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Forward to the Spring 2026 Edition of ILM JAHM

Issues in Law and Medicine was founded in 1985 by the National Legal Center for the Medically Dependent & Disabled, Inc. and was published w/o interruption until 2025 when acquired by the Alliance for Hippocratic Medicine. In this inaugural edition of Issues in Law and Medicine: a Journal of the Alliance for Hippocratic Medicine (ILM JAHM), under new owners and leadership, we continue the tradition of ILM by presenting insightful articles at the nexus of law and medicine that address issues important to the most vulnerable populations.

Our first article, **Beyond Genetic Discrimination: Emerging Challenges in the Age of Artificial Intelligence,** explores the legal and policy issues that are rapidly emerging in the application of AI to governmental, educational, and other fields. The current regulatory framework is inadequate to address the subtle and powerful biases that may manifest accidentally or intentionally, and suggestions for mitigating these risks are proposed.

Our second article, **Anti-Progesterone in Environmental Water**, reports on a preliminary investigation into the presence or absence of the endocrine-disrupting compound mifepristone in environmental surface water. Although a small study, this work provides preliminary evidence suggesting the need for further investigation into the presence and effects of endocrine-disrupting compounds on mammalian life.

Our third article, **Risk factors predictive of post-abortion distress demonstrate that most abortions are contraindicated: A retrospective cross-sectional study,** examines the effectiveness of an 8-item scale for risk assessment as a screening device to identify women who are perceiving pressure to undergo unwanted (coerced) abortion. This screening device may aid in identifying women at highest risk of post abortion distress, leading to better informed consent prior to abortion.

Our fourth article, **Viewing D&E Abortion Procedure Promotes Negative Emotions,** explores the effects of a visual depiction of a D&E abortion on prolife/prochoice identification, knowledge of the procedure, and emotional response after viewing. This article provides interesting insights into immediate responses to viewing an accurate visual description of a D&E procedure.

We hope you will enjoy reading these well-written articles and consider submitting your future work to Issues in Law and Medicine: A Journal of the Alliance for Hippocratic Medicine.

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Beyond Genetic Discrimination: Emerging Challenges in the Age of Artificial Intelligence

Li Zhenkang

Abstract: With the deep integration of artificial intelligence and biotechnology, the paradigm of genetic discrimination is undergoing a fundamental transformation. Rather than relying on specific genetic markers, AI systems may infer individuals' underlying biological risks through proxy data. This emerging form of discrimination, conceptualized in this article as "Algorithmic Proxy Genetic Discrimination" (APGD), is predictive, opaque, and structural. However, China's existing Personal Information Protection Law and fragmented antidiscrimination framework remain insufficient to address this problem. In addition, APGD raises profound ethical and social challenges. To mitigate these risks, this article proposes a tiered regulatory approach: (1) controlling the misuse of proxy variables at the data input stage; (2) strengthening transparency and auditing in algorithmic decision-making; and (3) establishing an outcome-oriented mechanism for anti-discrimination liability and rights protection.

Keywords: APGD; Proxy Data; Anti-Discrimination Law; Bioethics; AI

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Introduction

Genetic discrimination is a distinctive subtype of discrimination that has emerged primarily alongside advances in commercial DTC genetic testing and gene-editing technologies.[1] This issue has become increasingly salient as DTC genetic testing has moved from a niche biomedical service to a rapidly expanding consumer market.[2] According to industry reports, the global DTC genetic testing market was valued at approximately USD 2.17 billion in 2025 and is projected to reach approximately USD 11.02 billion by 2035.[3] In fact, genetic discrimination is not a new phenomenon. The first case of genetic discrimination emerged in the late 1970s in the United States, particularly in private insurance and employment.[4] Since then, many countries across Europe, Asia, and Oceania have successively enacted anti-discrimination laws to prevent such practices.[5] For example, a civil service recruitment dispute in Foshan, Guangdong, in 2010, in which a candidate was disqualified for carrying the thalassemia gene and later filed an administrative lawsuit, is widely regarded as China's first genetic discrimination case.[6]Following intense public and medical debate, the local government revised the physical examination standards in 2011, removing genetic testing for the thalassemia trait.[7] This historical trajectory underscores a critical point: traditional genetic discrimination was relatively visible, and its direct association with physical biomarkers made the resulting injustice easier to identify and address through legal and policy reform.

However, by the late 1990s, legal scholars had already begun to warn that the more serious threat in the future would lie beyond these visible forms of discrimination.[8] For example, Susan M. Wolf argued that restricting access to physical DNA alone would not prevent "geneticism."[9] Today, that warning has materialized through a technological pathway she could scarcely have foreseen. With the deep integration of AI and biotechnology, the paradigm of genetic discrimination has been fundamentally transformed.[10] Rather than relying solely on visible physiological differences or specific genetic markers, AI systems combine electronic health records (EHR), behavioral data, and other proxy indicators to infer probabilistic risks relating to future illness, incapacity, or cost.[11] In this process, individuals are no longer assessed primarily based on their present ability or actual conduct; they are sorted according to predicted biological risk.[12]

To better understand this shift, consider an everyday scenario: During pre-employment screening, a healthy engineer might be flagged as "high risk" by an AI HR system based on his EHR or regional health data. The resulting disadvantage stems not from a manifested disease or identifiable genetic defect, but from a purely algorithmic inference regarding his future biological vulnerability.[13] More importantly, the scenario has moved beyond the realm of theory; it is an emerging reality in the era of AI. As Anya Prince and Daniel Schwarcz have shown, even when the law prohibits algorithms from using protected traits such as race, gender, or genetic data, they may still maximize predictive power through "rational" proxy discrimination by relying on facially neutral variables correlated with those traits, regardless of discriminatory intent.[14] In other words, genetic discrimination has not disappeared; rather, it is increasingly being reconstituted through AI-driven, big data–enabled forms of predictive screening — a practice I call "algorithmic proxy genetic discrimination" (APGD).

Current legal and theoretical scholarship has yet to adequately respond to this emerging threat. Substantial research has addressed traditional genetic discrimination, general algorithmic discrimination, and algorithmic proxy discrimination (APD), and legislative protections for genetic data, such as the *Genetic Information Nondiscrimination Act of 2008* (GINA) in the United States, are already in place.[15] However, existing scholarship has largely failed to address the intersection between algorithmic proxy mechanisms and genetic discrimination, leaving a critical regulatory gap. Properly identifying and resolving this new issue is crucial for the effective future regulation of this novel form of discrimination.[16]Although this Article draws upon the antidiscrimination frameworks of China and the United States as its primary analytical backdrop, the institutional challenges posed by APGD are inherently universal.[17]As such, the normative proposals and legal analysis developed herein offer highly relevant, forward-looking insights for global policymakers.

Methodology

This article adopts a doctrinal and conceptual legal analysis to frame "Algorithmic Proxy Genetic Discrimination" (APGD) as a distinct form of discrimination, rather than as a mere extension of traditional Genetic Discrimination (GD) or a simple subcategory of Algorithmic Proxy Discrimination (APD). It deliberately draws on literature on genetic discrimination, algorithmic fairness, and health data governance, selected because these bodies of scholarship most directly address the intersection between genetic risk, proxy inference, and data-driven decision-making. Empirical examples, such as the Obermeyer algorithm study, are used not as comprehensive empirical evidence, but as illustrative cases showing how proxy variables may reproduce forms of biological exclusion without relying on direct genetic testing. The legal analysis focuses on GINA, *China's Personal Information Protection Law* (PIPL), and other selected policy materials because these instruments represent major comparative regulatory approaches to genetic information, health data, and algorithmic governance.

Contributions and Structure of the Article

This Article makes three main contributions. First, it identifies the regulatory gap created when AI systems infer genetic or biological risk through proxy variables without directly using genetic data. Second, it offers a conceptual innovation by defining "algorithmic proxy genetic discrimination" (APGD) as a distinct form of discrimination that bridges, yet differs from, traditional genetic discrimination (GD) and algorithmic proxy discrimination (APD). Third, it proposes a tiered doctrinal response that combines proxy-data control, algorithmic transparency and auditing, and outcome-based anti-discrimination liability.

