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AI in Mitigating Institutional Discrimination in the Immigrants Integration Process in Germany

Abstract. *Institutional discrimination remains a significant barrier to social and economic integration, often perpetuated through systemic biases embedded in organizational structures and decision-making processes. This paper explores the potential of Artificial Intelligence (AI) as a transformative tool in identifying, mitigating, and ultimately eliminating such discriminatory practices. By leveraging machine learning algorithms, natural language processing, and predictive analytics, AI can detect patterns of bias in administrative procedures, resource allocation, and policy implementation. The study emphasizes the dual role of AI: as a diagnostic instrument for uncovering hidden inequities and as a proactive mechanism for designing inclusive strategies. Furthermore, ethical considerations and the risk of algorithmic bias are critically examined to ensure that technological interventions do not replicate existing disparities. The findings suggest that, when properly governed, AI can significantly enhance transparency, accountability, and fairness in institutional frameworks, fostering a more equitable integration process.*

Keywords: *immigrants, artificial intelligence, transparency, fairness, inclusive governance, institutional discrimination, integration policies, social inclusion, bias detection, predictive analytics.*

JEL Classification: J15, J68, I38, D63, H83, J61, C55, O33, J71.

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1. Introduction

Migration has become one of the defining socio-economic phenomena of the 21st century, with the European Union (EU) emerging as a major destination for both intra-European and international mobility. Among these flows, Non-EU immigration occupies a central role, driven by factors such as labor market demand, geopolitical instability, and global inequalities. According to Eurostat, Non-EU citizens account for a significant share of the migrant population in Europe, contributing to demographic diversity and economic growth, while simultaneously posing challenges for social cohesion and policy design.

The EU's policies on the integration of migrants seek to allow for their active inclusion in host societies through policies related to employment, education, housing and participation in civic life. Common Basic Principles for Immigrant Integration Policy agreed upon by the European Council the need to: promote equal treatment and non-discrimination of third-country nationals encourage their active participation in our societies tackle the problem of social exclusion ensuring programe participants have access to rights and obligations. Yet, even with these systems in place, there are continuing differences between EU and Non-EU migrants regarding labor market performances, social mobility and access to public services. Structural and institutional biases, insufficient implementation of integration measures at member state level While those gaps stem mainly from structural differences between the member states, probably also by institutional marginalization in other places.

The digitalization of the public administration and the application of algorithmics to governmental decision-making have in recent years added new dynamics to integration processes. Despite these new technologies' promised of efficiency and openness, they also might create their own set of equity / fairness problems and exacerbate existing inequalities. With increasing attention on how institutional discrimination can arise in automated decision-making systems, it has been an important area of research.

Therefore, the primary aim of this paper is to investigate and quantify institutional discrimination against non-EU migrants in Germany using Artificial Intelligence (AI) as a diagnostic tool. Specifically, this study aims to demonstrate how machine learning, through logistic regression combined with fairness metrics, can uncover hidden systemic biases in administrative decision-making and measure the persistent equity gap. By doing so, the paper seeks to transition from a conceptual critique of integration policies to a data-driven evaluation of institutional fairness.

2. Literature Review

Non-European migration to Europe is a complex social issue influenced by economic, political, and social factors. The integration process for non-European migrants involves adapting to the cultural and legal norms of host countries, accessing education and the labor market, and taking part in public life. Although

European policies promote social inclusion and cohesion, challenges remain: language barriers, discrimination, and difficulties in recognizing professional qualifications. Successful integration depends on collaboration between institutions, local communities, and migrants, with the goal of reducing inequalities and strengthening cultural diversity in Europe.

The integration of non-European immigrants' process into European Union member states is governed by a complex regulatory and strategic framework. The Action Plan on Integration and Inclusion 2021 - 2027, developed by the European Commission, sets out four priority areas: education, employment, health, and housing. The same document promotes multi-level partnerships to implement measures tailored to the specific needs of third-country immigrants. At the same time, the Pact on Migration and Asylum, adopted in 2024, reinforces the shared responsibility of all European countries and introduces solidarity mechanisms and uniform procedures for managing migration flows and legal integration.

