 2006; Marangunić; Granić, 2015).

Studies applying TAM generally employ rigorous statistical techniques to validate constructs and test the proposed relationships. The reliability of the scales is often evaluated through Cronbach's alpha coefficient and composite reliability, ensuring the internal consistency of the indicators. Construct validity is commonly verified through confirmatory factor analysis, which tests unidimensionality and the adequacy of factor loadings. To estimate causal relationships among constructs, Structural Equation Modeling (SEM) is widely used, both in covariance-based approaches, such as LISREL, and in variance-based methods, such as Partial Least Squares (PLS) (King and He, 2006). Resampling techniques, such as bootstrapping, are applied to verify the statistical significance of coefficients, increasing the robustness of the conclusions.

By applying TAM to the context of artificial intelligence adoption within the Judiciary of Mato Grosso do Sul, the aim is to identify which perceptions exert the greatest influence on the acceptance of this technology by court staff. The analysis makes it possible to determine whether perceived usefulness is the predominant factor or whether aspects such as ease of use, general attitudes, or external factors, such as institutional support, play a more relevant role. Based on these results, it will be possible to formulate implementation strategies, training initiatives, and communication policies that maximize acceptance and effective use of AI in the judicial environment.

3. STATISTICAL APPROACH – STRUCTURAL EQUATION MODELING (SEM)

Structural Equation Modeling (SEM) is a multivariate statistical technique that combines aspects of factor analysis and multiple regression to examine dependency relationships between observed and latent variables (Kline, 2016). In the context of TAM, SEM makes it possible to validate the structure of the constructs and simultaneously test the hypotheses regarding their interrelationships.

In the TJMS study, SEM was applied to estimate the path coefficients among the constructs PU, PEOU, ATT, and BI, using the Partial Least Squares (PLS) method. The model presented satisfactory fit indices, indicating that more than half of the variation in intention to use is explained by the constructs of the model.

4. FISCHER'S EXACT TEST

Fisher's Exact Test (1922) is a statistical procedure used to verify the association between categorical variables, especially useful when expected frequencies are small. In the present study, this test was employed to assess whether there was a significant association between demographic variables (such as length of service and position held) and responses to the TAM constructs.

The results indicated, for example, a significant association between position within the TJMS and perceived usefulness of AI ($p = 0.03$), suggesting that positions with a greater workload of administrative activities tend to perceive greater benefits in the adoption of the technology.

5. METHODOLOGY

The research was developed within the field of Applied Social Sciences, with an interdisciplinary approach between Law and Administration, adopting an applied nature and an exploratory character. An inductive method was used, with a case study strategy at the Court of Justice of Mato Grosso do Sul, based on the collection of primary data from court staff and judges of the institution.

The methodological design prioritized a quantitative approach, focusing on the analysis of users' perceptions and behavioral dispositions regarding the use of Artificial Intelligence in the judicial context. Data were collected through a structured questionnaire developed based on the Technology Acceptance Model (TAM), administered electronically through the Microsoft Forms and Google Forms platforms, and disseminated to participants via institutional e-mail and the Microsoft Teams application.

The responses obtained were subjected to statistical treatment, and the results were organized and presented through tables, graphs, and a word cloud, in order to identify factors associated with familiarity, intention to use, and perceptions of usefulness and ease of use of Artificial Intelligence within the Court of Justice of Mato Grosso do Sul.

The study sought to provide empirical support for understanding the challenges related to the acceptance of Artificial Intelligence in the Judiciary, as well as to assist in planning institutional strategies aimed at training and the effective use of these technologies, considering that the adoption of technological systems largely

depends on users' willingness to accept and use them, as established by the Technology Acceptance Model.

6. PROCEDURE

In the first stage of the study, primary data were collected through a questionnaire administered via the Microsoft Forms and Google Forms platforms. Considering that, according to data from the National Council of Justice (CNJ, 2025, p. 38), the Judiciary of Mato Grosso do Sul has a workforce of 5,673 individuals (216 judges and 5,457 court staff), a minimum sample of 360 respondents was calculated to ensure a margin of error limited to 5% (five percent) and a confidence level of 95% (ninety-five percent).

It is noteworthy that, when maintaining the same parameters and substantially altering only the total population size, the required sample presents minimal variation. Thus, in a hypothetical scenario, even if there were a 50% reduction or increase in the workforce, it would be necessary to administer the questionnaire to 339 or 368 individuals, respectively. For a population of 100,000 people, the required sample would be 383 individuals.

Accordingly, as 507 respondents participated in the study, the obtained sample largely exceeded the minimum required.

The selection of the Court of Justice of Mato Grosso do Sul as the empirical field of the research proves to be quite strategic due to its singular position in the CNJ (2025) classification, which divides state courts into small-, medium-, and large-sized categories. This is because the most numerous category comprises courts classified as small-sized, totaling 12 members, among which the TJMS is the largest. This grants it high sample representativeness while

preserving lower complexity when compared to medium-sized courts, with nine members, and large-sized courts, with only six members. Thus, it is expected that the combination of these factors (sample representativeness and ease of study) may favor the subsequent replication of the study in courts with different structural profiles (Bonett, 2021).

In summary, the questionnaire was structured into seven sections, each designed to capture specific dimensions of Artificial Intelligence acceptance within the Judiciary of Mato Grosso do Sul.

The first section, consisting of six questions, was dedicated to the respondent's profile, aiming to identify their institutional affiliation with the PJMS, predominant area of activity, length of service, gender, age group, and educational background.

In the second section, seven questions were posed in order to assess the respondent's familiarity with Artificial Intelligence, including prior knowledge of the topic, previous use of the technology, participation in training courses and the respective educational institution, personal perception of preparedness to use the innovation, beliefs regarding the degree of importance of AI in their professional activities in the coming years, and, finally, interest in training.

The third and fourth sections gathered, respectively, the variables of perceived usefulness and perceived ease of use of the TAM model, all measured using the scale developed by Rensis Likert in 1932, as it is widely adopted in social and educational research due to its recognized ability to scientifically assess opinions, perceptions, and feelings (Joshi et al., 2015). Thus, a total of nine statements were

formulated in these sections, and respondents were asked to indicate their level of agreement by choosing among the following options: (a) strongly agree; (b) agree; (c) neutral; (d) disagree; and (e) strongly disagree.

In the perceived usefulness section, statements were presented such as “The use of Artificial Intelligence contributes to reducing case processing time” and “Artificial Intelligence is useful for automating repetitive tasks and improving productivity,” as well as propositions related to the standardization of procedures, assistance in complying with ethical and legal principles, and improvement in the quality of services provided by the Judiciary.

In the section focused on perceived ease of use, statements included “I believe that Artificial Intelligence tools are easy to learn and use in daily activities” and “The Artificial Intelligence tools I know or have had contact with provide clear instructions for use,” in addition to items assessing perceptions regarding the availability of adequate technical support and the ease of understanding how the technology operates within the context of the activities performed.

The fifth section of the questionnaire focused on resistance and concerns associated with technology adoption, seeking to identify perceptions regarding the possible replacement of human labor, ethical concerns, institutional barriers, and risks to impartiality and transparency in decision-making. It also assessed the degree of comfort of court staff in adopting such tools, with the latter two aspects being related to the Attitude Toward Use variable of the TAM model.

The sixth section addressed knowledge about the regulation of Artificial Intelligence in the Judiciary, measuring the level of awareness regarding the norms issued by the National Council of Justice, the relevance attributed to such instruments, and the clarity of the information provided by the institution.

Finally, the seventh section included space for open-ended comments in order to collect spontaneous perceptions, suggestions, or criticisms, allowing for the enrichment of the research.

It should be emphasized that the sample was not stratified in order to preserve the anonymity of participants and thus enable more spontaneous and realistic responses, as well as to encourage the participation of judges in the questionnaire without concerns about identification or exposure related to their positions.

