A Five-Phase Framework for Fair Insurance: Reviewing Strategies for Digital Price Differentiation

RIJK MERCUUR, HU University of Applied Sciences Utrecht, Netherlands
SIEUWERT VAN OTTERLOO, HU University of Applied Sciences Utrecht, Netherlands
HUIB ALDEWERELD, HU University of Applied Sciences Utrecht, Netherlands

Insurers increasingly use machine learning to assess financial risk and determine personalized premiums with the aim of ensuring income and financial stability. Despite the recent focus on fairness, insurance companies and software developers struggle to bridge the gap between fairness principles and practical implementation. Justifying digital price differentiation in terms of both fairness and profit is a socio-technical problem: it requires an integration of organizational processes, ethical-legal considerations on indirect discrimination, and technical fairness metrics and mitigation techniques. The paper proposes a structured list of 33 strategies designed to help organizations navigate these challenges, derived from a survey of Dutch insurance professionals, a systematic review of academic literature, and expert evaluations. The strategies are organized into five phases: Understand, Determine, Adjust, Evaluate and Communicate, with a particular emphasis on aligning fairness principles with actuarial accuracy and compliance with legal standards. This work contributes to the literature by offering an overview of actionable strategies that go beyond fairness metrics, addressing both technical and social aspects of digital price differentiation. Practically, the strategy list supports insurance professionals — including data scientists, actuaries, auditors, compliance officers, and communication staff — by (1) providing a comprehensive overview of strategies to balance fairness and profitability in digital price differentiation, and (2) offering a framework to structure organizational processes and internal communication around this balance.

Keywords: strategies, insurance, pricing, price differentiation, price discrimination, fairness metrics, algorithmic bias, solidarity, discrimination, literature review, AI, machine learning

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1 Introduction

Financial institutions increasingly implement artificial intelligence (AI) to improve financial performance, yet this raises concerns about the fair treatment of clients [52]. As of 2024, 37% of Dutch financial institutions have adopted AI [9]. In particular, insurance companies and software providers in the insurance sector use AI to calculate individualized premiums based on the specific circumstances of the client, a practice known as price

Authors' Contact Information: Rijk Mercuur, HU University of Applied Sciences Utrecht, Utrecht, Netherlands, rijk.mercuur@hu.nl; Sieuwert van Otterloo, HU University of Applied Sciences Utrecht, Utrecht, Netherlands; Huib Aldewereld, HU University of Applied Sciences Utrecht, Utrecht, Netherlands, huib.aldewereld@hu.nl.

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differentiation. Following Zuiderveen Borges [51], we refer to the use of machine learning to determine these individual premiums as *digital price differentiation*. Insurance is an essential service, and reasonable pricing that does not make insurance unaffordable for specific groups is therefore important. Consequently, insurance companies, regulators, legislators, and other stakeholders seek to ensure that any price differentiation does not lead to discrimination or unfairness[19, 28, 30, 51].

Balancing the need for accurately pricing risk while avoiding unfair bias and discrimination is challenging for insurance companies and their software developers. This challenge stems from a broader socio-technical dilemma in which technical solutions alone cannot resolve the ethical and strategic complexities of fairness in digital price differentiation. Four key factors contribute to this dilemma:

(1) The significant risks to insurance companies if their pricing models are not accurate due to adverse selection [10]. If insurers' prices are too high, they will lose customers to the competition since many consumers use price comparison websites and are price-sensitive [10]. If prices are too low, insurers will attract more customers but will have to pay more out in expected damages than they will earn in premiums for each customer, effectively losing money.
(2) A fundamental tension between fairness and maximizing financial returns. Insurers aim to refine digital price differentiation to reflect individual risks as precisely as possible. However, fairness considerations often require treating similar clients equitably, even when granular risk assessments suggest otherwise. For example, insurers may use ZIP codes to differentiate premiums based on neighborhood-based risk variations, increasing returns while potentially exacerbating socio-economic disparities. This inherent conflict requires organizations to navigate trade-offs between fairness principles and actuarial accuracy.
(3) Ambiguity remains regarding how to mitigate indirect discrimination and translate fairness principles into organizational strategies. While direct discrimination—explicit differentiation based on protected characteristics such as gender or ethnicity—is relatively straightforward to identify and eliminate [32, 48], indirect discrimination is more complex. Seemingly neutral variables, such as ZIP codes or vehicle types, may serve as proxies for protected attributes, leading to disparate impacts [20, 25, 32, 35, 50]. The legal and ethical boundaries of such practices remain uncertain, making it difficult for insurers to establish clear and defensible fairness policies [14, 51].
(4) Integrating scientific and technical methods for improving and measuring fairness into social processes presents significant challenges. The literature provides various fairness metrics and bias mitigation techniques (e.g., synthetic data augmentation)[36]. However, selecting appropriate metrics, defining target fairness thresholds, and implementing mitigation strategies require integration of ethical, legal, technical, and organisational aspects. Effective integration demands not only technical expertise but also organisational alignment on understanding, mitigating, evaluating and communicating fairness. Especially, since the insurance industry is regulated and insurance pricing experts need to present their pricing models and risk calculations to internal and external supervisors. The requirements and expectations of stakeholders put additional social and organisational constraints of what models or inputs can be used.