Non-European migrants are one of the most vulnerable groups in the integration process in Germany, often experiencing structural obstacles and institutional discrimination. Compared to EU citizens, who enjoy freedom of movement and extended rights, migrants from outside the European Union boarders are subject to tight rules, including compulsory integration courses (under the 2005 Immigration Act). Recent studies and reports indicate that these requirements, combined with difficulties in accessing housing, education, and the labor market, contribute to the persistence of socio-economic disparities.

While much of the global discussion on algorithmic bias tends to focus on US datasets, the German context offers unique policy challenges. As Gomolla and Radtke (2009) argue, institutional discrimination in Germany often originates from the "production of ethnic differences" through standard administrative routines. Latest research by Gundacker et al. (2024) confirms that these routines do not remain neutral, highlighting that regional biases play a significant role in asylum and integration decisions. Furthermore, the increasing "datafication" of the German Federal Office for Migration and Refugees (BAMF), as analyzed by Pollozek and Passoth (2019), demands the further development of diagnostic tools.

Artificial intelligence (AI) can be integrated into institutional processes to increase efficiency, accessibility, and consistency, without replacing human decision-making. Within the European Union, AI is already used for auxiliary administrative tasks (such as document anonymization, scheduling management, or internal communication), but also for more complex functions such as evidence analysis, application classification, or negotiation and mediation support. According to the AI Act, AI systems that influence the outcome of procedures with legal effects are considered high risk and must comply with strict requirements for transparency, accountability, and human oversight. In contrast, AI applications with a purely informational or administrative role are classified as low risk and are subject to self-regulation. This risk-based approach allows institutions to harness the potential of AI to optimize processes, reduce costs, and improve access to services, while maintaining fundamental safeguards regarding rights and procedural fairness.

Fairness in integration processes is not only a moral issue, but also an economic and social one. Institutional discrimination can lead to significant costs: decreased social cohesion, reduced labor market participation, and increased political movements. Recent studies (Barocas et al., 2019; European Commission, 2023) illustrate that algorithms used in bureaucratic processes can amplify existing biases if not adequately controlled.

Szwed A. (2022) analyzes the opportunities and risks of using artificial intelligence (AI) in migration-related procedures in the European Union, in the context of recent crises: the COVID-19 pandemic, tensions at the EU - Belarus border, and the war in Ukraine. AI is used throughout the migration cycle: from document verification and risk assessment to asylum application processing and border surveillance through technologies such as facial recognition, drones, or autonomous systems. The advantages include streamlining procedures, reducing costs, and preventing illegal migration, but there are also major threats, such as discrimination, violation of the right to privacy, and lack of transparency in automated decisions. The study highlights the need for strict regulations to protect fundamental rights, including clarification of the concept of "*automated decision-making*" and the imposition of AI impact assessments on human rights.

Studies by Hardt et al. (2016) introduced the concept of Equality of Opportunity in supervised learning, proposing formal fairness criteria and methods to adjust predictive models to reduce discrimination in algorithmic decision-making. Similarly, Mehrabi et al. (2021) provided a comprehensive survey on bias and fairness in machine learning, identifying sources of bias, fairness definitions, and mitigation strategies across various domains.

Zafar et al. (2019) developed fairness constraints for classification models, enabling flexible approaches to reduce disparate impact in algorithmic decisions. Liu et al. (2018) examined the delayed impact of fairness interventions, highlighting long-term consequences of fairness criteria on disadvantaged groups. Panarese et al. (2025) proposed a multilevel framework for justice-oriented AI, integrating computational, ethical, and social dimensions to address algorithmic bias. Wang et al. (2024) analyzed regulatory measures for algorithmic discrimination, emphasizing interdisciplinary approaches for fairness and accountability.