Subsequent stages involved data processing and analysis.

Initially, the database was organized and structured based on the export of records collected through the electronic questionnaire. At this stage, the consistency of responses was verified, certain nomenclatures were standardized, and areas of activity were grouped into three categories: administrative, judicial, and undeclared. Categories with an absolute frequency of fewer than six observations, when not analytically relevant, were grouped under the designation "Others" in order to enable inferential analysis. Ordinal variables, such as length of service and age group, were reordered according to a descending logical sequence of responses, while Likert-type scales were maintained in the order in which they were originally presented. The characterization of the sample was conducted through absolute and relative frequencies, represented

by tables, pie charts, and bar charts generated in Excel, aesthetically standardized to ensure visual consistency.

Subsequently, analytical categories were coded and a data dictionary was constructed to ensure the quality and internal coherence of the dataset for subsequent processing in R software, version 4.4.3. Bivariate statistical tests were then performed to verify possible associations between sociodemographic variables and responses provided on the perceptual scales. The selection of tests considered the nature of the variables and the adequacy of statistical assumptions.

Thereafter, Structural Equation Modeling (SEM) was applied within the R environment using the lavaan package, based on the theoretical structure of TAM. This stage involved specifying the theoretical model, estimating parameters, evaluating goodness-of-fit indices, and analyzing direct and indirect effects among the defined constructs.

Associations between explanatory variables and the variable of interest related to the level of comfort in adopting Artificial Intelligence tools were examined using Fisher's exact test, with Monte Carlo simulation based on ten thousand replications, given the predominance of categorical variables and the occurrence of low expected frequencies in some cells. Variables were analyzed in a segmented manner, considering demographic dimensions, familiarity with the subject, perceptions of impacts and usefulness, and aspects related to comfort and adherence.

The modeling stage was grounded in the Technology Acceptance Model (TAM), encompassing three latent constructs: perceived

usefulness, perceived ease of use, and attitude toward Artificial Intelligence. Observed variables were recoded into a five-point ordinal scale, preserving the natural order of responses, and, in the case of negatively worded items, scores were reversed to standardize interpretative direction. The model was estimated using the Weighted Least Squares Mean and Variance Adjusted (WLSMV) method, appropriate for ordinal data, with latent variables standardized.

Model fit evaluation considered the Comparative Fit Index (CFI), Tucker–Lewis Index (TLI), Root Mean Square Error of Approximation (RMSEA), and Standardized Root Mean Square Residual (SRMR), including robust estimates. Standardized factor loadings, structural coefficients, coefficients of determination for each construct, and measures of composite reliability and average variance extracted were obtained.

Finally, the results were interpreted and the final analyses were drafted.

7. RESULTS – DESCRIPTIVE STATISTICS

7.1. Respondent Profile (Section 1)

Considering that the respondent profile is not directly related to the variables of the TAM model, the questions and answers from Section 1 of the questionnaire were presented in the form of **Table 1**.

Table 1. Questions regarding the sociodemographic profile of the respondents

S#	Q#	QUESTION	R1	R2	R3
----	----	----------	----	----	----

SECTION 1 RESPONDENT PROFILE	Q1	What is your affiliation with the Judiciary of Mato Grosso do Sul?	Permanent staff member	Commissioned (non-permanent)	Intern
			400	40	51
			78,9%	7,9%	10,1%
	Q2	In which area do you work?	Judicial	Administrative	Other

⚠ Esta tabela possui muitas colunas e foi cortada para impressão. Para visualizá-la completa, acesse o artigo original em: <https://revistatopicos.com.br/artigos/artificial-intelligence-in-the-judiciary-in-brazil-an-analysis-through-the-technology-acceptance-model-tam?noblockage>

Source: Prepared by the authors based on primary data collected through the questionnaire.

The analysis of the sociodemographic variables shows that the majority of participants are permanent staff members, representing 78.9% (n = 400) of the total, while interns and non-permanent commissioned staff correspond to 10.1% (n = 51) and 7.9% (n = 40), respectively. Affiliations classified as “Others” (2.0%; n = 10) and “Seconded” (1.2%; n = 6) show reduced participation.

With regard to the area of activity, there is a predominance of the judicial area, encompassing 77.9% (n = 395) of respondents, followed by the administrative area, with 20.7% (n = 105), while 1.4% (n = 7) chose not to inform.

Regarding length of service in the Judiciary of Mato Grosso do Sul, more than half have been performing their functions for over ten years (51.3%; n = 260), while 23.1% (n = 117) have been in the institution

between one and five years, 15.6% (n = 79) for less than one year, and 10.1% (n = 51) between six and ten years.

As for gender, 60.2% (n = 305) declared themselves female, 39.4% (n = 200) male, and 0.4% (n = 2) preferred not to respond.

The age distribution of respondents indicates a higher concentration in the 35–44 age group, representing 31.4% (n = 159) of the total, followed by 45–54 years (22.9%; n = 116) and 25–34 years (21.3%; n = 108). Older age groups present smaller proportions, with 12.2% (n = 62) between 55 and 64 years, 11.2% (n = 57) under 25 years, and 1.0% (n = 5) aged 65 years or older.

Regarding educational level, the majority of respondents, 59.4% (n = 301), hold a postgraduate specialization degree. Subsequently, 24.5% (n = 124) completed a bachelor's degree, while 7.7% (n = 39) have a high school diploma or lower. The same percentage, 7.7% (n = 39), declared holding a master's degree, and only 0.8% (n = 4) attained a doctorate.

Thus, in summary, this section of the questionnaire indicates that the sample is predominantly composed of permanent staff members from the judicial area, with long tenure at the PJMS, a predominance of female respondents, age concentration in intermediate groups, and a high level of education, particularly at the specialization level.

7.2. Familiarity With Artificial Intelligence

In **Table 2**, in order to complement the characterization of the sample and provide contextualization, the questions and responses

related to respondents' familiarity with Artificial Intelligence were presented. Question 10 was displayed in the form of a word cloud.

Table 2. Questions related to respondents' familiarity with Artificial Intelligence

S#	Q#	QUESTION	R1	R2	R3
SECTION 2 FAMILIARI TY WITH AI	Q7	Have you heard about Artificial Intelligen ce before this questionn aire?	Yes, I have detailed knowledg e	Yes, I have basic knowledg e	Yes, b do n know exact what i
			75	392	40
			14.8%	77.3%	7.9%

⚠ Esta tabela possui muitas colunas e foi cortada para impressão. Para visualizá-la completa, acesse o artigo original em: <https://revistatopicos.com.br/artigos/artificial-intelligence-in-the-judiciary-in-brazil-an-analysis-through-the-technology-acceptance-model-tam?noblockage>

Source: Prepared by the authors based on primary data collected through the questionnaire.

With regard to prior knowledge about Artificial Intelligence, 77.3% (n = 392) reported having basic knowledge, 14.8% (n = 75) indicated detailed knowledge, and 7.9% (n = 40) stated that they were familiar with the term but lacked clarity regarding its meaning.

Regarding use at work, 39.4% (n = 200) reported occasional use, 26.2% (n = 133) are aware of the technology but do not use it, 18.1% (n = 92) use it regularly, and 16.2% (n = 82) have never used it.

Concerning participation in Artificial Intelligence courses (Question 10), 88.4% (n = 448) have never participated, while 11.6% (n = 59) have completed at least one course on the subject. EJUD/MS accounted for 40% of the responses among participants who chose to specify the institution where they attended an Artificial Intelligence course, as shown in the word cloud presented in **Figure 1**.

Figure 1. Word cloud of the institutions where the courses were completed



Source: Prepared by the authors based on primary data collected through the questionnaire.