In this regard, this article proceeds as follows: Part II examines the paradigm shift from traditional genetic discrimination to algorithmic proxy genetic discrimination. It clarifies why APGD constitutes a distinct new category of discrimination, identifies its core characteristics, and examines the key driving forces behind its emergence. Part III analyzes the emerging challenges posed by APGD in the Chinese context, focusing on its ethical risks, legal loopholes, and broader social implications for multi-stakeholder governance and the balance between governance and innovation. Part IV proposes a tiered regulatory approach for addressing APGD. Finally, Part V concludes.

The Paradigm Shift from Genetic Discrimination to Algorithmic Proxy Genetic Discrimination

APGD as a Distinct Form of Discrimination in the AI Era: Why It Is Not Merely a Subset of GD or APD.

In this article, APGD is defined as a novel form of discrimination in which AI systems, without relying on physical genetic samples or formal genetic test results, mine and analyze an individual's proxy data to infer underlying genetic traits or biological risks, thereby producing outcomes that are tantamount to genetic discrimination in effect. These algorithmic inferences are then used to subject individuals to unfair treatment in the allocation of essential socioeconomic opportunities, such as employment, insurance, and healthcare.[18]

It is necessary to further clarify why APGD should be treated as an independent analytical category rather than subsumed under existing frameworks. First, APGD is doctrinally distinct from traditional Genetic Discrimination. Current legal regimes addressing genetic discrimination, with GINA being the most prominent example, generally confine protection to explicitly defined genetic information, such as DNA test results.[19]

In other words, under 42 U.S.C. § 2000ff of GINA, traditional genetic discrimination is generally premised on the acquisition of substantive biological genetic data, such as DNA sequencing or chromosomal analysis.[20] By contrast, the underlying logic of algorithmic proxy genetic discrimination (APGD) departs from this reliance on physical DNA, instead employing predictive algorithms to infer health risks from non-genetic proxy data. Therefore, if legal analysis rigidly adheres to the traditional GD framework, using GINA as an example, will the law inevitably be consigned to an institutional blind spot marked by regulatory failure and statutory silence? More specifically, should the definition of "genetic information" under GINA be reconsidered or modestly expanded to cover proxy data that can be used to infer genetic traits or biological risks?

Second, APGD cannot be reduced to a subset of algorithmic discrimination and algorithmic proxy discrimination (APD). Algorithmic discrimination is the broader category under which APD falls;[21]APD is a specific mechanism within algorithmic discrimination, whereby algorithms reproduce discrimination based on protected social attributes through the use of proxy variables. More specifically, general algorithmic discrimination usually concerns how automated systems reproduce social bias, such as unequal treatment based on race, gender, age, disability, or socioeconomic status.[22] At the level of algorithmic operation, APD focuses more specifically on how algorithms indirectly reproduce such bias through facially neutral proxy data.

Although the framework of APD recognizes the use of neutral proxy data to reproduce bias, it remains primarily concerned with discrimination based on sociological attributes, such as race, gender, or socioeconomic status.[23] However, it does not adequately account for a distinct form of harm arising from predictions about an individual's future biological condition. Unlike APD, which focuses on relatively static sociological attributes such as race and gender, APGD seeks to

infer human biological vulnerability and the future probability of disease onset, treating genetic risk as a dynamic and probabilistic attribute of life and health.

In addition, there is a critical divergence in the underlying ethical harms (Social Bias vs. Geneticism). APD tends to amplify entrenched social prejudices, such as the marginalization of vulnerable groups. APGD, however, triggers a far more profound bioethical crisis: geneticism and biological determinism. Beyond merely depriving individuals of employment opportunities, APGD fundamentally subjects individuals to social stratification based on their perceived "biological destiny".[24] This practice deeply implicates medical ethics and human dignity, thereby transcending the conventional boundaries of algorithmic fairness discourse.[25] To better clarify the paradigm shift from GD to APGD, Table 1 compares their key differences in data sources, mechanisms, and legal implications.

To sum up, although APGD shares certain features with traditional genetic discrimination and APD, it cannot be fully subsumed under either framework. Unlike traditional genetic discrimination, APGD does not depend on explicit genetic data; unlike APD, it concerns inferred biological vulnerabilities and prospective health risks rather than static sociological attributes. Therefore, APGD is a new form of discrimination in the AI era. Failure to recognize APGD as a distinct category leaves a profound form of discrimination unprotected by existing laws.

A Summary of the Core Characteristics of APGD

It is crucial to emphasize that APGD is a new form of discrimination in the AI era. It represents a hybrid and distorted evolution of both genetic discrimination and APD. APGD has three main core characteristics:

(1) It is proxy-based. Even where the decision-making process does not directly collect or use genetic information, AI systems may still infer an individual's underlying biological susceptibility from proxy data.[26,27] Legally, this exposes a structural limitation. Because current regulations mainly focus on clearly defined sensitive data, such as genetic information. However, AI systems can rely on proxy data to infer similar risks, allowing discriminatory practices to bypass existing legal controls.

(2) It is AI-driven. Once proxy data is collected, it is processed through AI systems as mediating mechanisms that generate probabilistic assessments of biological vulnerability and convert risk signals into preemptive adverse outcomes.[28] Due to the inherent "black box" nature of AI systems, their decision-making processes are often insufficiently transparent, making it difficult for affected individuals to understand why they have been classified as high-risk, let alone to meet the evidentiary burden required to legally challenge such determinations.[29]

(3) It is structural. This new discrimination rarely operates in isolation; instead, it readily interacts with preexisting disadvantages associated with poverty, illness, disability, or geography, and may reinforce and entrench social inequality through continuous data-driven feedback loops.[30] It should be noted that APGD is still primarily applied in the fields of employment, insurance, and healthcare.

Table 1: The Paradigm Shift from Traditional Genetic Discrimination to APGD

Comparison	GD	APGD
Data Source	Physical biological samples, direct DNA sequencing	EHR, digital behavioral trajectories, consumer data, zip codes, online searches.
Mechanism	Exclusion based on clear biological facts or diagnosed genetic traits.	Complex mathematical probability inference and high-dimensional feature matching extracting proxy variables via machine learning (ML).
Transparency	High. Victims generally know they face exclusion due to submitting genetic or medical reports.	Extremely low. Due to black-box algorithms and mathwashing, causal links are nearly impossible to prove.
Legal Regulation	Partially regulated. Covered by specific laws (e.g., GINA) or strict medical ethics guidelines.	Legal vacuum. Current privacy and antidiscrimination frameworks struggle to address data-correlated predictive penal

The Driving Forces Behind the Shift Toward APGD

Capital's Strategic Exploitation of the Gray Areas in Anti-Discrimination Law

Laws have a strong deterrent effect.[31] With the enactment of anti-discrimination laws exemplified by the U.S. GINA, employers and health insurers were expressly prohibited from directly obtaining and using individuals' DNA sequences in hiring or underwriting decisions.[32] This strict regulation of "substantive biological data" significantly increased the legal risks and compliance costs associated with traditional genetic discrimination. In other words, the enactment of GINA reduced the risk of genetic discrimination to some extent and, in turn, helped alleviate public concerns in the United States about the misuse of genetic information. One empirical finding shows that prior to GINA's enactment, approximately 26% of high-risk individuals refused to undergo genetic testing due to concerns about insurance denial or employer discrimination; by 2013, five years after its implementation, this proportion had fallen to about 3.2%, indicating a significant downward trend.[33]

However, the underlying drive of capital to minimize risk and maximize profit did not disappear.[34] Given that APGD is predominantly deployed in commercial sectors such as employment, healthcare, and insurance, it is inextricably linked to the concept of commercial capital. Unless the inherent profit-driven logic of "minimizing risk and maximizing profit" changes, laws will only force capital's discriminatory practices to mutate through technological upgrades. Consequently, these practices may cloak themselves in the guise of big data, becoming

increasingly insidious and slipping through existing legal loopholes. A clear example is GINA: although it regulates the acquisition and use of explicitly defined "genetic information," its statutory definition does not clearly extend to proxy data that can be used by AI systems to infer genetic traits or biological risks.[35] This displacement effect became the fundamental driver of technological evolution: Discrimination was not eliminated; rather, it was transformed into forms capable of evading existing regulation.