In short, addressing fairness in digital price differentiation requires more than just technical tools or laws — it demands a structured socio-technical approach that also involves legal checks and communication. To support professionals in this balancing act, a concrete and ordered list of strategies is needed. The list presented below offers clear guidance on how insurers and software providers can evaluate and justify digital price differentiation.

This paper addresses the question:

> "What can insurance companies and software providers for the insurance sector do to justify the use of digital price differentiation from the perspectives of both fairness and financial returns?"

Unlike optimization-focused approaches, which aim at maximizing outcomes, our focus is on justification—ensuring that digital price differentiation meets ethical, legal, and financial standards. We define a strategy as a series of actions aimed at upholding or achieving (organizational) values [42]. To answer our research question, we create a structured list of 33 strategies to help insurance companies and software providers justify digital price differentiation while balancing fairness and financial return (see Table 1-6).

The primary contribution of this paper is this structured strategy list, which was created through a survey of Dutch insurance practitioners, a systematic review of academic and industry papers, and evaluated with professionals and experts. Scientifically, this list is unique for its comprehensive scope, addressing both technical and social aspects, and for its focus on digital price differentiation, which is a regression problem, rather than a classification one. Our work goes beyond fairness metrics to offer practical strategies that fit into organizational processes. Practically, the strategy list supports insurance professionals — including data scientists, actuaries, auditors, compliance officers, policymakers, and public relations teams — by (1) providing a comprehensive overview of strategies to balance fairness and profitability in digital price differentiation, and (2) offering a framework to structure organizational processes and internal communication around this balance.

The remainder of the paper is structured as follows: Section 2 reviews related work on legislation, protocols, and technical metrics; Section 3 details the scoping of the literature review, the systematic selection of literature from academia and practice, and the construction of the strategy list; and Section 4 presents the resulting strategy list, followed by a conclusion and suggestions for future research. As described in Appendix A: a full interactive version of the strategy list including explanations per strategy can be found on https://explainable-ai.nl/4d/. Appendix B shows the methodology and result of the survey used for scoping the literature. The structured strategy list is presented both in the main paper in Table 1 -6 and Appendix C.

2 Background & Related Work

This section reviews current work aimed at optimizing digital price differentiation for insurance companies and software developers, focusing on Dutch and European regulations. While regulations across European countries vary, they are largely similar due to overarching EU laws, such as the AI Act, GDPR, and the European Convention on Human Rights.

2.1 Dutch and European Union Legislation

The European Convention on Human Rights (Article 14) prohibits discrimination based on attributes such as sex, race, religion, and other status. This primarily addresses direct discrimination. The Convention does not specify whether indirect discrimination is forbidden, leaving room for interpretation by individual countries.

Dutch law, particularly Article 1 of the Dutch Constitution and the General Equal Treatment Act [35], forbids direct discrimination based on categories race, religion, gender, and sexual orientation (Article 1.1.1c) but not age.

The law also prohibits indirect discrimination, defined as practices that disproportionately affect protected groups (Article 1.1.1c), unless such practices have a legitimate aim, are necessary and proportionate (Article 2.2.1). This leaves insurers and regulators responsible for ensuring that their practices are justifiable under these terms.

At the EU level, laws such as the GDPR and the AI Act emphasize non-discrimination and fairness but leave specific interpretations of indirect discrimination to existing legal frameworks and public interpretations [15, 52]. The GDPR stresses fairness (Article 5) but lacks detailed criteria for measuring fairness or assessing proportionality and necessity. The AI Act, intended to address AI-related risks, attempts to protect human rights by requiring AI providers to examine data for possible biases that could lead to discrimination. However, the Act does not provide clear guidelines on what constitutes an adequate examination of such biases, thresholds, or how they should be measured. As noted by Deck et al. [15], "the AI Act lacks clear substantive standards for determining when unequal treatment is inadmissible".

Although the AI Act is particularly aimed at high-risk AI, such as people's health or work performance are assessed, similar principles apply to limited- and low-risk AI applications, property insurance. The European Insurance and Occupational Pensions Authority (EIOPA) highlights that fairness considerations must be incorporated into risk assessments, regardless of whether the AI is classified as high-risk. A 2025 consultation paper from EIOPA reinforces this, emphasizing the need for fairness governance and risk assessments for all AI applications in insurance [19].

2.2 Protocols & Technical Metrics

Current law does not specify how to measure fairness and how to determine what level of fairness is sufficient. Practitioners aim to bridge this gap by using comparisons with previously approved models applying guidelines or using checklists. One widely cited fairness guideline is the four-fifths rule [6], which states that the hiring rate of any protected group must be no less than 80% of the rate for non-protected groups. This rule, developed in the US in the 1970s, provides a clear and easy-to-implement benchmark but can be arbitrary when applied to multiple protected groups or complex scenarios. As Deck et al. [15] observes, "technical fairness metrics such as statistical parity or equalized odds offer an actionable approach to measure and mitigate 'bias'. However, it remains unanswered what kind of evidence would signal sufficient efforts of bias detection and correction" [15].