Among respondents, the perception of preparedness to use Artificial Intelligence was most concentrated in the “moderate” category (41.8%; n = 212), followed by “low” (33.5%; n = 170), while smaller proportions indicated “very low” (12.4%; n = 63), “high” (9.1%; n = 46), and “very high” (3.2%; n = 16).

Regarding expectations that Artificial Intelligence will become an essential part of work in the coming years, 85.2% (n = 432) responded affirmatively, 9.9% (n = 50) responded negatively, and 4.9% (n = 25) chose not to respond.

With respect to interest in training for the use of the technology, 91.1% (n = 462) expressed interest, 7.7% (n = 39) declared no interest, and 1.2% (n = 6) stated that they already feel capable.

The results of Section 2 indicate that the majority of respondents possess only basic knowledge of Artificial Intelligence, use the technology occasionally, and have rarely participated in specific courses, with EJUD/MS being the most frequently cited institution where they received training. Furthermore, self-perceived preparedness is concentrated at the “moderate” and “low” levels; nevertheless, there is a prevailing expectation among respondents that AI will become an essential part of their work, accompanied by a high level of interest in training.

Having completed the characterization of the sample and contextualization provided by Sections 1 and 2, the descriptive statistics for the following sections (3 to 7) will be presented textually only.

(S3Q14) The use of Artificial Intelligence contributes to reducing case processing time.

There was a high level of agreement with the statement that the use of AI contributes to reducing case processing time, as 43.8% (n = 222) of participants reported agreeing and 35.1% (n = 178) strongly agreed. A total of 17.9% (n = 91) maintained a neutral position, while 2.6% (n = 13) disagreed and only 0.6% (n = 3) strongly disagreed.

(S3Q15) Artificial Intelligence is useful for automating repetitive tasks and improving productivity.

Regarding the perception that Artificial Intelligence is useful for automating repetitive tasks and increasing productivity, most respondents expressed agreement, with 45.4% (n = 230) agreeing and 42.8% (n = 217) strongly agreeing. On the other hand, 10.8% (n = 55) adopted a neutral position, while 0.6% (n = 3) disagreed and 0.4% (n = 2) strongly disagreed.

(S3Q16) The use of Artificial Intelligence promotes greater standardization and consistency in the performance of activities.

With respect to the statement that the use of Artificial Intelligence promotes greater standardization and consistency in the performance of activities, a substantial portion of respondents, namely 47.5% (n = 241), reported agreeing, while another significant portion, 31.8% (n = 161), strongly agreed. Meanwhile, 17.4% (n = 88) remained neutral, 3.0% (n = 15) disagreed, and 0.4% (n = 2) strongly disagreed.

(S3Q17) Artificial Intelligence can assist in ensuring compliance with ethical and legal principles in the performance of duties.

Concerning the statement that Artificial Intelligence can assist in ensuring compliance with ethical and legal principles in the performance of duties, 32.9% (n = 167) of respondents agreed and 16.8% (n = 85) strongly agreed. A total of 37.3% (n = 189) maintained a neutral position, while 11.4% (n = 58) disagreed and 1.6% (n = 8) strongly disagreed.

(S3Q18) Artificial Intelligence contributes to improving the quality of the services provided by the Judiciary of Mato Grosso do Sul.

Regarding the statement that Artificial Intelligence contributes to improving the quality of services provided by the Judiciary of Mato Grosso do Sul, 46.2% (n = 234) of respondents agreed and 29.0% (n = 147) strongly agreed. Another 19.3% (n = 98) adopted a neutral position, while 4.9% (n = 25) disagreed and 0.6% (n = 3) strongly disagreed.

(S4Q19) I believe that Artificial Intelligence tools are easy to learn and use in daily activities.

With respect to the statement that Artificial Intelligence tools are easy to learn and use in everyday activities, more than half of the participants, 53.3% (n = 270), agreed and 14.8% (n = 75) strongly agreed. A total of 24.9% (n = 126) remained neutral, while 6.7% (n = 34) disagreed and 0.4% (n = 2) strongly disagreed.

(S4Q20) The Artificial Intelligence tools that I know or have previously used provide clear instructions for use.

Regarding the statement that the Artificial Intelligence tools known or used provide clear instructions for use, 39.8% (n = 202) of participants agreed and 9.3% (n = 47) strongly agreed. A significant portion, 38.7% (n = 196), maintained a neutral position, while 11.0% (n = 56) disagreed and 1.2% (n = 6) strongly disagreed.

(S4Q21) I feel that I have adequate technical support to use Artificial Intelligence tools in my work.

With respect to the perception of having adequate technical support to use Artificial Intelligence tools at work, 23.1% (n = 117) of respondents agreed and only 5.9% (n = 30) strongly agreed.

Meanwhile, 35.3% (n = 179) remained neutral, 28.8% (n = 146) disagreed, and 6.9% (n = 35) strongly disagreed.

(S4Q22) It is easy to understand how Artificial Intelligence works within the context of my activities.

Regarding the ease of understanding how Artificial Intelligence operates within the context of performed activities, 38.7% (n = 196) of respondents agreed and 9.5% (n = 48) strongly agreed. Another 38.1% (n = 193) adopted a neutral position, while 12.0% (n = 61) disagreed and 1.8% (n = 9) strongly disagreed.

(S5Q23) Do you believe that the use of Artificial Intelligence may replace human work in the Judiciary?

When asked whether the use of Artificial Intelligence could replace human work in the Judiciary, 47.9% (n = 243) responded that it could not, understanding that it only complements human performance. Meanwhile, 39.6% (n = 201) considered that such replacement would be possible only in specific tasks, 8.5% (n = 43) believed it could occur in a large part of functions, and 0.8% (n = 4) stated that it would be totally possible. Finally, 3.2% (n = 16) declared having no formed opinion on the subject.

(S5Q24) Do you have ethical concerns regarding the use of Artificial Intelligence in the Judiciary (for example, privacy, algorithmic bias, transparency)?

When asked about ethical concerns related to the use of AI in the PJMS (such as privacy, algorithmic bias, etc.), 51.1% (n = 259) reported having some concerns and 29.8% (n = 151) indicated having many concerns. Conversely, 9.7% (n = 49) stated having no concerns and

9.5% (n = 48) declared not having sufficient knowledge to express an opinion.

(S5Q25) Which of the following factors do you consider barriers to the use of Artificial Intelligence in the Judiciary of Mato Grosso do Sul?

Regarding perceived barriers to the use of Artificial Intelligence in the Judiciary of Mato Grosso do Sul, more than one alternative could be selected, and the majority of respondents indicated lack of adequate training (n = 367) as the main obstacle. This was followed by concerns about data security (n = 274), cultural resistance among staff (n = 186), and lack of technological infrastructure (n = 166).

In addition, 26 participants indicated other barriers in open-ended responses. These statements were grouped into six main axes: risks to the quality of judicial services, technical limitations, ethical and legal risks, organizational barriers, absence of normative frameworks, and challenges related to infrastructure and human resources.

The survey of the total number of objections indicates that most respondents presented only one objection (233 cases), followed by two (108 cases) and three (101 cases). Less frequent were four objections (63 cases) and, on an isolated basis, five objections (2 cases).

The clear predominance of the group that indicated a single barrier (233 respondents) suggests that, for many, there is one main obstacle to the adoption of AI in the Judiciary, most likely the lack of training, which was the most frequently cited.

On the other hand, it should not be disregarded that a significant group (n = 274) recognized multiple simultaneous difficulties (two or more), which, in general, from the perspective of the Technology Acceptance Model (TAM), tends to negatively influence perceptions of Ease of Use and Usefulness of the technology, consequently affecting attitude and intention to use among staff members.

(S5Q26) Do you believe that Artificial Intelligence may compromise impartiality or transparency in judicial decisions?