Mathematical Cleansing: The Illusion of Objectivity

APGD operates on the principle of "mathwashing"—a term popularized by data scientist Fred Benenson to describe the false assumption that mathematically grounded algorithms are inherently objective.[36] In fact, because ML or AI models optimize solely for predictive accuracy without inherent moral constraints, they easily absorb the human biases and historical inequalities embedded within their training data. A stark example is Amazon's scrapped AI recruiting tool: trained on 10 years of male-dominated tech industry resumes, the algorithm mathematically concluded that male candidates were preferable and automatically downgraded resumes containing the word "women".[37] This perfectly illustrates how AI can blindly automate historical discrimination. Therefore, this allows decision-making institutions to easily pass the buck to algorithms. They can dodge the accusation of discrimination by calling it data-driven business intelligence based on neutral data. This opacity leaves victims with little way of knowing whether they were denied services because an algorithm had effectively classified them as resembling a group associated with certain genetic defects.[38]

Empirical Mapping: Proxy Data Entrenches Inequality Again

The danger of proxy variables in medical and social sorting is vividly demonstrated by empirical studies. In a landmark 2019 study published in *Science*, researchers led by Ziad Obermeyer examined a commercial algorithm used to manage healthcare for millions of patients.[39-40] The algorithm exhibited severe racial bias because it used "historical healthcare costs" as a convenient proxy for "future health needs". Due to systemic inequalities and unequal access to care, Black patients historically incurred lower healthcare costs than White patients with the same level of actual illness. However, the algorithm falsely inferred that Black patients were healthier, cutting by more than half the number of Black patients identified as eligible for additional clinical support. This argument is not intended to claim that all proxy-based prediction produces APGD. Rather, it shows how proxy-based inference may create APGD-like risks when used in exclusionary decision-making without transparency, justification, or safeguards.

If this logic of algorithm proxy discrimination (APD) is mapped onto the framework of APGD, the implications become deeply troubling. Just as "healthcare costs" functioned as a flawed and biased proxy for "health needs," algorithms can readily use variables such as gym attendance, dietary purchases, or zip codes as proxies for genetic vulnerability. In this way, APGD can quietly reproduce and entrench structural inequality, giving rise to a form of genetic redlining in the digital age.[41]

The Emerging Challenges Posed by APGD in the Chinese Social Context

When evaluating the impact of Algorithmic Proxy Genetic Discrimination (APGD), one must recognize that emerging technologies often trigger ethical crises before they generate legal responses. It is precisely in the effort to address these ethical crises that the vulnerabilities of existing legal frameworks and the core challenge of governance become exposed.

The Core Ethical Challenges of AI-Driven "New Discrimination"

The Erosion of Fairness and Equality

The erosion of fairness is most clearly reflected in the shift in allocation standards from equal evaluation based on actual ability to predictive screening based on future risk.[42] Under a traditional conception of fairness, individuals should be assessed primarily on the basis of their present physical condition, actual capacity, or real conduct. However, APGD imposes a form of "algorithmic determinism." Once proxy data is incorporated into ML or AI, individuals may be identified, categorized, and excluded in advance—even though no actual harm has occurred and no present incapacity can be shown. Fairness thus no longer consists in treating real individuals equally; instead, it is displaced by a technical logic of preventing uncertain future risks.[43]

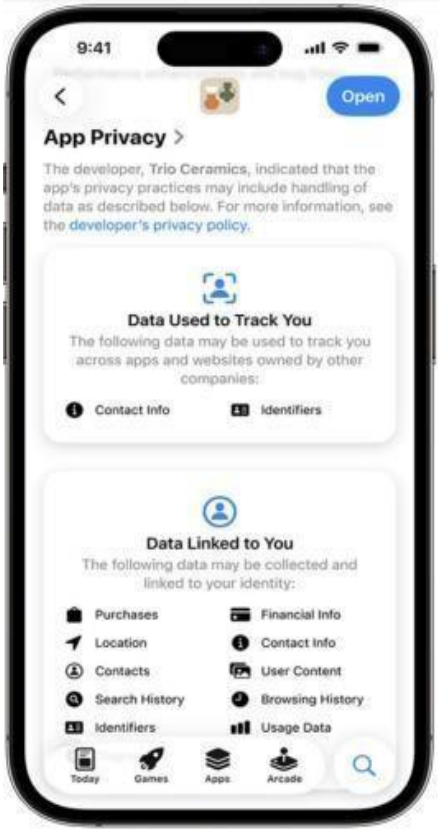
More importantly, during the training process, algorithmic models often absorb the biases and inequalities embedded in existing social data and reproduce stereotypical representations of certain groups as "high risk."[44] For example, if the training data come from an industry long dominated by men, the algorithm may learn the implicit bias that male candidates are better suited for technical positions. Even without directly using gender as a variable, the system may still rely on indirect signals—such as work experience, educational background, or patterns of word choice—to classify female applicants as a poorer fit. So, once members of particular families or regional populations are repeatedly identified as groups likely to generate high healthcare costs, these probabilistic judgments may gradually harden into institutionalized labels.[45] Over time, algorithms may not only magnify existing social prejudice, but also further entrench structural inequality through feedback loops, leaving disadvantaged groups persistently marginalized.

The Undermining of Informed Consent and Individual Autonomy

In the course of algorithmic decision-making, AI systems may not rely on DNA data itself, but instead infer an individual's future health risks by combining proxy data.[46] Considering a frequently used app interface, as shown in Figure 1, users of shopping apps often consent to the collection of their "location data" and "shopping habits" in order to access delivery services or personalized product recommendations. In their perception, this merely involves exchanging relatively harmless data for convenience. However, within the opaque "black box" of algorithmic systems, AI conducts deep correlation and integrative analysis of these fragmented data points.[47] By aggregating records such as late-night purchases of high-sugar fast food and over-the-counter medications, together with behavioral patterns indicating a lack of outdoor activity, the system can, even without directly accessing blood samples or family medical history, generate highly accurate predictions regarding an individual's future risk of cardiovascular diseases or diabetes.[48]

The core problem is that, even when individuals consent to the collection of certain types of data, such as location information or shopping habits, they often do not truly understand how those data may be combined and what they are used for. In this sense, what appears to be "consent" on the surface does not amount to real informed consent.

Figure 1: Example of APP-Associated Data[49]



Predatory Marketing and Exploitation of Vulnerability

While traditional precision marketing seeks to predict what consumers want, marketing driven by genetic inference directly targets what they fear. When algorithms leverage proxy data—such as purchasing habits, search histories, and geolocation—to infer an individual's latent genetic traits or health risks, the fundamental nature of precision marketing undergoes a radical transformation.[50] It ceases to be mere "product recommendation" and mutates into the targeted predation of human physiological and psychological vulnerabilities.