There are multiple examples of checklists designed to help practioners with fairness decisions. Directly related to our aim is the socio-technical fairness checklist by Madaio et al. [34]. This checklist, co-designed to tackle organizational challenges related to fairness, focuses on aligning fairness assessments with the needs of practitioners. As Madaio et al. [34] states, other fairness checklists [1, 8, 12, 17, 23, 24, 28] are too broad, overly specific, or narrow in scope, often focusing solely on aspects like data collection. Madaio et al.'s approach is distinct because it emphasizes co-designing tools that match practitioners' needs, rather than providing rigid checklists. We extend their work by applying a similar framework to the specific context of insurance and digital price differentiation, focusing on actionable strategies and addressing the balance between fairness and financial returns, particularly through communication and justification.

Dutch ethical protocols, such as DEDA [46] and IAMA [45], emphasize the need to evaluate fairness based on human rights principles. While these frameworks offer useful structured approaches, they remain general and not sector- specific, lacking specific guidance on operationalizing fairness in practice. On an international scale, the

ISO 42001 standard for AI management identifies fairness as an essential component of AI risk assessment but does not provide concrete instructions for implementing fairness within organizational contexts.

In terms of technical fairness metrics, there are several tools available, such as statistical parity and equalized odds, which are designed to assess and mitigate bias in AI systems [6]. However, there is no consensus on what constitutes an adequate level of fairness or what evidence is needed to demonstrate sufficient efforts at bias mitigation. Therefore, technical metrics need to be part of a broader, structured process that helps practitioners justify digital price differentiation in a transparent and fair manner.

3 Literature Selection

3.1 Type of Literature Review

The primary aim of this literature study is to identify strategies for insurers and software developers to justify digital price differentiation in terms of fairness and financial returns. We adopt a 'realist synthesis' approach, following Turnhout et al. [44]. This approach is characterized by: (1) its focus on addressing the practical problem of how to create solutions for real-world challenges (referred to as the 'problem in context') and (2) its emphasis on observable elements, namely interventions (strategies in our terminology) and outcomes (in our case, the justification of digital price differentiation in terms of fairness and financial returns). The remainder of this section details the scoping, query development, literature selection, extraction of strategies, organization of findings, and validation through feedback from practice.

3.2 Scoping the Review

To scope the literature review (and research question) we conducted a mall survey on 36 subjects of professionals in the insurance sector to ensure we focus on the relevant values for digital price differentiation. Appendix B details our findings. First, we found that fairness and wealth are deemed important for justifying digital price differentiation. Second, fairness is deemed slightly but significantly more important. Third, solidarity is relevant for our literature selection and is included in our query. Fourth, transparancy and explainabilty are mentioned as important but considered to be instrumental to fairness. Their importance is reflected in several strategies (e.g., Strategy 25 in Table 2) and further explored in Section 5. Fifth, other mentioned 'values' are either encompassed by fairness and wealth or do not refer to actual abstract values (as defined by Oosterlaken [37]). We used these findings to formulate our search query.

3.3 Query Development

To formulate the search query, we identified key terms derived from our research questions. The final query was structured as follows:

```
TITLE-ABS-KEY ( "fair*" OR "solidarity" OR "discriminat*" OR "
    antidiscriminat*" OR "non-discriminat*" OR "equal*" )
AND TITLE-ABS-KEY ( "premium␣differentiation" OR ( ( "pric*" AND ( "insur*
    " OR "actuarial" ) ) ) )
```

```
AND TITLE-ABS-KEY ( "algorithm*" OR "machine␣learning" OR "AI" OR "
    artificial␣intelligence" OR "generalized␣linear␣model" OR "extreme␣
    gradient␣boosting" )
AND PUBYEAR > 1999 AND PUBYEAR < 2025
AND ( LIMIT-TO ( DOCTYPE , "ar" ) OR LIMIT-TO ( DOCTYPE , "cp" ) OR LIMIT-
    TO ( DOCTYPE , "ch" ) )
AND ( LIMIT-TO ( LANGUAGE , "English" )
```

This query aimed to produce a manageable number of results, avoiding both an insufficient (<5) and an overwhelming (>60) number of papers. Earlier iterations, such as:

```
TITLE-ABS-KEY ( "fair*" ) AND TITLE-ABS-KEY ( "premium␣differentiation" )
    AND TITLE-ABS-KEY ( "generalized␣linear␣model" )
```

```
TITLE-ABS-KEY ( "fair*" ) AND TITLE-ABS-KEY ( "premium␣differentiation" )
```

yielded too few results. Applying the final query resulted in 54 papers.

Key considerations in the query formulation included:

Use of Synonyms for Fairness Multiple terms were included to ensure comprehensive coverage. ‘Solidarity’ was added based on the results in Section 3.2, while ‘equal*’ and ‘discriminat*’ were incorporated based on domain knowledge and iterative refinements to maintain a pragmatic number of results.

Focus on Insurance The search specifically targeted terms related to insurers and price differentiation to ensure relevance.

Use of Synonyms for digital price differentiation digital price differentiation refers to the use of machine learning algorithms to assess financial risk per client [51]. Since computational methods for price differentiation often overlap with algorithmic and AI-based approaches, these terms were included alongside specific techniques used in practice, such as generalized linear models and extreme gradient boosting.