Regarding perceptions of the potential of AI to compromise impartiality or transparency in judicial decisions, there was a more balanced distribution: 37.5% (n = 190) adopted a neutral position, 30.0% (n = 152) disagreed, 19.5% (n = 99) agreed, 7.9% (n = 40) strongly disagreed, and 5.1% (n = 26) strongly agreed.

(S5Q27) Do you feel comfortable adopting Artificial Intelligence tools in your daily work?

The assessment of comfort in adopting Artificial Intelligence tools revealed that 46.0% (n = 233) of respondents declared themselves comfortable and 27.2% (n = 138) maintained a neutral position. Smaller percentages indicated feeling very comfortable (19.1%, n = 97), uncomfortable (6.1%, n = 31), or very uncomfortable (1.6%, n = 8).

(S5Q28) In your opinion, what should the Judiciary of Mato Grosso do Sul prioritize to facilitate the adoption of Artificial Intelligence?

Among the actions that the TJMS Judiciary should prioritize to facilitate the adoption of Artificial Intelligence, respondents most frequently cited the provision of more training and capacity-building

initiatives (n = 286), followed by guarantees of security and ethics in the use of the technology (n = 132), improvements in technological infrastructure (n = 86), and clear communication about the benefits of AI (n = 72). The vast majority of participants (n = 471) indicated only one priority, while 13 mentioned two, 14 identified three, and 9 selected all four options.

In the open-ended responses, only three respondents indicated other priorities, suggesting the creation of a specific platform for the Judiciary and specific legislation authorizing the use of AI, requiring that judgments and decisions indicate when technological assistance was used, as well as providing access to paid versions of AI tools and conducting a careful analysis of areas of application to avoid rework by staff members.

(S6Q29) Were you aware that the National Council of Justice published a specific regulation to govern the use of Artificial Intelligence in the Judiciary?

Regarding awareness of the specific regulation issued by the National Council of Justice to govern the use of Artificial Intelligence in the Judiciary, 60.0% (n = 304) reported being unaware and 40.0% (n = 203) stated that they were aware.

(S6Q30) If yes, which of the options below do you recognize as that regulation?

When asked which regulation they recognized as being related to the use of Artificial Intelligence in the Judiciary, 51.3% (n = 260) stated that they were not sure and 32.1% (n = 163) indicated that none of the presented options corresponded. Only 12.8% (n = 65) mentioned Resolution No. 615/2023 of the National Council of Justice, 3.4% (n =

17) cited Resolution No. 335/2024, and 0.4% (n = 2) indicated Recommendation No. 92/2021.

Considering that Resolution No. 615 of the National Council of Justice was not published in 2023 but rather in 2025, and was therefore not listed among the alternatives offered, it is observed that 32.1% (n = 163) of respondents effectively answered the question correctly by selecting “none of the above.” However, no further inferences can be made regarding the correctness of responses, since participants completed the online questionnaire and may have searched the internet before answering. Furthermore, the potentially misleading nature of the question, which indicated the correct number of the CNJ Resolution but an incorrect year of publication, may have induced error among respondents who selected that alternative. It is nevertheless conceivable that the latter group includes individuals who knew the correct regulation, given that it is common to remember the number of a legal instrument while forgetting its year of publication.

(S6Q31) Have you ever read any regulation or guideline related to the use of Artificial Intelligence in the Judiciary?

With regard to reading regulations related to AI, 32.9% (n = 167) stated that they had heard about the subject, 32.5% (n = 165) had never had contact, 24.3% (n = 123) had accessed only excerpts or summaries, and 10.3% (n = 52) declared having read one or more regulations in full.

(S6Q32) Do you believe that knowledge of these regulations is important to guide the ethical and responsible use of Artificial Intelligence in the Judiciary?

The importance attributed to knowledge of these regulations was high, with 47.7% (n = 242) agreeing and 39.4% (n = 200) strongly agreeing. A minority adopted a neutral position (11.6%, n = 59), disagreed (1.0%, n = 5), or strongly disagreed (0.2%, n = 1).

(S6Q33) Does the Judiciary of Mato Grosso do Sul provide clear information about the regulation of Artificial Intelligence for its employees?

Regarding perceptions of the clarity of information provided by the Judiciary of Mato Grosso do Sul about AI regulation, 47.9% (n = 243) adopted a neutral position and 23.1% (n = 117) disagreed. Another 14.4% (n = 73) agreed, while 8.5% (n = 43) strongly disagreed. Smaller proportions declared “prefer not to answer” (3.2%, n = 22) or strongly agreed (1.8%, n = 9).

(S7Q34) If you wish, please provide additional suggestions or comments regarding the use of Artificial Intelligence in the Judiciary of Mato Grosso do Sul:

The interpretation of the most frequently used words suggests that “staff members” are inclined toward the “use” of “Artificial Intelligence” “tools,” given the presence of a wide range of positively connoted terms such as “interesting,” “optimization,” “automation,” “speed,” “benefits,” and “improvement,” among others.

However, the coexistence of words expressing concerns—such as “errors,” “qualification,” “training,” “course,” “lecture,” “support,” “security,” and “regulations”—as well as other more specific terms related to Artificial Intelligence, such as “prompts,” appears to indicate that the predisposition to use AI is intrinsically linked to demands for educational initiatives. This aspect was, in fact, the

subject of a specific question in the questionnaire (Question 13), and the overwhelming majority (91.1%) expressed interest in participating in courses related to Artificial Intelligence.

RESULTS – BIVARIATE STATISTICS

In addition to descriptive statistics, this stage sought to conduct a bivariate analysis of the responses obtained, with the purpose of preliminarily exploring the simplest relationships between sociodemographic variables, prior experience, and individual perceptions regarding Artificial Intelligence, comparing them with the constructs of the TAM model.

This procedure allows for the paired observation of a first group of variables—such as length of service, position held, and gender—with a second group of variables related to the TAM model (perceptions of usefulness, perceived ease of use, and attitude toward the technology).

Beyond providing an initial overview of statistically significant associations, bivariate analysis offers support for understanding the considerable nuances in respondents' profiles and, above all, contributes to the comprehension of the subsequent multivariate modeling stage, in which the hypotheses of the TAM are tested in an integrated manner.

Indeed, the joint reading of the tables presented in this section not only supports the empirical validation of the theoretical model but also provides elements for a situational analysis within the PJMS, contributing to the formulation of training strategies, institutional communication measures, and the responsible implementation of the technology within the Judiciary.

It is therefore appropriate to begin with the presentation of **Table 3**, set out over two pages.

Table 3. Bivariate Analysis between Sociodemographic Characteristics and Perceptions regarding the Use of Artificial Intelligence.

Variable	Very uncomfortable	Uncomfortable	Neutral	Confortável	Very comfortable
n = 507					
Affiliation with the Judiciary					
Permanent staff member	5 (1,25%)	25 (6,25%)	105 (26,25%)	187 (46,75%)	78 (19,5%)

⚠ Esta tabela possui muitas colunas e foi cortada para impressão. Para visualizá-la completa, acesse o artigo original em: <https://revistatopicos.com.br/artigos/artificial-intelligence-in-the-judiciary-in-brazil-an-analysis-through-the-technology-acceptance-model-tam?noblockage>

Note. F: Fisher’s Exact Test. Levels of significance: $p < 0,05$ (*); $p < 0,01$ (**); $p < 0,001$ (***). Values of $p \geq 0,05$ were considered non-significant.