Should an algorithm deduce that a consumer has a heightened risk for Alzheimer's disease or a specific hereditary cancer, the marketing system may systematically bombard them with unproven, exorbitant health supplements, aggressive preventive medical interventions, or overpriced private health insurance. Trapped in a state of severe information asymmetry, consumers remain oblivious as to why they are targeted by such advertisements. Consequently, their health-related anxieties are subconsciously amplified, driving irrational consumption

decisions. From an ethical standpoint, this constitutes the covert exploitation of vulnerable populations—specifically, those rendered psychologically fragile by their potential disease risks.[51]

Challenges to the Current Legal Landscape in China

PIPL: Struggling to Keep Pace with AI-Driven Genetic Inference

As discussed above, APGD gives rise to the effects of genetic discrimination. But in terms of anti-discrimination laws, China currently faces a legislative vacuum. Compared to the limited jurisdictional scope of the U.S. GINA, there remains a significant legislative lacuna in China's legal system concerning dedicated regulations for bioethical discrimination. Why has China yet to enact specific, direct legislation addressing bioethical discrimination? (1) The *Personal Information Protection Law of the People's Republic of China (PIPL)* categorizes genetic information as "sensitive personal information," mandating separate consent and the execution of a Personal Information Protection Impact Assessment.[52] (2) The primary impetus behind the enactment of GINA in the U.S. stemmed from its highly commercialized health insurance market, where the public harbored profound concerns that genetic predispositions might lead to the loss of commercial coverage.[53] In contrast, China implements a broad-based basic medical insurance system; an individual's genetic information does not compromise their access to fundamental public healthcare.

However, unlike the United States, China, much like the EU, tends to address these issues primarily through a data governance framework rather than an anti-discrimination framework.[54] In the context of mainland China's civil law system, genetic data falls within the regulatory framework of the *Personal Information Protection Law of the People's Republic of China (PIPL)*. The PIPL, which came into force on November 1, 2021, is a comprehensive statute enacted to protect personal information rights and interests and to regulate personal information processing activities. Article 28 of the PIPL classifies information such as "biometric identification" and "medical health" information as sensitive personal information, and defines sensitive personal information as personal information that, once leaked or unlawfully used, is likely to result in harm to the dignity of natural persons or endanger their personal or property safety.[55] Although Article 28 does not expressly list "genetic data" as an independent category, genetic data usually possesses biometric, medical health-related, and identity-identifying attributes. Therefore, as a matter of legal interpretation, it should be included within the protective scope of sensitive personal information.

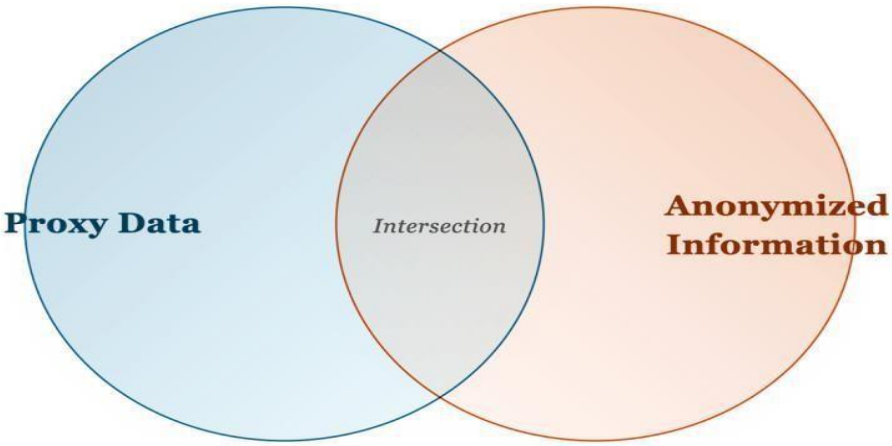
By the same logic, should non-genetic proxy data involved in APGD also be brought within the regulatory scope of the PIPL? If not, would such data fall outside the Personal Information Protection Law and therefore remain beyond its effective regulatory reach?

On this basis, I identify a deficiency in the current framework concerning the legal consequences of anonymization. This concerns the legal consequences of anonymization. Under Article 73 of the Personal Information Protection Law, anonymization requires that personal information be processed in such a way that a specific natural person can no longer be identified and the information cannot be restored.[56] Once data satisfies this standard of full anonymization, it is, in principle, removed from the scope of the PIPL. Yet this exclusion may create a regulatory

loophole. In China, when proxy data used for APGD is exploited by commercial actors, it will almost inevitably be processed in anonymized form. This raises a further question: what is the relationship between APGD proxy data and anonymized data?

For a clearer illustration, Figure 2 shows the relationship between the two. Anonymized pharmaceutical purchase records provide a useful example of their overlap. In other words, this overlapping category may formally evade the regulatory logic of the PIPL's anonymization rules, which are intended to create space for legitimate commercial innovation. However, despite the loss of direct identifiability, such data may still enable AI systems to infer biological vulnerabilities or future health risks, thereby generating the very discriminatory risks that APGD seeks to capture.

Figure 2: The Set Relationship Between Anonymized Data and Proxy Data.
(Source: Author's own elaboration.)



Fragmented Anti-Discrimination Rules: Inadequate Protection Against APGD

As noted above, China does not have anti-discrimination legislation comparable to the U.S. GINA. Instead, anti-discrimination in China is mainly reflected in a fragmented set of constitutional principles, labor law provisions, PIPL rules, and sector-specific regulatory norms.

However, traditional anti-discrimination rules generally rest on two assumptions: first, that the prohibited ground of discrimination can be identified; and second, that the unfair treatment is sufficiently visible to be proven. APGD challenges both assumptions.[57] It operates through prediction, proxy variables, and opaque algorithmic processes, making it difficult to determine

precisely why a person has been disadvantaged or to establish the causal link required under traditional legal frameworks.

Challenges to Social Governance

APGD as a Cross-Sectoral Governance Problem

The new form of discrimination generated by APGD cannot be effectively governed through any single area of law. This is because APGD is not merely a privacy issue or a discrimination issue. Rather, it is a complex governance problem involving law, medicine, artificial intelligence, data governance, and public policy.[58]

From a privacy-law perspective, APGD involves the collection, processing, and secondary use of health-related, behavioral, consumer, and lifestyle data. Yet privacy law alone is insufficient, because APGD often operates through proxy data rather than explicit genetic information. Such data may appear neutral or non-sensitive on its face, but it can still be used to infer biological vulnerability, disease predisposition, or future health risks.

From an anti-discrimination and AI-governance perspective, APGD also challenges existing legal frameworks. Traditional anti-discrimination rules usually depend on the identification of a protected ground and a visible act of unequal treatment, while AI governance focuses on transparency, explainability, accountability, and contestability. APGD complicates both approaches because discriminatory effects may be produced through opaque algorithmic correlations, probabilistic predictions, and seemingly neutral variables. Therefore, APGD should be understood as a cross-sectoral governance challenge requiring coordination among personal information protection, anti-discrimination law, medical ethics, AI governance, consumer protection, insurance regulation, employment law, and public health policy.[59]

Counterarguments: The Tension Between Governance and Innovation

One possible objection to this article's argument is that predictive risk assessment should not be regarded as inherently discriminatory. In fields such as healthcare, insurance, employment, and public administration, predictive models may serve legitimate functions. For example, risk prediction may help identify high-risk patients, optimize the allocation of medical resources, and support preventive medicine.[60] Actuarial assessment in insurance has long been used to classify risk pools and maintain the sustainability of insurance systems. Predictive tools in public administration may also be used to detect fraud, anticipate public health risks, or improve the distribution of welfare resources.[61] Therefore, the use of proxy variables and predictive analytics is not necessarily objectionable in itself.

This objection is important because a complete prohibition on predictive risk assessment would be neither realistic nor desirable. In the age of artificial intelligence, predictive analytics has become an important driver of technological progress, institutional innovation, and business

development. If the law were to adopt a blanket prohibition, it might unduly suppress beneficial innovation, weaken incentives for enterprises to develop socially valuable AI applications, and reduce institutional capacity to respond to complex risks. Accordingly, the problem addressed by APGD should not be understood as a general rejection of prediction, risk assessment, or AI innovation.[62] Rather, it concerns how to strike a balance between encouraging technological progress and preventing biological-risk inferences from being used for exclusionary or discriminatory treatment.

It is precisely against this background that China has advocated "agile governance" in the development of AI.[63] Agile governance itself is a common concept in international technology governance, digital governance, and AI governance. It emphasizes the use of flexible, dynamic, and adjustable regulatory approaches to respond to rapidly changing technological risks. China has incorporated this concept into its own AI governance framework and has recognized it as one of the principles of AI governance.[64] Why, then, has China proposed or adopted agile governance? There are three main reasons. First, AI technology develops so rapidly that unified legislation may easily lag behind technological change. Second, China needs to balance development with security in AI governance. Third, AI-related risks are highly context-specific.