Omitting Wealth We did not restrict our search to papers explicitly mentioning ‘wealth’ or synonyms like ‘profitability’ or ‘returns.’ As discussed in Section 3.2, optimizing returns is generally assumed in practice. Papers addressing digital price differentiation with a fairness focus were deemed sufficient for covering both aspects.

To ensure quality and consistency, only peer-reviewed, English-language papers were selected. The final query was executed in Scopus on October 18, 2024, yielding 54 papers.

3.4 Selection Process, Exclusion Criteria, and Additional Papers

Figure 1 illustrates the selection process for the literature review. The 54 papers retrieved via Scopus were screened against the following exclusion criteria, leading to the removal of 25 papers:

Different Type of Insurance Papers focusing on niche insurance domains, such as weather insurance for wind farms or agricultural insurance, were excluded.

Not Applied and Only Mathematical Papers that did not apply digital price differentiation in a real-world context but instead focused solely on mathematical proofs were excluded.

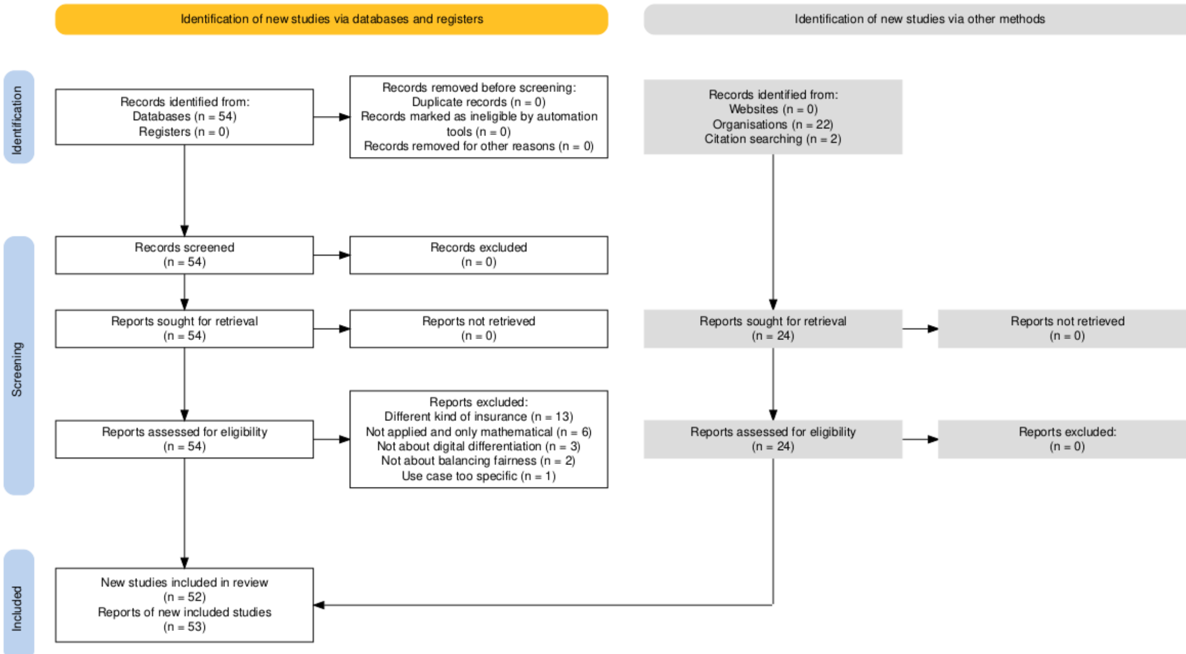

Fig. 1. PRISM selection process to distill papers.

Not About digital price differentiation Papers that discussed price differentiation without involving algorithms or computational models were excluded.

Not About Balancing Fairness Papers that optimized wealth through algorithmic techniques without addressing fairness considerations were excluded.

Use Case Too Specific Papers focusing on very specific regional studies (e.g., a single study on insurance in Thailand) were excluded.

These criteria ensured that our selection remained focused on the socio-technical challenge of how insurers and software developers can justify digital price differentiation. We prioritized papers discussing justification strategies rather than those purely analyzing algorithmic optimization techniques.

In addition to the 28 academic papers selected, 24 additional papers were identified through academic experts and practice partners (n=22) and citation searching (n=2). Practice partners comprise a core group of two software makers for insurance, one insurance company and a Dutch insurance association, and a (periphal) support group of one additional insurance company, one software maker, one insurance consultancy company and one independent regulator. Academic experts comprise 3 scientist working at the (applied) university on fairness and AI.

At the beginning of our research, we contacted practice partners and academic experts with our main research question and requested relevant literature. Additional papers were suggested from our core group during workshops and discussions related to the broader research project. These non-academic sources, including manuals and protocols, provided valuable practical insights. Combining the academic papers (n=28) and practice-oriented papers (n=24), we obtained a final set of 52 papers for extracting strategies to justify digital price differentiation in terms of both fairness and financial returns.