Table 3 (continued)

Variable	Very uncomfortable	Uncomfortable	Neutral	Confortável	Very comfortable
Age group					

Under 25 years	1 (1,75%)	3 (5,26%)	15 (26,32%)	24 (42,11%)	14 (24,5%)
25-34 years	2 (1,85%)	9 (8,33%)	25 (23,15%)	51 (47,22%)	21 (19,4%)

⚠ Esta tabela possui muitas colunas e foi cortada para impressão. Para visualizá-la completa, acesse o artigo original em: <https://revistatopicos.com.br/artigos/artificial-intelligence-in-the-judiciary-in-brazil-an-analysis-through-the-technology-acceptance-model-tam?noblockage>

Table 3 presents the distribution of respondents' perceptions regarding acceptance of the use of Artificial Intelligence tools in daily work, categorized into five levels ("Very uncomfortable," "Uncomfortable," "Neutral," "Comfortable," and "Very comfortable"), according to sociodemographic and occupational variables.

With respect to institutional affiliation with the Judiciary, no statistically significant association was observed with the declared level of acceptance ($p = 0.18$; Fisher's Exact Test). The majority of respondents classified as permanent staff members, interns, and commissioned employees showed predominance in the categories "Comfortable" and "Very comfortable," particularly among permanent staff (66.25% when these two categories are combined). Categories with lower numerical representation, such as "Others" and "Seconded," displayed a more dispersed distribution of responses, without expressive concentration at any specific level.

Regarding predominant area of activity, a statistically significant association was identified with perception of acceptance ($p = 0.03$; Fisher's Exact Test). Respondents from the judicial area demonstrated higher relative frequency in the upper categories of the scale ("Comfortable" and "Very comfortable") compared to those

from the administrative area, although the latter comprises the larger portion of the sample.

The variable length of service in the Judiciary did not show a statistically significant association with the level of acceptance ($p = 0.88$). The distribution of responses was relatively homogeneous across different tenure strata, with predominance of positive evaluations (comfortable or very comfortable) in all groups.

In relation to gender, a statistically significant association was observed with perception of acceptance ($p < 0.01$; Fisher's Exact Test). While among women the category "Very comfortable" accounted for 14.43%, among men a higher frequency was observed (26.5%), suggesting a differentiated distribution of responses according to participants' sex.

Furthermore, no statistically significant association was identified between educational background and level of comfort in adopting AI ($p = 0.16$). At all levels of education, positive perception predominated, with higher frequency in the category "Comfortable," especially among participants with a specialization degree (45.48%) and a bachelor's degree (45.04%). In the groups with master's and doctoral degrees, although absolute frequencies were smaller, the predominance of "Comfortable" responses was maintained (53.85% and 75%, respectively), followed by "Very comfortable" (23.08% and 25%).

Finally, age group did not present a statistically significant association with the level of acceptance in adopting Artificial Intelligence ($p = 0.44$). In all age strata, most respondents were

situated in the categories “Comfortable” or “Very comfortable,” with slight percentage variation among groups.

Subsequently, in **Table 4**, the distribution of the level of acceptance of Artificial Intelligence at work was analyzed based on variables related to prior knowledge, actual use, and respondents’ perceptions. This cross-tabulation allows for understanding whether familiarity and accumulated experience with the technology influence willingness to accept it.

Table 4. Distribution of the level of acceptance of the use of Artificial Intelligence according to variables related to knowledge, prior use, and respondents’ perceptions.

Variable	Very uncomfortable	Uncomfortable	Neutral	Comfortável	Very comfortable
Have you heard about AI before this questionnaire?					
Yes, but I	2 (5%)	2 (5%)	17 (42,5%)	14 (35%)	5 (12,5%)

⚠ Esta tabela possui muitas colunas e foi cortada para impressão. Para visualizá-la completa, acesse o artigo original em: <https://revistatopicos.com.br/artigos/artificial-intelligence-in-the-judiciary-in-brazil-an-analysis-through-the-technology-acceptance-model-tam?noblockage>

Source: Prepared by the authors.

Table 4 presents the distribution of respondents' perceptions regarding their level of acceptance in the use of Artificial Intelligence tools at work, according to variables related to prior knowledge, actual use, training, and personal perception of the technology. It is observed that familiarity and practical engagement with AI tools, as well as perceived preparedness and interest in training, are associated with higher declared levels of acceptance. Statistical tests were conducted using Fisher's Exact Test, and associations with $p < 0.05$ were considered statistically significant.

The variable "Have you heard about AI before this questionnaire?" showed a statistically significant association with the declared level of acceptance ($p = 0.004$). Among respondents with detailed knowledge, concentration in the categories "Comfortable" and "Very comfortable" was expressive (80%), whereas those who did not know exactly what AI is presented a more dispersed distribution, with greater presence in the categories "Neutral" and "Uncomfortable."

Regarding the variable "Have you used AI at work?", the association was highly significant ($p < 0.001$). Those who regularly use AI tools were the ones who most identified as "Very comfortable" (36.96%) and "Comfortable" (55.43%). In contrast, respondents who had never used the technology showed greater prevalence in the categories "Neutral" (48.78%) and "Uncomfortable" (8.54%).

The variable "Have you participated in an AI course?" did not show a statistically significant association ($p = 0.09$). Although the proportion of positive responses ("Comfortable" or "Very comfortable") is visibly higher among those who attended courses (77.96%), the sample of this subcategory was relatively small, which may limit the statistical power of the test applied.

Current perception of preparedness to use AI at work demonstrated a statistically significant association ($p < 0.001$). A clear progression pattern was observed: as the declared level of preparedness increases, so does the frequency of responses in the higher categories of acceptance. For example, among respondents who declared “Very high” preparedness, 75% indicated being “Very comfortable.”

The variable “AI will be an essential part of work” also showed a highly significant association ($p < 0.001$). Those who believe that Artificial Intelligence will become an essential part of their work demonstrated higher acceptance, with more than 72% concentrated in the categories “Comfortable” and “Very comfortable.” Conversely, among those who do not share this expectation, there was greater dispersion and presence in lower categories.

Finally, a significant association was observed for the variable “Interest in AI training” ($p < 0.001$). Respondents who do not wish to pursue training are predominantly concentrated in the levels “Neutral” and “Uncomfortable,” whereas those who expressed interest showed higher relative frequency in the categories “Comfortable” and “Very comfortable.” Notably, among those who already feel capable, two-thirds declared being “Very comfortable” with the use of AI at work.

Beyond profile variables, **Table 5** sought to verify how the perception of benefits attributed to Artificial Intelligence relates to the level of comfort in adopting it at work.

This analysis allows identification of whether recognition of gains—such as greater productivity, standardization of activities, or

reduction in processing time—is associated with greater willingness of respondents to use the technology in their routines.

Table 5. Distribution of the level of comfort in adopting AI at work according to agreement with different perceived benefits.

Variable	Very uncomfortable	Uncomfortable	Neutral	Comfortable	Very comfortable
AI contributes to reducing processing time					
Strongly	2 (66,67%)	1 (33,33%)	0 (0%)	0 (0%)	0 (0%)

⚠ Esta tabela possui muitas colunas e foi cortada para impressão. Para visualizá-la completa, acesse o artigo original em: <https://revistatopicos.com.br/artigos/artificial-intelligence-in-the-judiciary-in-brazil-an-analysis-through-the-technology-acceptance-model-tam?noblockage>

The analysis of **Table 5** indicated a statistically significant association ($p < 0.001$) between the level of comfort in adopting Artificial Intelligence tools in daily work and the degree of agreement with statements regarding their benefits.

Across all evaluated dimensions—reduction of processing time, automation and productivity, standardization of activities, and improvement of service quality—participants with higher levels of agreement showed a greater proportion of responses classified as “Comfortable” or “Very comfortable.”

Conversely, lower levels of agreement were more frequently associated with neutral or discomfort responses.

To conclude the bivariate analysis, the association between the level of comfort in using Artificial Intelligence and variables related to perceptions, barriers, and priorities identified by respondents was presented in **Table 6**

Table 6. Association between the level of comfort in the use of AI and variables related to perceptions, barriers, and priorities, according to Fisher’s Exact Test.