The real legal problem arises when predictive assessment shifts from supportive intervention to exclusionary classification. The decisive issue is not whether prediction is used, but how it is used, for what purpose, and with what consequences. When inferred genetic or biological vulnerability is used to deny opportunities, impose additional burdens, or inflict other forms of unfair treatment without justification, proportionality, and substantive safeguards, heightened legal scrutiny should be triggered. By contrast, when prediction is used to provide support, improve prevention, or allocate assistance, it may be legally and ethically justified. The purpose of regulating APGD is therefore not to impede innovation, but to ensure that predictive technologies remain compatible with equality, dignity, and the individual's right to an open future.

Constructing a Well-Calibrated Regulatory Approach for APGD

Controlling the Misuse of Proxy Variables at the Data Input Stage

Although data such as EHRs, physical examination results, place of residence, occupation, and consumption patterns may not appear to constitute genetic data on their face, they can readily function as proxy variables in big-data and machine-learning systems for predicting an individual's future risk of illness or biological vulnerability. Therefore, addressing APGD cannot be limited to asking whether an algorithm directly uses genetic test results. The central concern is that APGD may operate through algorithmic systems that infer an individual's genetic risk without ever accessing genetic data itself.[65]

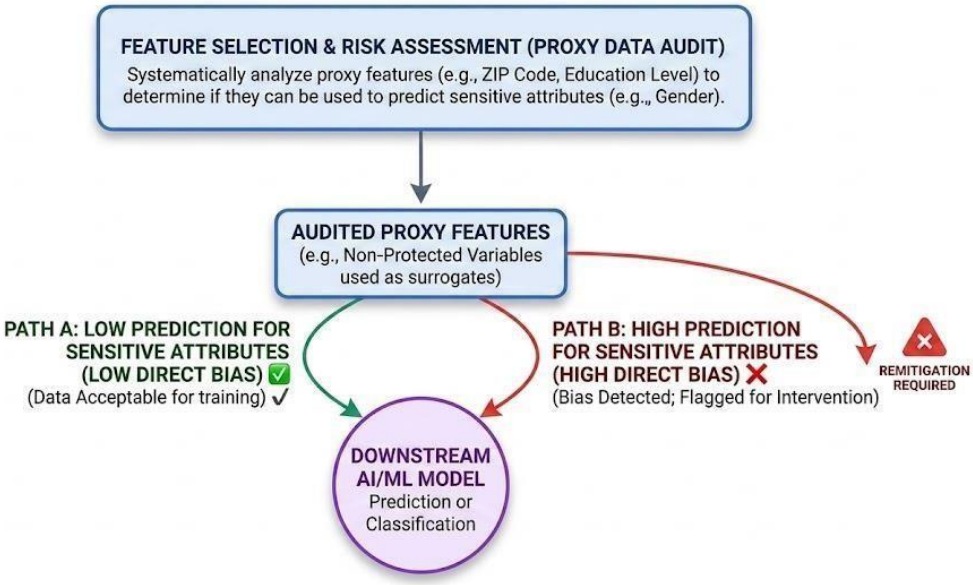
This article argues that a "risk test" should be introduced at the upstream stage of proxy data processing. Even where certain data appear neutral and objective on their face, they should be

subject to regulatory scrutiny if their use in machine-learning or algorithmic systems may produce harmful or discriminatory outcomes.[66] As shown in Figure 3, the central concern is not merely the nature of the data itself, but the risks generated by its computational use.

It should nevertheless be emphasized that not all proxy data should be subject to blanket restrictions. An overly broad approach would risk overregulation, inhibit socially beneficial innovation, increase compliance costs, and undermine legal certainty. Accordingly, in high-risk sectors such as employment, insurance, and healthcare, the use of high-risk proxy variables should be subject to targeted restrictions, so as to prevent algorithms from engaging in genetic discrimination under the guise of "neutral" data.[67]

Figure 3: Proxy Data Risk Test in AI and ML Systems

(Source: Author's own elaboration.)



Strengthening Transparency and Auditing in Algorithmic Decision-Making

The hidden nature of APGD lies in the fact that it does not always appear in the form of direct discrimination. Rather, it is often embedded in black-box models, statistical inferences, and seemingly neutral technical processes, through which adverse outcomes are packaged as objective computational results.[68]

In this circumstance, a rational way to regulate this problem is to make sure that harmful decisions cannot be justified merely by saying that "the algorithm produced the result." If an algorithm is used to deny a person an opportunity, service, or benefit, the decision-maker should be required to explain the main reasons behind the outcome, notify the individual that algorithmic tools were involved, and provide a meaningful opportunity to challenge the result and request human review. At the same time, regulation should not focus only on whether the input data were collected lawfully; it should also examine whether the final outcome is unfair or discriminatory in practice. In high-risk settings such as healthcare, insurance, and employment, algorithmic systems

should therefore be subject to record-keeping, risk assessment, and regular auditing, so that "objective computation" cannot become a shield for hidden discrimination.[69]

An Outcome-Oriented Mechanism for Anti-Discrimination Liability and Rights Protection

Regulating APGD requires more than examining whether data collection is lawful or whether algorithmic procedures are formally compliant. It also requires asking whether a decision, in substance, imposes adverse consequences on an individual.[70] This argument has two layers. First, regulation cannot stop at the level of formal legality. Even if data collection, data processing, and algorithmic operation formally comply with existing legal requirements, this does not necessarily mean that the resulting decision is substantively fair. Second, the central issue is whether the outcome effectively excludes, disadvantages, or restricts individuals on the basis of inferred biological vulnerability.

For this reason, individuals harmed by algorithmic decisions should not be left to passively accept the result. They should be granted a comprehensive set of procedural and remedial rights, including the right to be informed, the right to object, the right to explanation, the right to correction, and the right to an effective remedy. At the same time, the law should reduce the practical difficulty of proving algorithmic discrimination.[71] One of the central problems in this area is that ordinary individuals cannot see inside the algorithmic black box. Therefore, the burden of proof should not rest entirely on the affected individual. Instead, the law should ease this burden through appropriate evidentiary and procedural mechanisms.[72]

In Chinese tort law, this remedial framework may be supported by the doctrine of preventive liability. Article 1167 of the Civil Code provides that where a tortious act endangers another person's personal or property safety, the affected person has the right to request the tortfeasor to assume tort liability, including cessation of infringement, removal of obstruction, and elimination of danger. This provision provides a useful doctrinal basis for addressing APGD.[73] Where algorithmic systems create a substantial risk of discriminatory exclusion based on inferred biological vulnerability, the legal response should not wait until concrete damage has already occurred. Instead, preventive remedies should be available to stop, correct, or constrain high-risk algorithmic practices before they produce irreversible harm.

Conclusion

This article proposes a paradigmatic shift from traditional genetic discrimination to Algorithmic Proxy Genetic Discrimination (APGD). It argues that, in the AI era, discrimination may no longer depend on the direct use of genetic test results, family medical history, or explicit genetic data. Instead, algorithmic systems may rely on apparently neutral proxy variables— such as health records, consumer behavior, lifestyle data, or pharmaceutical purchasing patterns—to infer an individual's future biological risks, thereby producing outcomes that are tantamount to genetic discrimination in effect. APGD therefore represents a new form of discrimination in the age of AI. However, it should not be understood merely as a subset of traditional genetic discrimination or algorithmic proxy discrimination. Rather, APGD occupies an intermediate and

distinctive position: it inherits the normative harm of genetic discrimination, but operates through the technical mechanism of proxy-based algorithmic inference.