3.5 Constructing and Arranging The List

Extracting strategies and synthesise these in the resulting list in Tables 2-4 was an iterative proces reading papers, noting down strategies, ordering these in categories, merging strategies that are similar and redefining and re-ordering the phases and categories. To define the categories [34] was used as a basis. Similarly to Madaio et al. [34], we use temporal phases in our construction and have a determination ('define' in Madaio et al. [34]) and adjusting phase ('build' in Madaio et al. [34] but in our case a model already exists and mainly needs to be adjusted to improve fairness). Unlike Madaio et al. [34], we focus on five phases (1) *Understand* (2) *Determine* (3) *Adjust* (4) *Evaluate* and (5) *Communicate*, making both understanding and communication an explicit phase. Creating understanding within an organization is a necessary prerequisite to enable cooperation on balancing fairness and wealth and focus on evaluating and communicating the model. The evaluation is based on the crisp-dm cycle and the fairness handbook. Communication is a key social factor in justifying the choices mentioned in our literature selection but often overlooked. A main focus of the work was combining and reformulating strategies to make them mutually exclusive and complete in relation to our papers. Our main choices regarding this were on the granularity of presenting the strategies, the wording and separating the legal and ethical aspects (Table 6) and referring to them in other strategies.

We conducted semi-structured interviews with our 4 core practice partners (i.e., one policy adviser from a Dutch insurer association, one actuary and manager from an insurer software company, and one ML expert from the same company, see section 3.5). The interviews, held in Dutch on MS Teams, included a list of strategies with an additional explanation column (see Appendix B). For each strategy, we asked: (1) Do you understand the strategy? (2) If not, does the explanation help? (3) If not, why? We also inquired if the list covered all important aspects for justifying digital price differentiation.

Most strategies (22) were understood immediately, with a few minor rewording suggestions. Sixteen were fully understood, and ten required further explanation but were understood after that. Participants suggested shortening the list for ease of use but had no further improvements. We used their feedback to rephrase, remove, or merge strategies and align terminology with practitioner language, such as changing 'subsidiarity' to 'necessity' (see Table 6). Domain knowledge was also integrated, such as emphasizing information asymmetry between insurers (not customers and insurers) in strategy 9. We also simplified the depth of certain strategies for broader understanding.

We shared the list with academic experts for feedback on wording and completeness. Academics were selected by e-mailing our periphal support group and Dutch (applied) university departments related to AI and Fairness. Technical details, like adjusting interactions between sensitive variables (principle 21, Table 3), were added, along with adjustments to emphasize intersectionality and the self-propagating effects of bias (see the full interactive list, Appendix A).

4 Result

Table 1-6 presents our main contribution: a list of strategies for justifying digital price differentiation in terms of fairness and wealth, organized into five phases: *(1) Understand* (Table 1), *(2) Determine* (Table 2), *(3) Adjust*

(Table 3), *(4) Evaluate* (Table 4) and *(5) Communicate* (Table 5). Additionally, eight legal and ethical principles are referenced throughout these phases, influencing the strategies (Table 6). Principles and strategies thus differ in that the principles are relevant in all phases while strategies are split into five phases.

4.1 List of Strategies Organized into Five Phases

The first phase, *Understanding*, is crucial for justifying fair and profitable price differentiation [33]. This phase stresses the importance of recognizing the nuances of discrimination, different forms of bias, and the critical role of sensitive variables in achieving fairness. By understanding these factors, organizations can balance fairness with predictive accuracy, address legal uncertainties, and mitigate privacy concerns. Moreover, market dynamics like information asymmetry and non-risk-based pricing must be considered to maintain competitiveness while adhering to ethical standards. This understanding ensures alignment, creating clarity and focus on how fairness and wealth can be justified, minimizing internal debates.

In the *Determination* phase, various strategies balance fairness and profitability. For example, determining the target group for insurance (strategy 11) directly affects both fairness and profitability. Smaller, homogeneous groups may reduce premium disparities but lead to discrimination risks, as discussed by [25]. The handling of sensitive variables (strategy 12) also plays a critical role, with different levels of rigor affecting fairness outcomes [25]. Depending on this level of rigor one needs to investigate which variables are ethically and legally sensitive and which ones are not (strategy 15); in particular, as understanding why variables are sensitive helps in justifying (the extent of) the use of these variables. Including non-risk factors like discounts (strategy 13) is increasingly regulated in markets like the U.S. and U.K. [29, 50], while setting lower bounds for fairness and expected return (strategy 14) can help assess discrimination risks using principles like the "80% rule" [39]. Next, one should determine which fairness measure one uses; strategy 16-19 describe the core choices such as the choice between indivudal and group fairness and wheter one directly uses a protected variable to measure fairness (or a proxy)[2, 40]. Finally, fairness mitigation strategies (strategy 20) focus on reducing bias at different stages, making determination a pivotal step in justifying fair and profitable price differentiation.