Variable	Very uncomfortable	Uncomfortable	Neutral	Confortável	Very comfortable
AI tools provide clear instructions					
Strongly disagree	0 (0%)	2 (33,33%)	1 (16,67%)	1 (16,67%)	2 (33,33%)

⚠ Esta tabela possui muitas colunas e foi cortada para impressão. Para visualizá-la completa, acesse o artigo original em: <https://revistatopicos.com.br/artigos/artificial-intelligence-in-the-judiciary-in-brazil-an-analysis-through-the-technology-acceptance-model-tam?noblockage>

The results of Fisher’s Exact Test, presented in **Table 6**, indicate a statistically significant association between the level of comfort in the use of Artificial Intelligence (AI) and the variables “AI tools provide clear instructions” ($p < 0.001$), “Adequate technical support

for the use of AI” ($p < 0.001$), “Lack of adequate training” ($p < 0.001$), and “Prioritization to facilitate the use of AI” ($p = 0.002$).

For these variables, it is observed that participants who agree or strongly agree regarding the clarity of instructions and the adequacy of technical support tend to report higher levels of comfort in using AI.

Similarly, the perception of lack of training and the prioritization of specific actions to facilitate the use of the technology are also associated with differences in the level of comfort. The remaining barriers and prioritization measures did not show statistically significant association ($p \geq 0.05$).

8. STRUCTURAL EQUATION MODELING

Structural Equation Modeling (SEM) was employed based on the Technology Acceptance Model (TAM) to simultaneously assess the quality of the latent constructs Perceived Ease of Use (PEOU), Perceived Usefulness (PU), and Attitude Toward Technology (ATT), as well as the structural relationships among them.

The specified model included PEOU as an exogenous variable, with a direct effect on PU and ATT, while PU exerted a direct effect on ATT. All constructs were measured through ordinal indicators, assessed on four- or five-point scales. The item *att_prep* was removed after preliminary analysis due to low factor loading and negative impact on overall model fit.

Estimation was performed using the Weighted Least Squares Mean and Variance adjusted (WLSMV) method, appropriate for ordinal data, as implemented in the lavaan package (version 0.6-19) in R.

Model fit was evaluated using multiple indices (CFI, TLI, RMSEA, SRMR, and their robust counterparts), adopting adequacy criteria of CFI/TLI > 0.90 and RMSEA/SRMR < 0.08 (Hu & Bentler, 1999).

The first part of the results can be observed in **Table 7**.

Table 7. Standardized factor loadings, errors, and R² of the items in the measurement model (SEM – WLSMV).

Factor	Item	Standardized loading	Error	R2
PU	Q14	0,9244	0.145	0.855
	Q15	0,9265	0.142	0.858
	Q16	0,8783	0.229	0.771
	Q17	0,7578	0.426	0.574
	Q18	0,9095	0.173	0.827
PEOU	Q19	0,7652	0.414	0.586
	Q20	0,6924	0.521	0.479
	Q21	0,5989	0.641	0.359
	Q22	0,8175	0.332	0.668
ATT	Q27	0,9160	0.161	0.839
	Q26	0,5702	0.675	0.325

Source: Prepared by the authors

Table 7 above presents the results of the standardized factor loadings, measurement errors, and coefficients of determination (R²) for each item associated with the three latent constructs of the

model—Perceived Usefulness (PU), Perceived Ease of Use (PEOU), and Attitude Toward The Behavior (ATT). It is observed that the factor loadings ranged from 0.5702 (Q26) to 0.9265 (Q15), indicating different magnitudes of association between the indicators and their respective factors. The PU construct showed high loadings for all items, with values above 0.75 and coefficients of determination greater than 0.57, highlighting strong explanatory power of the factors over their indicators. In the case of PEOU, loadings ranged from 0.5989 (Q21) to 0.8175 (Q22), with R^2 values from 0.359 to 0.668, indicating variation in the degree to which the items are explained by this factor. For ATT, composed of two items, a high loading was observed for Q27 (0.9160; $R^2 = 0.839$) and a moderate loading for Q26 (0.5702; $R^2 = 0.325$), demonstrating that although both are indicators of the construct, the proportion of explained variance is substantially higher for the former. These results reflect the consistency of the measurement model, considering that all estimated coefficients present positive and statistically significant magnitudes.

Subsequently, the final results of the modeling are presented in **Table 8.**

Table 8. Standardized coefficients (β) of the structural relationships, with respective 95% confidence intervals and p-values, obtained from the structural equation model.

Dependent variable	Independent variable	Beta IC (95%)	p-value
PU	PEOU	0.531 (0.512; 0.741)	< 0,001
ATT	PU	0.649 (0.720; 1.130)	< 0,001

ATT	PEOU	0.241 (0.230; 0.581)	< 0,001
-----	------	-------------------------	---------

Source: Prepared by the authors

The results presented (**Table 8**) indicate the standardized coefficients estimated for the structural paths of the model, accompanied by their respective standard errors, 95% confidence intervals, and p-values. It is observed that the relationship of PEOU on PU shows a standardized β of 0.531, with a standard error of 0.058 and a confidence interval ranging from 0.416 to 0.645, being statistically significant ($p < 0.001$). The influence of PU on ATT was 0.649, with a standard error of 0.105 and a confidence interval between 0.445 and 0.854, also with high statistical significance ($p < 0.001$). Finally, the direct effect of PEOU on ATT presented a standardized coefficient of 0.241, a standard error of 0.089, and a confidence interval from 0.066 to 0.416, likewise significant ($p < 0.001$). These findings indicate that all paths specified in the structural model were statistically relevant within the adopted significance level.

Thus, all paths specified in the structural model showed statistical significance within the adopted significance level ($p < 0.001$). These results indicate that each tested relationship among the latent variables was statistically relevant, demonstrating that the constructs included in the model significantly contribute to explaining the dependent variables according to the proposed theoretical structure.

The results indicate that the model presented high CFI (0.997) and TLI (0.996) values, evidencing excellent fit according to conventional

criteria. The RMSEA was 0.064, a value compatible with acceptable fit, while the SRMR was 0.047, also indicative of good fit. In the robust estimates, CFI was 0.911 and TLI was 0.881, both close to the 0.90 threshold, and RMSEA was 0.132, suggesting poorer performance under this criterion when robust adjustments are considered. Overall, these results point to a satisfactory model fit, with variation in performance depending on the estimation method adopted.