The analysis further shows that the emergence of APGD is not merely a product of artificial intelligence, but is also driven by deeper structural factors, including the logic of capital-driven profit seeking and the mechanism of "mathematical cleansing." As an emerging phenomenon, APGD inevitably gives rise to a series of new challenges. At the legal level, it exposes regulatory gaps within China's existing normative framework, because current rules on anti-discrimination law, privacy protection, and algorithmic governance cannot fully capture discrimination based on inferred biological risk. At the social level, APGD also raises the difficult question of how to construct multi-stakeholder governance while maintaining an appropriate balance between governance and innovation.

In response, this article proposes a well-calibrated regulatory framework. First, at the data input stage, the misuse of proxy variables should be controlled through a risk-based classification model. Second, during the algorithmic decision-making process, transparency and auditing should be strengthened to prevent apparently neutral models from producing discriminatory outcomes. Third, at the remedial stage, an outcome-oriented mechanism for anti-discrimination liability and rights protection should be established. This mechanism focuses not only on whether data collection and algorithmic procedures are formally lawful, but also on whether the resulting decision imposes adverse consequences on individuals on the basis of inferred biological vulnerability. In Chinese law, this approach may also be supported by Article 1167 of the Civil Code, which provides a doctrinal basis for preventive tort liability where a tortious act endangers another person's personal or property safety.

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Anti-Progesterone in Environmental Water

Elise Rose*, Michael Varveris**

Abstract: Past research has shown that steroid hormones and other endocrine-disrupting compounds (EDCs) are present in environmental water, with implications for human and wildlife health. Abortion providers have shifted a large part of their practice to medication-induced abortion, using the anti-progesterone synthetic steroid hormone mifepristone. We wanted to see if mifepristone, an EDC, could be detected in water sources. Water samples were collected from sites upstream and downstream of water treatment facilities and from municipal tap water in each of 3 American cities. The water samples were tested for mifepristone using the PR CALUX® assay. There were significant levels of anti-progesterone activity (up to 0.041 µgram/l) in the water of all but one of the nine sampling classes. Given progesterone's numerous effects, this contaminant could affect the physiology of aquatic animals and human health, including fertility, pregnancy, and fetal development. The findings indicate the significant need for additional investigation into the levels of various hormones and EDCs, including mifepristone, in water sources.

Keywords: **mifepristone, endocrine-disrupting compounds (EDCs), water quality**

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** Dr. Michael Varveris has no institutional affiliations.

Introduction

Past research has shown that endocrine-disrupting compounds (EDCs), including steroid hormones, synthetic estrogens, and progestins found in oral contraceptives, are present in water supplies [1, 2]. This problem remains an environmental and health concern, especially given the widespread use of contraceptives [3] and the increased prevalence of medication abortion in recent years [4]. These compounds have a number of deleterious effects on human and animal biology, particularly aquatic animals [5, 6, 7, 8, 9, 10]. Small amounts of these chemicals (parts per trillion) can affect the endocrine system of animals and humans [10]. Progestins, including specifically the anti-progesterone synthetic steroid hormone mifepristone, have been found to have disruptive effects on the fertility and reproduction of fish [6, 7]. Moreover, further highlighting the potential for environmental toxicity and contamination, the FDA recommends treating any unused mifepristone pills as hazardous waste [11].

Removal from the water supply of EDCs, including estrogens, progesterone, and other steroids, by either basic wastewater treatment or basic drinking water treatment, has proved to be problematic [12, 13, 14, 15, 16, 17], though recently hybrid water treatment methods have shown more promise, especially those including both reverse osmosis and activated carbon filters [12, 14, 17].

Abortion providers have shifted a large part of their practice from surgical to chemical (medication-induced) abortion. In 2023, 642,700 of the abortions in the US were medication abortions, forming 63% of the total [4]. The first drug given in this type of abortion is the anti-progesterone synthetic steroid hormone mifepristone, or RU-486. Mifepristone is an antagonist of progestational and glucocorticoid hormones. Mifepristone competitively binds to the progesterone receptor, thereby inhibiting the effects of endogenous or exogenous progesterone [18, 19, 20, 21]. The drug is thought to disrupt attachment of the placenta to the uterine lining in early pregnancy [20, 22, 23]. The prostaglandin-like drug misoprostol is administered several days later to induce uterine contractions and preterm labor [24].

The increased use of the anti-progesterone hormone mifepristone indicates it might be present in water supplies. Given the potential negative impacts of mifepristone on the environment, human and animal health, and the lack of studies addressing these issues, we sought to investigate the presence of unmetabolized mifepristone in water supplies at three sites in the United States. Cities with moderate populations of women of childbearing age were selected for this initial testing. A statistically significant amount of anti-progesterone activity was found in all but one of the nine water sources.

Materials and Methods

We collected 4 water samples from 3 sites upstream of water treatment facilities; 4 water samples from 3 sites downstream of water treatment facilities; and 4 samples from municipal tap water in each of 3 American cities: Austin, Texas; Blacksburg, Virginia; and Carbondale, Illinois. The water in the upstream locations does not contain untreated sewage.

In all 3 cities, municipal sewage water is routed directly to the water treatment facilities and then discharged into environmental waters after treatment. Municipal drinking water comes from surface waters, not from groundwater wells [25, 26, 27, 28]. For each location, water treatment facilities located within the area of highest population density and/or treating wastewater from a university were chosen. Each sampling location was chosen based on accessibility and proximity to the discharge location of the water treatment facilities.

Sample bottles were prepared by ALS Environmental in Cincinnati, Ohio, for analysis of anti-progesterone CALUX®. Samples were collected utilizing grab sample techniques. Each city also contained a "field blank" sample filled with laboratory-supplied distilled water. All samples were shipped to SafeBridge Regulatory & Life Sciences Group overnight for next-day delivery. The water samples were sent blind (without source identification) to the BioDetection Systems laboratory in the Netherlands, which dissolved the samples in DMSO and used PR CALUX® bioassays to test for mifepristone and anti-progesterone activity [29]. The PR CALUX® activity was determined after 24 h exposure and benchmarked against mifepristone (Ru486). Briefly, optimized solid-phase extraction (SPE) was applied to extract water samples. The enriched extract, containing a mixture of compounds, was exposed to genetically modified cell lines in CALUX® bioassays. Firefly luciferase gene, coupled with responsive elements (REs) such as reporter genes, is incorporated into the DNA of these cell lines. The presence of an appropriate substrate, in this case mifepristone, triggers the activation of such REs, thus initiating the creation of luciferase, which then emits light. The amount of light produced is measured by a luminometer and is proportional to the amount of ligand-specific receptor binding, which is benchmarked against a reference level of mifepristone.

Statistical Analysis

For the purpose of the analysis, values that were below the detectable threshold were considered as zero (0). We calculated the t-test statistic as follows:

$$\text{t-test statistic} = \frac{\text{observed value - expected value (control)}}{\text{population standard deviation } (\sigma x)}$$

For the t-test of statistical significance, differences were considered significant at $p < 0.05$. While not considered significant, p-values within the range of $0.05 < p < 0.1$ indicate a tendency towards significance. The results of that analysis are included in Tables 1 and 2 and in Appendix A.

To be more rigorous, we asked Dr. Michael New to recommend a non-parametric statistical test that would not rely on the assumption of a normal distribution among the findings. We used Dr. Michael New's method to perform an analysis based on the straight probability of rankings. The results of that analysis are included in Tables 1 and 2 and in Appendix B.

Results

Results are given in Table 1, RU486 equivalent concentration vs. controls, t-test and ranked test; Table 2, Differences in RU486 equivalent concentration between water sources, t-test and ranked test; and Figure 1, RU486 equivalent concentration vs. controls, below.

Table 1. RU486 equivalent concentration vs. controls, t-test and ranked test.