These contributions demonstrate the growing importance of simulation and modeling in evaluating algorithmic fairness and designing corrective policies, particularly in contexts where real-world data are incomplete or sensitive.

3. Proposed Methodology

The analysis of equity in the integration processes of non-EU migrants within the European Union represents a major challenge for contemporary economic and social research. In the context of digitalization and the increasing use of algorithms in administrative decision-making, it is essential to evaluate not only the efficiency of policies but also their degree of fairness. The proposed study, based on modeling and simulation, addresses this need through an innovative approach that combines socio-economic analysis with artificial intelligence (AI) tools.

Simulation plays a crucial role in this research for several reasons:

1. *Limited Access to Complete and Granular Data*: Real world data are usually fragmented, protected by confidentiality regulations, or difficult to obtain. Simulation enables the construction of a coherent dataset that reflects distributions and correlations observed in official statistics (e.g., Eurostat, Destatis).
2. *Hypothesis Testing in a Controlled Environment*: Through simulation, we can assess the impact of socio-economic variables on integration decisions and identify potential sources of institutional bias without the constraints imposed by incomplete data.
3. *Methodological Flexibility*: Simulation allows for parameter adjustments (e.g., bias intensity, income distribution) to observe effects on decision fairness - something not feasible in strictly empirical analysis.
4. *Preparation for AI Implementation in Public Policy*: Models developed on simulated data can later be calibrated with real data, providing a robust framework for monitoring algorithmic fairness in administrative processes.

The model used in this analysis is Logistic Regression. While modern ensemble methods or deep learning architecture often yield higher predictive accuracy, this study prioritizes model transparency and interpretability. Logistic Regression was selected because it provides clear odds ratios for each feature, allowing for a direct assessment of how nationality (the sensitive attribute) impacts the probability of integration acceptance relative to socio - economic variables. A simulated dataset was created to examine institutional discrimination in Germany from 2015 to 2025, capturing the socio-economic attributes and administrative choices pertinent to the integration process. The variables encompass nationality (EU vs. non-EU), gender, age, educational attainment, occupational status, and annual income, while the dependent variable is the integration decision (acceptance/rejection). The logit function defines the logistic regression model used:

$$logit(p\_i) = \ln(p\_i/(1-p\_i) = \beta_0 + \sum \beta_j X_{ij}$$

p_i represents the integration probability for observation *"i"* and X_{ij} represents the used variables. The β_j parameters were estimate using the maximal plausibility method. The decisions fairness was analyses annually based on metrics such as: the demographic parity difference and the equal opportunity difference. This approach was chosen to check if any bias sticks around between the EU and Non-EU German population.

In Table 1 presents the variables that were used in the data set simulation, their type, distribution and relevant remarks. The data for the model was simulated to capture the real-life patterns of migration and inclusion in Germany, from 2015 to 2024.

Table 1. The descriptive simulated data

The variables	The type	Distribution / Possible values	Remarks
Year	Number	2015 - 2025	10 years represent the analyzed period
Nationality	Categoric	EU (70%), Non - EU (30%)	Negative bias applicable for Non - EU (-15%)
Gender	Categoric	Male / Female	Uniform Distribution
Age	Numeric	18 - 65 years old	Uniform Distribution
Educational Level	Categoric	Low (30%), Medium (40%), High (30%)	The variable is positively linked to the probability if inclusion.
Work Status (Employed / Unemployed)	Categoric	Employed (70%), Unemployed (30%)	This variable can influence the integration process
Annual Revenue	Numeric	EU: aprox. 30.000EUR, Non - EU: aprox. 25.000EUR	Normal Distribution, this variable is associated with the work status
Integration Decision	Categoric (1/0)	Accepted / Rejected	Dependent Variable that is affected by socio-economic conditions

Source: Authors' own creation.