The *Adjustment* phase consists of strategies aimed at mitigating bias and enhancing fairness through pre-processing, in-training, and post-processing techniques. In pre-processing, strategies such as removing sensitive variables and their correlated interactions (strategy 21) or adjusting correlations around sensitive variables (strategy 22) help reduce bias. However, these techniques might reduce fairness and obscure the information of the original data [6, 36, 50]. Another method, adding synthetic data points to balance sensitive relationships (strategy 23), helps mitigate fairness while keeping original data in tact [6]. In-training adjustments, such as optimizing an algorithm for both accuracy and fairness (strategy 24), offer a compromise between performance and fairness, though their implementation can be complex [6, 36]. Furthermore, making the algorithm explainable (strategy 25) improves transparency, ensuring risk assessments are understandable [6, 50]. Lastly, post-processing strategies (strategy 26) involve transforming predicted risk assessments to improve fairness, which can avoid recalibrating models and keeps the original data model pipeline and dataset intact. However, this strategy's effectiveness depends on the accuracy of the original model and fairness measures [6, 36, 50]. These adjustment strategies are the bread and butter of actually improving the model such that digital price differentiation becomes fair and remains profitable.

The *Evaluation* phase and *Communication* phase focus on assessing the fairness and profitability of the model and communicating these aspects to stakeholders. Evaluation strategies include comparing the original and modified models to assess fairness and profitability, ensuring that the adjusted model meets predefined thresholds (strategy 27) [50]. It's also crucial to evaluate the pre-launch model against ethical and legal standards (strategy 28) to ensure compliance with societal and legal expectations [43]. After launch, it is important to monitor the model's fairness through audits and statistical evaluations (strategy 29), verifying that it remains fair and non-discriminatory [6]. On the communication side, it's vital to explain the role of insurance in risk spreading to customers (strategy 30), emphasizing the social aspect [25]. Insurers must also communicate the necessity of risk assessment in determining fair premiums (strategy 31) [25]. Furthermore, fairness decisions should be transparently communicated to regulators, explaining sensitive variables, fairness measures, and model thresholds (strategy 32), ensuring accountability and regulatory compliance [3, 6, 21, 25, 32, 43, 49]. Finally, enabling stakeholders such as customers, competitors, and regulators to challenge the model (strategy 33) promotes transparency and shared responsibility [7].

4.2 The Ethical and Legal Principles

The principles for evaluating the legality and ethics of price differentiation are applied through various strategies across different phases of the pricing process. These principles consist of two parts: (1) a three-step framework to determine the legality of a distinction, and (2) five ethical criteria to assess the sensitivity of a variable. The legal assessment criteria are grounded in regulations concerning indirect discrimination. To determine whether a distinction constitutes indirect discrimination, one must first assess whether the differentiation serves a legitimate aim. In the context of insurance, this usually pertains to the provision of essential services and the accurate assessment of risk (i.e., underwriting) [25, 35, 49] (Principle 1).

Second, the necessity of the variable in achieving this goal is evaluated—often through empirical methods to verify whether it contributes to more accurate risk classification [49]. Necessity is also considered by comparing the variable in question to possible alternatives that might yield comparable results with less negative impact on fairness [21, 35, 49]. The third step involves assessing proportionality, which ensures that the insurer's actions are not excessively burdensome relative to the interests of the insured [35, 49]. This step resembles a cost-benefit analysis, weighing the gains in predictive accuracy against the social or ethical costs of grouping individuals based on specific variables.

While insurers primarily focus on legal compliance, five ethical principles can further illuminate why certain variables are considered sensitive, and to what extent their use may be justifiable. First, the more mutable or influenceable a variable is, the less ethically sensitive it tends to be. For example, gender is generally more ethically sensitive than the number of claim-free years. Second, the stronger the correlation between a variable and the relevant risk—and the weaker its correlation with protected characteristics—the less sensitive it is. Comparing correlations effectively amounts to assessing proportionality (Principle 3).

Third, causal relationships offer a plausible, comprehensible rationale for using a variable. For instance, College voor de Rechten van de Mens [11] argues that a well-established causal link between education level and mortality can justify the use of education as a rating factor in life insurance. Fourth, variables associated with a history of social injustice or discrimination are considered more sensitive (e.g., skin color versus, say, foot size). Fifth, if the use of a variable for differentiation negatively influences individual behavior or broader societal outcomes, it becomes more ethically sensitive. An example is the decision not to use DNA information in life insurance pricing, as this could discourage voluntary DNA registration and hinder scientific progress.

In sum, these five ethical principles help assess the defensibility of using specific variables—or proxies thereof—in pricing decisions.

4.3 Papers not linked to strategies

Tables 1–6 list all papers that propose strategies, as indicated in the 'source' column. However, not every paper identified in the literature review could be directly linked to a specific strategy. Some works focus primarily on technical implementations or broader conceptual issues. The following section describes papers that were reviewed but not explicitly associated with any particular strategy.

4.3.1 Technical papers focused on algorithmic approaches

Several papers explore how specific modeling techniques can improve pricing accuracy and, in some cases, fairness. Aruk et al. [5] demonstrate how incorporating location-based risk through Markov-modulated tree-based gradient boosting can lead to fairer pricing outcomes. Kshirsagar [31] compares two modeling approaches and concludes that machine learning techniques outperform traditional Bayesian models, particularly for predicting risk in concession groups. Anzilli [4] shows how the use of fuzzy variables can enhance pricing accuracy. Saleiro et al. [40] introduce Aequitas, an open-source audit toolkit designed to facilitate the evaluation of fairness metrics across different population subgroups. Pe na-Sanchez [38] focuses on data-scarce insurance markets, such as in the Philippines, and demonstrates how the application of a generalized linear model with a Tweedie compound Poisson–Gamma distribution can improve pricing for bundled micro-insurance products.