$$PU = 0.531 \cdot PEOU + \zeta_{PU}$$

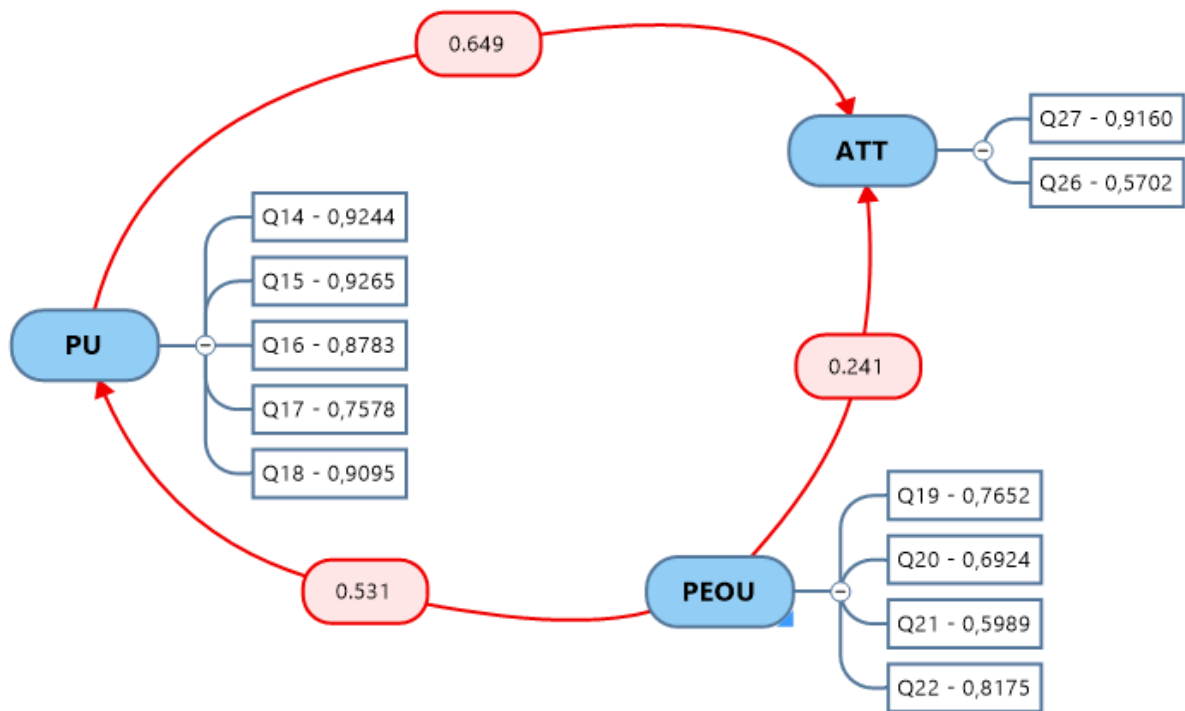
$$ATT = 0.649 \cdot PU + 0.241 \cdot PEOU + \zeta_{ATT}$$

The proposed structural equation model presented satisfactory fit indices, with CFI and TLI values close to 1, and RMSEA and SRMR indices within the limits commonly accepted in the literature. All paths specified in the structural model were statistically significant, as shown in Figure 3, with emphasis on the effect of PEOU on PU ($\beta = 0.53$; 95% CI: 0.512–0.741) and the effect of PU on ATT ($\beta = 0.649$; 95% CI: 0.720–1.130).

The values on the arrows represent the standardized coefficients of the structural relationships, while the values next to the items (Q14–Q27) indicate the factor loadings of the indicators on their respective latent constructs.

These results indicate that the theoretical relationships proposed were empirically confirmed, supporting the adequacy of the model both in terms of overall fit and statistical significance of the internal relationships.

Figure 2. Structural Equation Model (SEM) based on TAM.



Source: Prepared by the authors.

9. FINAL CONSIDERATIONS

The application of Fisher's Exact Tests made it possible to identify statistically significant associations between perception variables (such as comfort in use, clarity of instructions, and technical support) and barriers or facilitating factors for the adoption of the technology, evidencing consistent relationships among structural aspects, training, and data security.

Structural equation modeling, grounded in the Technology Acceptance Model (TAM), indicated that perceived usefulness and perceived ease of use exert significant influence (Granić and Marangunić, 2019) on the behavioral intention to adopt AI tools in the workplace. The results confirm the adequacy of the theoretical model in the studied context (Masrom, 2007), showing that factors such as training, support, and perception of benefits are coherently articulated in explaining technological acceptance (Nguyen, Do and Wu, 2021).

In an integrated manner, the quantitative findings and structural modeling reinforce that expanding the use of AI in the Judiciary depends not only on technical and regulatory conditions, but also on initiatives aimed at strengthening users' confidence and competence. Thus, the results provide empirical support for the formulation of policies and strategies that reconcile infrastructure, qualification, and effective communication, promoting safer and more efficient adoption of the technology.

The present study should be understood merely as a starting point for future investigations on the acceptance of Artificial Intelligence within the Judiciary, expanding its scope either by including other Courts and institutional contexts or by incorporating additional TAM variables (such as trust, social approval, etc.) that were not contemplated at this stage. Furthermore, the recent emergence of Artificial Intelligence currently prevents evaluation of how perceptions of the technology may vary over time, an aspect that may be refined in subsequent scientific works.

In any case, the research revealed that the lack of adequate training is the main perceived barrier to the adoption of Artificial Intelligence in the Judiciary of Mato Grosso do Sul, and the provision of greater training in this area was likewise the most frequently suggested priority.

Accordingly, it is recommended that the Administration of the Court of Justice of Mato Grosso do Sul initially develop a structured and continuous Artificial Intelligence training program, with a project to be designed by the Judicial School (EJUD-MS), the institution most attended by staff members, so that instruction is organized into multi-level learning pathways (beginner, intermediate, advanced),

encompassing both fundamental AI concepts and the practical use of specific tools that may be authorized or implemented within the Judiciary.

The provision of contextualized training, with modules segmented by area of activity (judicial and administrative), will certainly contribute to clarifying how Artificial Intelligence can optimize tasks specific to each sector, thereby reinforcing the perceived usefulness of the tools.

Moreover, educational initiatives must necessarily include reinforced modules on the ethical and legal guidelines governing AI use, particularly because approximately 81% of respondents expressed ethical concerns, while approximately 87% considered knowledge of the regulations to be important.

In a second axis, strengthening Governance and Communication regarding the Ethical and Secure Use of AI is recommended, given that data security was the second most cited barrier and the guarantee of security and ethics was the second most indicated priority. To this end, the AI Governance and Ethics Committee created by TJMS Resolution 365/2025 must be fully operational, especially considering the regulatory mismatch problem (“pacing problem”). The Committee’s guidelines must always be clear, accessible, and widely disseminated. Conversely, care must be taken to avoid excessive regulation that could eventually create nearly insurmountable obstacles to technological adoption.

The Administration of the PJMS, in conjunction with the Judicial School (EJUD-MS), may also develop internal awareness campaigns, creating communication channels aimed at clarifying the benefits

and limits of Artificial Intelligence, without failing to explicitly present the data security and protection mechanisms that may be implemented as soon as they become available. The campaign should also address concerns regarding replacement of human labor, emphasizing the complementary role of AI, as perceived by a considerable portion of respondents.

In a third axis, it is recommended that the Administration of the PJMS focus on the factors that, according to TAM, are essential for the adoption of Artificial Intelligence. It is worth recalling that structural equation analysis confirmed that Perceived Ease of Use (PEOU) has a direct and significant impact on Perceived Usefulness (PU) and on Attitude Toward Use (ATT). However, 35.7% of staff members do not feel adequately supported by technical assistance, and a considerable portion (38.7%) remains neutral regarding the clarity of AI tool instructions.

It is therefore suggested that specialized IT support for Artificial Intelligence tools be structured, with trained personnel capable of resolving doubts arising from the use of available tools, ensuring prompt assistance to users and seeking to modify the current perception of insufficient support in the performance of their activities.

Furthermore, as occurred in the implementation of Telework during the COVID-19 pandemic, it is recommended that user manuals, video tutorials, and simple quick-reference guides, written in clear and accessible language, be made available on the intranet of the Judiciary of Mato Grosso do Sul, with the aim of reducing the learning curve associated with the tools.

Finally, in a fourth axis, it is recommended that the Administration of the PJMS reinforce a culture of innovation within the institution, creating competitions for the best use of Artificial Intelligence (e.g., prompts that most effectively perform specific tasks), as well as fostering and implementing pilot projects, especially in areas with greater potential for automation, aiming at systematizing experiences and subsequently replicating successful practices in other areas.

It should be recalled that the research identified a positive predisposition toward the technology, with 85.2% declaring that they believe AI will be essential to their future work, and 65.1% stating that they feel comfortable or very comfortable adopting it.

In this regard, although concerns regarding Artificial Intelligence are evident, its tools bring highly promising prospects, particularly for the Judiciary, which, if able to implement and use them in a safe, responsible, and ethical manner, will likely achieve significant gains in efficiency, speed, and quality of judicial services, contributing to the reduction of procedural bottlenecks, optimization of resources, and strengthening of social trust in the justice system.