City	Water Source	Conc	t-test P	t-test S	Ranked test P	Ranked test S
Blacksburg VA						
	Upstream	0.0022	p < 0.0005	very highly significant	0.0143 p < 0.05	significant
	Downstream	0.0026	p < 0.005	highly significant	0.0143 p < 0.05	significant
	Tap	0.0006	p > .20	not significant	0.2143	not significant
	Control	0.0003				
Carbondale IL						
	Upstream	0.0261	>.10	not significant	0.0143 p < 0.05	significant
	Downstream	0.0235	0.05 < p < .10	tending towards significance	0.0143 p < 0.05	significant
	Tap	0.0026	p <0.005	highly significant	0.0143 p < 0.05	significant
	Control	0.0001				
Austin TX						
	Upstream	0.0108	p > .10	not significant	.0119 p < 0.05	significant
	Downstream	0.0128	p < 0.025	highly significant	.0079 p < 0.01	highly significant
	Tap	0.0161	p > .10	not significant	.0079 p < 0.01	highly significant
	Control	0.0002				

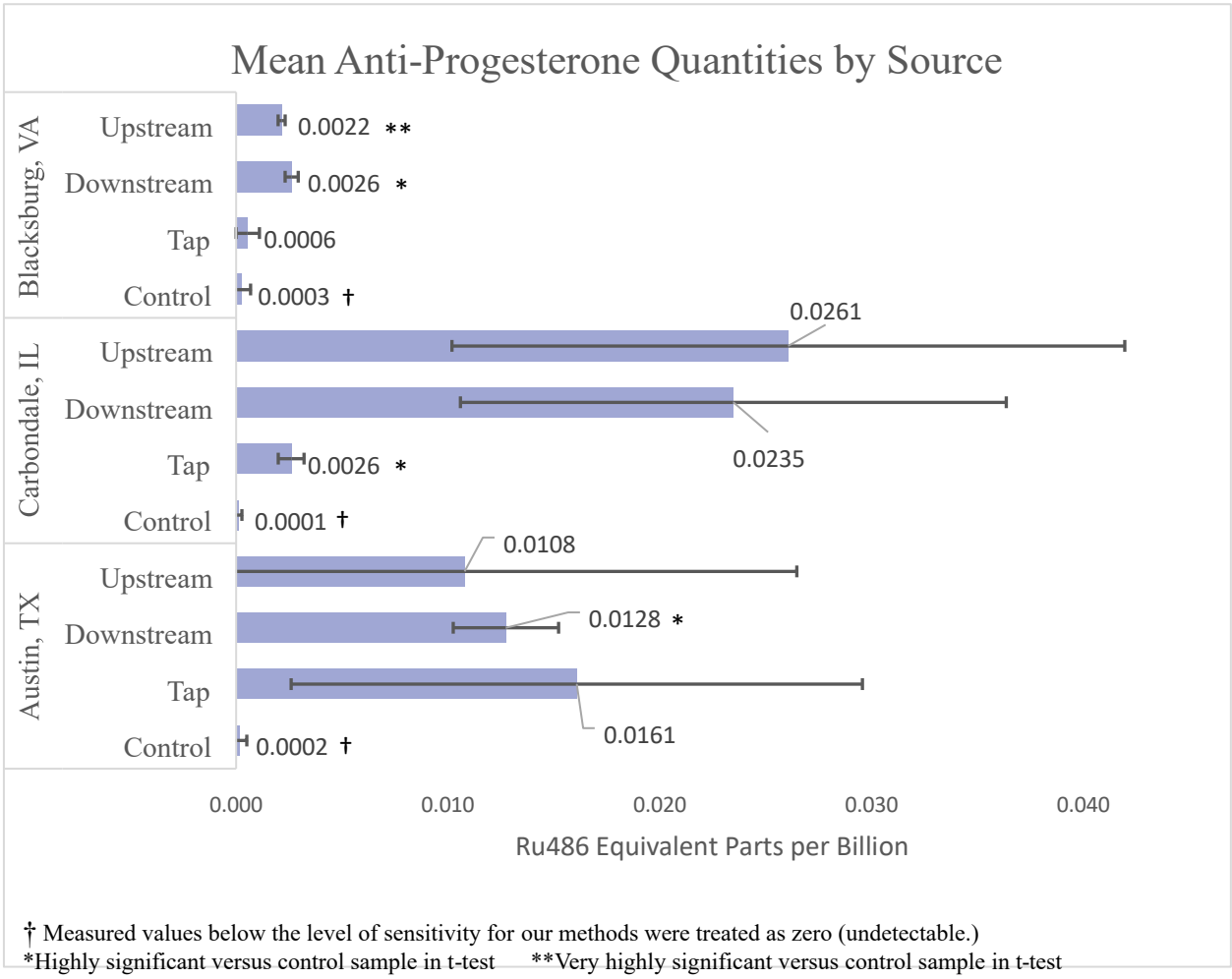
P = probability; S = significance; Conc = mean concentration of anti-progesterone (Ru486 equivalent), µgram/l

Table 2. Differences in RU486 equivalent concentration between water sources, t-test and ranked test.

City	Water Sources	% change	t-test P	t-test S	Ranked test P	Ranked test S
Blacksburg VA						
	U-D	27.9↑	<0.005	highly significant	0.0428 $p < 0.05$	significant
	U-T	38.1%↓	<0.0005	very highly significant	0.0143 $p < 0.05$	significant
	D-T	51.9%↓	<0.005	highly significant	0.0143 $p < 0.05$	significant
Carbondale IL						
	U-D	13.8%↓	>.10	not significant	.5	not significant
	U-T	90.0%↓	<0.0005	very highly significant	0.0716 $0.05 < p < .10$	tending towards significance
	D-T	88.9%↓	<0.0005	very highly significant	0.0571 $0.05 < p < .10$	tending towards significance
Austin TX						
	U-D	45.1%↓	>.10	not significant	0.0716 $0.05 < p < .10$	tending towards significance
	U-T	2.9%↓	>.10	not significant	.22	not significant
	D-T	77%↑	>.10	not significant	.5	not significant

U = upstream; D = downstream; T = tap; P = probability; S = significance.

Figure 1. RU486 equivalent concentration vs. controls.



† Measured values below the level of sensitivity for our methods were treated as zero (undetectable.)
*Highly significant versus control sample in t-test **Very highly significant versus control sample in t-test

Blacksburg

These statistics indicate that upstream and downstream differ significantly from each other and from both controls. The amount of RU486 equivalent in these environmental water sources is significantly greater than in the controls by the t-test ($p < .005$ or lower) and by the ranking test. The tap water here appears significantly cleaner than the water from the environment. Two of the four tap samples were below our levels of detection.

Carbondale

These statistics indicate that upstream and downstream differ significantly from both controls but not from each other. The tap water here is significantly cleaner than both sources of environmental water but contains a significantly greater amount of the contaminant than the controls, as indicated by the t-test ($p > 0.025$) and the ranking test.

Austin

The downstream samples have significantly more of the contaminant than the controls, as indicated by both the t-test ($p > 0.025$) and the ranking test. Neither upstream nor tap water differs significantly from the controls by the t-test due to the large standard deviation in the measurements. The tap water in the Austin area may contain higher levels of RU486 equivalent than the downstream water, but the t-test does not indicate a significant difference because of the large standard deviation in the tap water measurements. However, samples from both the upstream and tap water differ significantly from the controls according to the ranking test.

Water Treatment

The upstream locations should not be considered as water containing untreated sewage. In all 3 cities, sewage water is routed directly to the water treatment facilities and then discharged to environmental water after treatment [25, 26, 27, 28]. In all 3 cities, the level of RU486 equivalent in downstream water sources is not appreciably lower than in upstream water sources; in fact, in two of the cities it is higher. This may be expected. Untreated sewage may not be present in upstream samples, but above-ground streams could become contaminated by nearby sewage lines if the lines are damaged by frost heaving or other environmental disruptions. On the other hand, treated sewage water is expected to be included in the downstream samples. At any rate, water treatment was ineffective at removing this EDC. This downstream-treated environmental water is not equivalent to household tap water, which was tested by a different group.