4.3.2 Papers on practical applications in insurance pricing

Cunha and Bravo [13] investigate the value of telematics data in enhancing risk estimation and, consequently, pricing. Their work emphasizes the technical potential for price discrimination, though it does not directly address fairness concerns. Fabris et al. [22] conduct an audit of pricing algorithms used in the Italian car insurance industry. Based on an analysis of 2,160 driver profiles, they find that sensitive attributes such as birthdate and gender are used directly in pricing algorithms, a practice that violates existing regulations.

4.3.3 Alternative perspectives on fairness

Some studies approach fairness from non-outcome-based perspectives. Grgič-Hlača et al. [27] emphasize procedural fairness. They assess the acceptability of using certain features based on survey responses, showing how public perception can guide the fair use of variables. Donahue and Barocas [16] use game theory to theoretically examine the trade-off between solidarity and actuarial fairness—highlighting the tension between socially equitable pricing and precision in risk assessment.

5 Discussion, Conclusion & Future Work

This paper has addressed the challenge of ensuring fairness while maintaining financial returns in digital price differentiation within the insurance industry. The main contribution — summarised in Tables 1–6 — is a categorised and ordered set of 33 strategies (and 8 ethical-legal principles employed in several of these strategies). These strategies offer a practical guide for insurers and software developers to navigate the socio-technical dilemma of balancing fairness and profitability. This list is scientifically distinctive due to its comprehensive scope, its integration of both technical and social dimensions, and its focus on digital price differentiation as a regression problem rather than a classification problem. Thus, our work contributes to the literature on AI and fairness by moving beyond abstract fairness metrics and offering actionable strategies that align with organisational processes and values.

From a practical perspective, professionals in the insurance sector—including data scientists, actuaries, auditors, compliance officers, policymakers, and communications teams—can use this strategy list in three ways: (1) as a guide for selecting relevant strategies, (2) as a checklist to ensure that all necessary steps have been taken, and (3) as a communication tool to structure internal discussions about fairness and financial objectives. For example, the list provides a comprehensive overview of strategies, while the online tool and resources (see Appendix A) help users identify and implement those most applicable to their context. In short, the strategy list supports practice as a reference guide, checklist, and facilitation tool for cross-functional dialogue.

This review has centered on two human values: fairness and wealth. In line with value-sensitive design principles [26], we approached these values not as opposing forces but as dimensions that can be reconciled through thoughtful strategy selection. Although the survey (see Appendix B) could be improved through refinements such as a 7-point Likert scale, a broader and more representative sample, and additional open-ended questions, it confirmed the central importance of both values in digital price differentiation.

The value of wealth is especially interesting due to its multiple interpretations. On one hand, it refers to the financial stability of insurance companies—something required by regulators and essential for the industry's long-term viability and the public interest. On the other hand, wealth can be philosophically contested as a human value. While not a terminal value in Schwartz's theory, it is part of the broader value of power [41] and is commonly used in practice to contrast with fairness. Since our aim is to remain close to industry language while acknowledging philosophical nuance, we adopt wealth as a pragmatic proxy for financial returns. Similarly, although terms like solidarity appeared in our literature search, we have treated solidarity as instrumental to fairness in this paper. Future research should explore how both wealth and solidarity are understood and valued in the insurance context.

By combining a systematic literature review with empirical insights from industry professionals, we have tailored this strategy set to the specific needs of the insurance sector, ensuring both relevance and applicability. The findings offer valuable guidance for policymakers, auditors, actuaries, and developers working with algorithmic systems in insurance.

Future research should focus on validating and refining this strategy framework with a larger and more diverse group of professionals. Additional studies could investigate how these strategies can be operationalized in practice and adapted for use in other domains where AI is used for pricing and decision-making.

Category	Index	Strategy employed in the Understanding phase	Source
Discrimination & Bias	1	Understand the difference between direct discrimination and indirect discrimination and the related concepts of 'proxy variable' and 'disparate impact'.	[7, 25]
	2	Understand the difference between two forms of bias: bias because the data does not accurately represent the world (statistical bias) or bias because the data does not represent the world as it ideally could or should be (societal bias).	[7]
Technology & Fairness	3	Understand that removing bias also removes information; information that (potentially) leads to an accurate risk assessment and at the same time (potentially) leads to an unfair premium distribution.	[36]
	4	Understand that there is no one size fits all for fairness and that technology, ethics or law will not provide a definitive answer as to what is best.	[7, 48]
	5	Understand that there is not a single threshold value for what is an acceptable amount of bias, or acceptable amount of disparate impact	[6]
	6	Understand that information about sensitive variables is necessary to measure fairness and is privacy-sensitive.	[14, 47]
Legal & Ethical	7	Understand that the AI Act, EU law and national law specify protected variables that may not be directly discriminated against (e.g., the grounds for discrimination in the AWGB), but do not provide clarity on which variables can be used without indirect discrimination.	[14, 50]
	8	Understand that the justification for making distinctions on a variable depends on the legal and ethical criteria in Table 6.	[3, 6, 21, 25, 32, 43, 49]
Insurance	9	Understand the importance of information asymmetry, especially how unequal knowledge about customers' risk profiles can lead to adverse selection.	[10]
	10	Understand the difference between a risk-based premium and premiums based on non-risk factors (such as giving discounts to attract customers).	[25]

Table 1. Strategies for the Understanding phase.