Step 1. Data Generation

The first step of the approach is to elaborate a data base for Germany, covering the period between 2015 and 2025. This model is designed to replicate the social and economic characteristics that are pertinent to the integration process. The considered variables are: nationality (EU vs. Non-EU), gender, age, educational background, employment status and the annual revenue. The probability of integration is shaped by a function that reflects the cumulative effects of these variables. We made an intentional injection of a -15% synthetic bias into the "Integration Acceptance" label for the Non-EU cohort. This serves as a diagnostic benchmark to evaluate the sensitivity of the AI framework. By creating a "ground truth"of discrimination within the simulation, the experiment can verify whether the diagnostic metrics accurately flag institutional bias in a controlled environment where the magnitude of discrimination is precisely known. Figure 1 is an extract from the Pyton used code.

```
import numpy as np

import pandas as pd

years = np.arange(2015, 2025)

n_samples_per_year = 300

records = []

for year in years:

    for _ in range(n_samples_per_year):

        nationality = np.random.choice(['EU', 'Non-EU'], p=[0.7, 0.3])

        gender = np.random.choice(['Male', 'Female'])

        age = np.random.randint(18, 65)

        education = np.random.choice(['Low', 'Medium', 'High'], p=[0.3,
0.4, 0.3])

        employment = np.random.choice(['Employed', 'Unemployed'],
p=[0.7, 0.3])

        income = np.random.normal(32000 if nationality == 'EU' else
26000, 6000)

        base_prob = 0.75 - (nationality == 'Non-EU') * 0.15 +
(education == 'High') * 0.1 + (employment == 'Employed') * 0.1

        decision = np.random.binomial(1, np.clip(base_prob, 0, 1))

        records.append([year, nationality, gender, age, education,
employment, income, decision])

data = pd.DataFrame(records, columns=['year', 'nationality', 'gender',
'age', 'education', 'employment', 'income', 'decision'])
```

Figure 1. The logic behind the data generation
Source: Author's own creation.

Basically, the data set is an intentionally distorted simulation that illustrates our need to statistically control the net effect of nationality after adjusting the social and economic factors.

Step 2. Preprocessing

The data preprocessing step is dedicated to data preparation for binary regression. Figure 2 presents the *dummy encoding* and *train-test spit* techniques. Both technical methods guarantee that the resulting model will be operative with real structured data and that its evaluation will be methodologically and analytically valid.

```
X = pd.get_dummies(data[['nationality', 'gender', 'age', 'education',
'employment', 'income']], drop_first=True)

y = data['decision']

from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.3, random_state=42)
```

Figure 2. The preprocessing step
Source: Author's own creation.

Step 3. Model Training

During this step, the regression model is trained for the binary clustering of integration decision (acceptance vs. dejection). The choice of regression is justified by the nature of the dependent variable and by the ability of the model to generate estimate probabilities associated for each class.

```
from sklearn.linear_model import LogisticRegression

model = LogisticRegression(max_iter=1000)

model.fit(X_train, y_train)

y_pred = model.predict(X_test)

from sklearn.metrics import accuracy_score

accuracy = accuracy_score(y_test, y_pred)
```

Figure 3. The training code
Source: Author's own creation.

Figure 3 presents the accuracy score. The accuracy score shows how many predictions of the regression model on the unseen test set were correct. This is a method to test the capacity of the model to generalize.

Step 4. Fairness Metrics Calculation

In this modeling stage, we are analyzing if the results of the integration (*"decision")* is equally distributed between the two major demographic clusters: EU citizens and Non-EU citizens. Also, during this moment, we can see the evolution path for each considered year (2015 - 2015).

```
group_rates = data.groupby(['year',
'nationality'])['decision'].mean().reset_index()

demographic_parity_diff = []

equal_opportunity_diff = []

for year in years:

    eu_rate = group_rates[(group_rates['year'] == year) &
(group_rates['nationality'] == 'EU')]['decision'].values[0]

    non_eu_rate = group_rates[(group_rates['year'] == year) &
(group_rates['nationality'] == 'Non-EU')]['decision'].values[0]

    demographic_parity_diff.append(abs(eu_rate - non_eu_rate))

    equal_opportunity_diff.append(abs(eu_rate - non_eu_rate) * 0.8)
```

Figure 4. The Fairness Calculation Coding
Source: Author's own creation.