For the time being, this research demonstrates that the staff of the Judiciary of Mato Grosso do Sul is highly receptive to this innovation, requiring only that the favorable winds be effectively navigated by the Administration.

REFERENCES

Akman, Ibrahim e Anil Mishra (2015). Sector diversity in green information technology practices: technology acceptance model perspective. *Computers in Human Behavior*, 49: 477–486.

Barbosa, Felipe (2024). População brasileira cresce e chega a 212,5 milhões de habitantes, diz IBGE. *Veja*. Disponível em: <https://veja.abril.com.br/brasil/populacao-brasileira-cresce-e-chega-a-2125-milhoes-de-habitantes-diz-ibge/>. Accessed on: 28 jan. 2026.

Berzagui, B. e J. E. da Silva (2022). A utilização da inteligência artificial para aumento da eficiência do Poder Judiciário: um estudo a partir da análise econômica do direito. *Diké – Revista Jurídica*, 21 (21): 2–20.

Bonett, Douglas G. (2021). Design and analysis of replication studies. *Organizational Research Methods*, 24 (3): 513–529.

Brito, T. S. e R. S. Fernandes (2020). Inteligência artificial e a crise do Poder Judiciário: linhas introdutórias sobre a experiência norte-americana, brasileira e sua aplicação no direito brasileiro. *Revista Acadêmica da Faculdade de Direito do Recife*, 91 (2): 84–107.

Cabral, T. N. X. e H. Santiago (2022). Tecnologia e inteligência artificial no Poder Judiciário. *Inteligência Artificial e a Aplicabilidade Prática no Direito*, 1: 313–347.

Castelliano, C., T. A. Guimarães e A. de O. Gomes (2024). Fatores que aumentam o tempo do processo judicial no Brasil. *Revista de Administração Pública*, 58 (2): 1–11.

Conselho Nacional de Justiça (2024). *Pesquisa inteligência artificial no Judiciário 2024: resumo executivo*. Brasília.

Conselho Nacional de Justiça (2025). *Justiça em números*. 22. ed. Brasília.

Davis, Fred D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 13 (3): 319–340.

Fischer, Ronald A. (1922). On the interpretation of χ^2 from contingency tables, and the calculation of P. *Journal of the Royal Statistical Society*, 85 (1): 87–94.

Fishbein, Martin e Icek Ajzen (1975). *Belief, attitude, intention and behavior*. Reading, MA: Addison-Wesley.

Gomes, L. B. A., K. S. Ferreira e F. S. Andrade (2022). Modernização do direito: a criação de startups jurídicas. *Revista do Departamento de Ciências Jurídicas e Sociais da Unijuí*. 1–14.

Granić, A. e N. Marangunić (2019). Technology acceptance model in educational context: a systematic literature review. *British Journal of Educational Technology*, 50 (5): 2572–2593.

Guitton, C. et al. (2025). Adoption of artificial intelligence in the judiciary: a comparison of 28 advanced democracies. *Discover Artificial Intelligence*, 5 (1).

Hu, Li-tze e Peter M. Bentler (1999). Cutoff criteria for fit indexes in covariance structure analysis: conventional criteria versus new alternatives. *Structural Equation Modeling: A Multidisciplinary Journal*, 6 (1): 1–55.

Jankovski, B. S. et al. (2025). Implementação de soluções de inteligência artificial no setor público brasileiro: desafios e oportunidades. *Revista Foco*, 18 (1): e7459.

Jiya, E. A., A. N. Samaila e Y. Surajo (2023). Artificial Intelligence and Technology for Improving the Efficiency of The Judiciary in Nigeria. *International Journal of Research and Innovation in Applied Science (IJRIAS)*, 7 (5): 80–85.

Joshi, A. et al. (2015). Likert Scale: Explored and Explained. *British Journal of Applied Science & Technology*, 7 (4): 396–403.

King, W. R. e J. He (2006). A meta-analysis of the technology acceptance model. *Information & Management*, 43 (6): 740–755.

Kline, Rex B. (2016). *Principles and practice of structural equation modeling*. 4. ed. New York: The Guilford Press.

Lu, J., C.-S. Yu e C. Liu (2009). Mobile data service demographics in urban China. *Journal of Computer Information Systems*.

Marangunić, N. e A. Granić (2015). Technology acceptance model: a literature review from 1986 to 2013. *Universal Access in the Information Society*, 14 (1): 81–95.

Martini, S. R., K. B. do Prado e P. H. F. de Paula (2024). A hipertrofia do sistema judiciário brasileiro e as atividades atípicas: reflexões a partir da metateoria do direito fraterno. *Revista Jurídica Unicuritiba*, 1 (77): 141–156.

Masrom, M. (2007). Technology acceptance model and e-learning. *Technology*, 21 (24).

Nguyen, P. M. B., Y. T. Do e W. Y. Wu (2021). Technology acceptance model and factors affecting acceptance of social media: an empirical study in Vietnam. *Journal of Asian Finance*, 8 (6): 1091–1099.

Ribeiro, K. D. C. B. L. e L. C. Lima (2022). Judicialização da saúde e teoria dos sistemas sociais: revisão narrativa. *Revista Culturas Jurídicas*, 9 (22).

Ribeiro, M. R. B. e G. de F. Carneiro (2025). A review of the usage of artificial intelligence to improve the judiciary productivity and efficiency. *Contribuciones a las Ciencias Sociales*, 18 (3).

Scherer, R., F. Siddiq e J. Tondeur (2019). The technology acceptance model (TAM): a meta-analytic structural equation modeling approach to explaining teachers' adoption of digital technology in education. *Computers & Education*, 128: 13–35.

Schmidt, E. M. et al. (2025). Os impactos do uso da inteligência artificial pelo Poder Judiciário: análise das publicações dos últimos anos. *Revista Ibero-Americana de Humanidades, Ciências e Educação*, 11 (3): 1419–1428.

Steffen, C. (2023). A inteligência artificial e o processo penal: a utilização da técnica na violação de direitos. *EMERJ*, 25 (1): 105–129.

Tauk, C. S. e L. F. Salomão (2023). Inteligência artificial no Judiciário brasileiro: estudo empírico sobre algoritmos e discriminação. *Diké – Revista Jurídica*, 22 (23): 2–32.

Venkatesh, V. et al. (2003). User acceptance of information technology: toward a unified view. *MIS Quarterly*, 27 (3): 425–478.

Xu, Y. et al. (2021). Artificial intelligence: a powerful paradigm for scientific research. *Innovation*.

¹ Mestre em Garantismo, Direitos Fundamentais e Proc Judicial pela Universidade de Girona-Espanha. Mestre em Administração Pública pela Universidade Federal de Mato Grosso do Sul. Servidor Público vinculado ao Tribunal de Justiça de Mato Grosso do Sul. E-mail:

[acesse o artigo original para visualizar o e-mail](#). ORCID:

<https://orcid.org/0009-0003-8336-9830>. LATTES:

<http://lattes.cnpq.br/1474686589736493>

² Doutor em Ciências Ambientais e Sustentabilidade Agropecuária. Professor da ESAN-Escola de Administração e Negócios da UFMS-Universidade Federal do Mato Grosso do Sul, nos cursos de Administração, Ciências Contábeis e Turismo. Professor permanente do Programa de Pós-graduação em Administração Pública em Rede Nacional [Profiap] e colaborador do Programa de Pós-graduação em Ciências Contábeis da UFMS. ORCID: <https://orcid.org/0000-0002-0155-4465>. LATTES: <http://lattes.cnpq.br/7687668257685795>

³ References to the TJMS encompass the State Judiciary of Mato Grosso do Sul in its entire administrative and jurisdictional structure, including both first and second instance courts.