Category	Index	Strategy employed in the Determination Phase	Source
Target audience	11	Determine the target group to whom you wish to offer the insurance and estimate the consequences for the return and fairness of this choice.	[25]
Determine high-level strategy	12	Determine the level of rigor in dealing with sensitive variables, with the two extremes being (1) not using directly only legally protected variables and (2) completely equalizing premiums across all customers.	[25]
	13	Determine whether the premium will be partly based on non-risk factors (such as giving discounts to attract customers).	[29, 50]
	14	Determine lower bounds for the expected fairness (given a fairness measure) and the expected return of the price differentiation.	[11]
Determine sensitive variables	15	Determine the sensitivity of a variable and the extent to which it is justified to use it given the ethical and legal criteria in Table 6.	[3, 6, 21, 25, 32, 43, 49]
Fairness measurement	16	Determine whether the risk labels in the training dataset are sufficiently trustworthy to base a fairness score on.	[2, 40]
	17	Determine whether the fairness measure measures 'individual fairness' (equality between two matching individuals) or 'group fairness' (equality between two matching groups).	[36]
	18	Determine what the fairness measure compares between two groups or individuals. Fairness measures differ in particular in whether they (1) compare the risk assessment itself, (2) the margin of error in risk assessment (focusing on overestimation or underestimation), and (3) the extent to which they control for whether differences are caused by other nonsensitive variables.	[2, 40]
	19	Determine whether the fairness measure uses protected variables directly to measure fairness or whether the measure uses an estimate of a protected variable based on proxies.	[47, 50]
	20	Determine the implications of your fairness measure choices for selecting a strategy to increase fairness in pre-processing, in-training or post-processing (see strategy 21 to 27).	[3, 6, 21, 25, 32, 43, 49]

Table 2. Strategies for the Determination phase.

Category	Index	Strategy employed in the Adjustment phase	Source
Pre-processing	21	Adjust dataset by removing sensitive variables and any variables or interactions of variables that correlate.	[6, 36, 50]
	22	Adjust dataset by correcting any correlation around a sensitive variable.	[6, 36, 50]
	23	Adjust dataset by adding synthetic data points that level out the sensitive relationships.	[6]
In-training	24	Adjust algorithm so that it optimizes on an accuracy score while keeping the fairness score above a certain threshold.	[6, 36]
	25	Adjusting the algorithm to make it explainable.	[6, 50]
Post-processing	26	Transforming the predicted risk assessment to increase fairness.	[6, 36, 50]

Table 3. Strategies for the Adjustments phase.

Category	Index	Strategy employed in the Evaluation phase	Source
Evaluation	27	Evaluate quantatively whether the adjusted prediction model exceeds the fairness and return threshold..	[50]
	28	Evalualate qualitatively whether the adjusted prediction model is fair given the ethical and legal criteria in Table 6.	[43]
	29	Evaluate the model repeatedly in practice (after launch) for fairness through audits, statistics, experiments or observational studies.	[6]

Table 4. Strategies for the Evaluation phase.

Category	Index	Strategy employed in the Communication phase	Source
Communication	30	Communicating to the customer the social role of an insurance company in supporting risk spreading.	[25]
	31	Communicating to the client the need for risk assessment both to be profitable and to give an 'appropriate' premium for a risk.	[25]
	32	Communicate to regulators the choices regarding fairness: the estimation of sensitive variables, the fairness measure, the choice of a specific threshold value and the final model.	[3, 6, 21, 25, 32, 43, 49]
	33	Enabling customers, competitors and regulators to challenge the model by setting up procedures for doing so.	[7]

Table 5. Strategies for the Communication phase.

Category	Index	Principle	Source
Legal	1	The legality of a distinction depends on a *legitimate interest* for the distinction.	[18, 25, 35, 49]
	2	The legality of a distinction depends on whether the distinction is *necessary* to achieve the goal: the necessity of using the variable is to be assessed by analyzing whether there is another variable that achieves a similar result but has a less negative impact on fairness.	[21, 35, 49]
	3	The legality of a distinction depends on whether the insurer's goal is *proportionate* to the affected interests of the customers.	[35, 49]
Ethics	4	The *mutability* of a variable by the client partly determines how justified it is to make distinctions based on that variable.	[3, 25]
	5	The *statistic correlations* around a variable partly determine how justified it is to make distinctions based on this variable; in particular, the correlation with the predicted risk of a customer and the correlations with legally protected variables.	[25, 32]
	6	The *causal relationships* around a variable partly determine how justified it is to make distinctions based on this variable.	[25]
	7	The *prejudices from societal history* (such as around skin color) partly determine how justified it is to make distinctions based on this variable.	[25, 32]
	8	The *effect on desirable behaviour* partly determines how justified it is to make distinctions based on this variable.	[3, 25]

Table 6. Legal and ethical principles influencing the strategies.

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