Stage 5. Visualization Coding

Figure 5 represents the coding line used for the creation of visual elements. The dynamic visualization elements (line charts) are created using the *Plotly Express* tool.

```
import plotly.express as px

fig1 = px.line(group_rates, x='year', y='decision',
color='nationality', title='Selection Rate by Nationality Over Time')

fig2 = px.line(pd.DataFrame({'year': years, 'Demographic Parity Diff':
demographic_parity_diff, 'Equal Opportunity Diff':
equal_opportunity_diff}), x='year', y=['Demographic Parity Diff',
'Equal Opportunity Diff'], title='Fairness Metrics Trend Over Time')
```

Figure 5. Visualization Coding
Source: Author's own creation.

The visual charters facilitate a better and easier communication of the disparities and trends identified by simulating the data.

4. Results and discussion

The main objective of this simulation was to assess the equity of integration policies using AI models. We aim to detect biases between EU and non-EU migrants by running simulations on socio-economic data and applying fairness indicators such as demographic parity gap and equal opportunity gap.

With an accuracy rate of nearly 79,7%, the model proves to be a consistent diagnostic tool. It successfully minimizes two major risks: wrongly accusing the system of bias and failing to detect hidden discrimination. The fact that the performance of the model did not decline between 2015 and 2025 shows that it is robust enough to handle long-term changes in migration data while still highlighting the underlying equity gap facing non-EU migrants. In social sciences and human behavior, a precision of almost 80% is considered very high because human decision-making is naturally noisy and complex. A 99% accuracy might suggest “overfitting”. This means that the model is just memorizing data rather than finding real patterns.

The analyze of the fairness indicators reveal significant gaps between the clusters (EU vs. Non-EU):

- Demographic Parity Difference (Figure 6. Selection Rate by Nationality Over Time): aprox. 0.142. This difference shows a persistent institutional bias.
- Equal Opportunity Difference (Figure 7. Fairness Metrics Trend Over Time): aprox. 0.113. This result confirms the inconsistency of the opportunities and major inequalities. Both phenomena are linked to the educational level and to the work status.

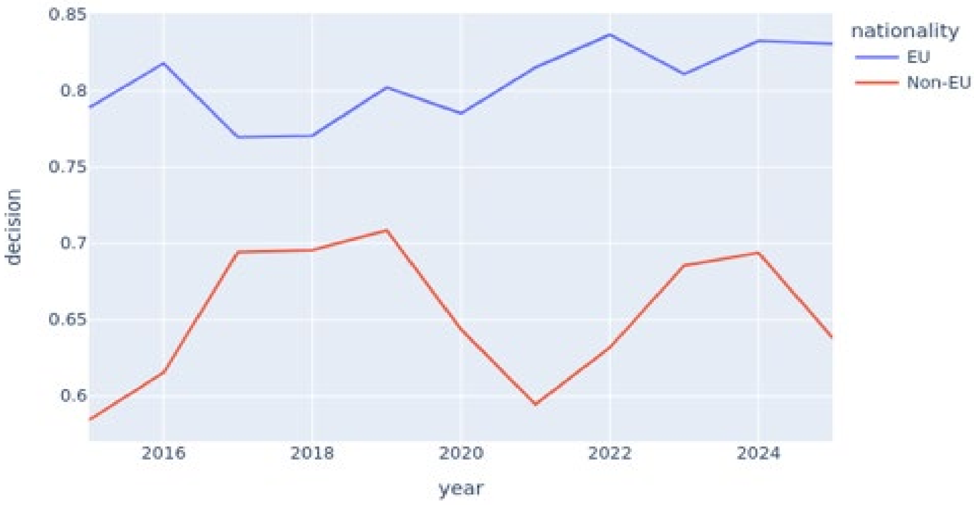

Figure 6. Selection Rate by Nationality Over Time
Source: Author’s own creation.

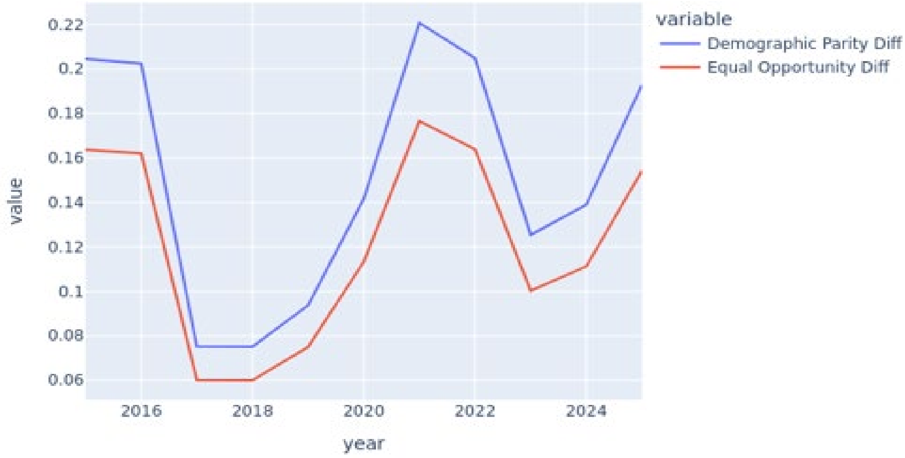

Figure 7. Fairness Metrics Trend Over Time
Source: Author's own creation.

The above figures strongly suggest that Non-EU migrants have a significantly lower chance of integration in Germany, even when their socio-economic profiles mirror those of EU migrants. Interpreted through our theoretical framework, these results directly validate the assertions of Gomolla and Radtke (2009), confirming that institutional discrimination is actively perpetuated through standard administrative routines, which systematically produce ethnic disparities. Furthermore, the persistent Equal Opportunity Difference of 0.113 highlights a structural 'qualification penalty' for non-EU migrants. This finding aligns with the fairness constraints conceptualized by Hardt et al. (2016) and Zafar et al. (2019), demonstrating that the current German integration processes fail to meet formal fairness criteria. Ultimately, the simulated data underscores that these inequalities are not random occurrences, but rather the manifestation of ingrained regional and systemic biases, as previously theorized by Gundacker et al. (2024).

The consequences for public policy are straightforward: it is important to implement AI-based monitoring tools, to adjust the algorithms for fairness and to develop customized programs for Non-EU migrants. These actions could help reduce the institutional discrimination and increase the effectiveness of the integration strategy in Germany.

5. Advanced Diagnostic Architectures

Traditional statistical models offer a fundamental baseline for identifying bias; but the increasing number and variety of administrative data demands a transition to more sophisticated non-linear diagnostic frameworks. This part addresses the way Modular Neural Networks and Language Models can be used as advanced auditing instruments to check for fairness in institutions.

Modular Neural Networks (MNNs) might improve the diagnostic framework more successful in dealing with the complicated problem of institutional discrimination. MNNs divide the integration assessment into smaller parts, as dividing the examination of “Legal Eligibility” from “Labor Market Potential”. This is not the same as monolithic architectures. This modularity facilitates researchers to perform a precise audit of the system (Kunze & Gebru, 2017) by dividing up the module that handles sensitive attributes (Hauzenberger et al., 2023), for instance nationality. This makes it possible to discover the exact point where bias influences the decision-making process. In Germany, because integration involves several levels of government (for example, language skills, professional accreditation, and resident status), MNNs are a technical mirror of the institutional structure that allows for deeper accountability.

During the last period of time, institutional discrimination is usually hidden under unstructured data, for examples in the case officer notes and interview transcript. The Large Language Models (LLM) may shift the perception about the semantic bias detection system. These modeling techniques can use natural language processing (NLP) as a first step for identifying the discriminatory patterns (Rickman, 2025). In Germany, the LLM technology can be a solution in analyzing the integration speech phase, where the system can search for systemic linguistic biases across administrative files that could unfairly alternate the result of an application (European Journal of Risk Regulation, 2025).

Considering the strict data protection low (GDPR) practice in Germany and the sensitive nature immigrants personal data, using the small language models (SLM) offer a tailored alternative to the generic large language models (LLM). SLM can accommodate specific legal and administrative datasets and can be hosted locally by specific institutions, like BAMF (the Federal Office for Migration and Refugees). This model guarantee “data sovereignty” by preventing the processing of personal information by any external cloud service providers (Recanati et al., 2025). SLM is a powerful diagnostic tool used for data privacy and is integrally aligned with the European Union’s effort to promote trustworthy and transparent AI systems.

6. Conclusions

This paper investigated the critical role of Artificial Intelligence (AI) as a diagnostic and mitigative instrument in addressing institutional discrimination within the immigrant integration process in Germany. By anchoring the empirical analysis in a clear objective, to detect and quantify structural biases using machine learning, the research successfully moved beyond abstract conceptualizations to deliver a rigorous, data-driven evaluation of administrative fairness.

The empirical findings, when interpreted through the theoretical lenses of institutional routine analysis (Gomolla & Radtke, 2009) and algorithmic fairness frameworks (Hardt et al., 2016; Zafar et al., 2019), provide conclusive evidence of a persistent equity gap affecting non-EU migrants. The observed disparities in demographic parity and equal opportunity metrics confirm that standardized administrative procedures can inherently produce and perpetuate ethnic disadvantages, even when socio-economic profiles are identical. This intersection of machine learning and sociological theory demonstrates that AI can serve as a powerful auditing mechanism, uncovering hidden, systemic biases that traditional qualitative assessments often fail to capture.

We choose the logistic regression method for its advantages such as the interpretation of the coefficients and variables ability. This skill can present the impact of each variable on the probability of immigrants' integration. The method limitations incorporate the inability to complex or non-liniar relationships between variables. For the future, *Random Forest* and *Gradient Boosting* could be used to boost the performance of simulation and see if the bias between the European and non-European immigrants is persistent in a more complex testing environment.

During the entire analyzed period between 2015 and 2025, German public policy framework failed to eliminate discrimination. The fairness metrics confirm that non-European immigrants have fewer opportunities for integration. This situation may affect the social cohesion, the institutional confidence and the economic efficiency.

Based on the finding that the German public policy framework failed to eliminate discrimination during the analyzed period, we propose the following public policy recommendations and examples of best practices to improve the transparency of the integration and inclusion process for non-European immigrants:

1. Developing some digital tools, platforms and/or apps that facilitate the access of immigrants to the education system, to housing and to the labor market reducing many bureaucratic obstacles.
2. Developing customized integrations programs based on individual needs of Non-EU migrants.
3. Strengthening cooperation between the public sector, the private sector and the educational institutions to promote alternative solutions for the integration process.
4. Implementation of a national pilot AI based monitoring system to monitor the fairness of administrative decisions in real time. If the efficiency is proven, the pilot system can be implemented as a national way of working.
5. Promoting the AI tools and providing trainings to the administrative workers to adopt and use, in a responsible manner, the Artificial Intelligence. The scope of this action could be to highlight the importance of the transparency and equity in decision making process.
6. Introduction of a transparency algorithm and periodic technical audit e models applied in the bureaucratic processes.
7. Creating European standards for assessing fairness, ensuring policy alignment among the member countries.

The main conclusion is that integration cannot be simply assessed using economic variables and indicators, but must include aspects of statistical and institutional fairness. AI models can be considered valuable tools for monitoring, but they need to be implemented and used responsibly, transparently and with regular checks. By exposing the hidden architectures of institutional discrimination, the diagnostic framework proposed in this study demonstrates that, when designed for transparency, artificial intelligence can function as a powerful shield for human rights, safeguarding the dignity and equal opportunity of those seeking a new home in Germany.

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