Discussion

The presence of mifepristone, or it's biologically active metabolites in environmental water could affect wildlife and even human health. Antiprogesterone compounds could affect the reproductive and other physiological functions of aquatic animals, such as fish and amphibians [5, 6, 7, 8, 9, 11, 12], and farm animals [10]. Steroid hormones have even been shown to negatively affect root growth in plants [11]. Mifepristone is considered by one manufacturer, Fass, to have "low potential for bioaccumulation" in fish, but "very high chronic toxicity", though Fass admits that both these claims are comparative rather than quantitative. Up to 10% of mifepristone remains in sediment after 239 days [30].

We do not know how long mifepristone remains in women's tissues or whether it bioaccumulates. We could find no studies on the levels of this hormone in human tissues such as liver or fat cells, either in the short term or over time with bioaccumulation. In a study of only 5 women, the half-life of mifepristone in serum varied from 24 to 44 hours [31], but serum is an aqueous milieu. The serum level is not the same as the tissue level, which was not measured in that study. Mifepristone is a steroid hormone and therefore a fat-

soluble molecule. Such a molecule might build up in fatty tissues rather than remain in the aqueous serum and be excreted. Further study of this possibility is warranted.

Steroid hormones have systemic effects on every cell in the body. Progesterone has numerous known effects [18, 19]. Its role in maintaining pregnancy by supporting placental attachment is well-known, but it is also involved in many other systems. An anti-progesterone such as mifepristone could inhibit any actions of normal progesterone, particularly on pregnant women, but also on pre- or post-menopausal women. The presence of an anti-progesterone in the water supply could also render previously effective clinical dosages of progesterone inadequate, because the anti-progesterone antagonizes progesterone by binding to its receptor.

Long-term use of low-dose mifepristone has been found to cause changes in the endometrium, including atypical thickening, the presence of carcinoma-like tissues [21], and to suppress ovulation and menstruation [32]. Low doses of mifepristone have also been shown to lead to amenorrhea [33]. Moreover, questions about the impact of such chemicals on maternal health and linkages to autism warrant further study [34]. Low progesterone levels in pre-menopausal, menstruating women have been associated with multiple health problems including lower fertility rates, higher rates of miscarriage, and higher rates of other medical complications during pregnancy [35, 36, 37, 8].

Mifepristone could even inhibit some actions of progesterone on men, who normally have small amounts of progesterone in their bodies. Low progesterone levels in men have been associated with multiple medical problems including alopecia, bone loss, erectile dysfunction, fatigue, and obesity [18].

Unmetabolized mifepristone or it's metabolites could be present in the tested waters for several reasons. We have no data on the sources of mifepristone in the water, nor can we scientifically rank their likelihood. Given the high number of chemical abortions (642,700 medication abortions in the US in 2023 [4]), the most probable source is fecal and urinary excretion by women ingesting mifepristone for chemical abortion. Clearance from the body was mainly through feces (83%) [39]. The standard dose of 200 mg may be excessive for some women. Alternatively, mifepristone or it's metabolites could enter the water from feces or urine of patients taking the medication for reasons other than abortion. One of the other conditions for which mifepristone is prescribed is Cushing's Syndrome or Cushing's Disease [40]. Fewer than 20,000 Americans are estimated to have a diagnosis of Cushing's [41], so this is a far less likely contributor. Mifepristone is also sometimes prescribed for endometriosis, meningioma, and mental illness [21], but these are also far less common uses. Other sources could be improper disposal of any unused product by the patient or manufacturer. Considering the regulations governing pharmaceutical manufacturing, the latter seems very improbable.

Another molecule with anti-progesterone activity could have triggered the REs (Responsive Elements) of the CALUX system and produced a luminescent response. Women who take the drug would be very likely to excrete metabolites of mifepristone as well as the intact compound. The 5 metabolites of mifepristone, including the 3 most common: metapristone (monodemethylated mifepristone), didemethylated mifepristone, and 22-OH

mifepristone [42, 43] are pharmacologically active, able to bind to human progesterone and glucocorticoid receptors, and therefore should be regarded as significant environmental pollutants [43, 44]. In the event that a metabolite of mifepristone or any other chemical did bind to the REs of the CALUX system and show a positive response, that molecule would have anti-progesterone effects and should be considered harmful and undesirable in our water supply. Future studies should investigate whether water samples contain these compounds.

Conventional water treatment was ineffective at removing this EDC from water across all cities we tested. Two cities showed significant mean concentrations even in tap water. Conventional treatment systems are primarily designed to remove infectious agents such as bacteria and viruses, with secondary treatment, according to the US Environmental Protection Agency, required to address hormones (49-99% removal) [45]. Maximum removal requires tertiary treatment, such as membrane bioreactors, oxidation, or ozonation [1, 2, 12, 13, 14, 15, 16, 17, 45].

Further investigation is necessary to better understand the impact of any levels of mifepristone or other anti-progesterone activity in the environment and the efficacy of its removal by treatment systems. Concerns about the environmental, clinical and public health impact of mifepristone raise urgent questions about the current lack of meaningful regulation of this widely-used pharmaceutical.

Acknowledgments

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Abbreviations

The following abbreviations are used in this manuscript:

EDC = endocrine-disrupting compound
Ru486 = mifepristone
DMSO = dimethyl sulfoxide
SPE = solid-phase extraction
RE = responsive element
FDA = Food and Drug Administration
CALUX = chemical-activated luciferase expression

The following abbreviations are used in the tables:

Conc = concentration of anti-progesterone (Ru486 equivalent), μgram/l
σx = Population Standard Deviation
P = probability
t test statistic =observed value-expected value (control)/σx
S = significance
* = below the detection limit (level of sensitivity) for our methods; considered as 0 for statistical calculations.

Appendix A

Table 3. RU486 equivalent concentration vs. controls, t-test.

State	Water Source	Conc	Mean Conc	(σx)	t-test statistic	t-test P	t-test S
All	Lab control	*					
	Lab control	*					
			.0000				
VA	Upstream	.0023					
	Upstream	.0023					
	Upstream	.0019					
	Upstream	.0021					
			.0022	0.0002	12.952	p < 0.0005	very highly significant
	Downstream	.0024					
	Downstream	.0031					
	Downstream	.0027					
	Downstream	.0023					
			.0026	0.0003	8.467	p < 0.005	highly significant
	Tap	.0011					
	Tap	.0013					
	Tap	*					
	Tap	*					
			.0006	0.0006	1.0	p > .20	not significant
	Field blank	.0010					
	Field blank	*					
			.0005				
IL	Upstream	.0014					
	Upstream	.0390					
	Upstream	.0410					
	Upstream	.023					
			.0261	0.0159	1.642	>.10	not significant
	Downstream	.0019					
	Downstream	.0270					
	Downstream	.0360					
	Downstream	.0290					
			.0235	0.0129	1.822	0.05 < p < .10	Tending towards significance

Conc = concentration of anti-progesterone (Ru486 equivalent), µgram/l; σx = Population Standard Deviation, P = probability; t test statistic =observed value-expected value (control)/σx; S = significance; * = below detection limit for our methods (<0.00096 Ru486 equivalent ug/l); considered as 0 for statistical calculations.

Table 3. RU486 equivalent concentration vs. controls, t-test. (continued)

State	Water Source	Conc	Mean conc	(σx)	t-test statistic	t-test P	t-test S
IL	Tap	.0024					
	Tap	.0035					
	Tap	.0018					
	Tap	.0027					
			.0026	0.0006	4.262	$p < 0.005$	highly significant
	Field blank	.0004					
	Field blank	*					
			.0002				
TX	Upstream	.0022					
	Upstream	.0380					
	Upstream	.0031					
	Upstream	*					
			.0108	0.0157	0.687	$p > .10$	not significant
	Downstream	.0170					
	Downstream	.0120					
	Downstream	.0110					
	Downstream	.0110					
			.0128	0.0025	5.12	$p < 0.025$	significant
	Tap	.0046					
	Tap	.0390					
	Tap	.0120					
TX	Tap	.0089					
			.0161	0.0122	1.193	$p > .10$	not significant
	Field blank	.0008					
	Field blank	*					
	Field blank	*					
			.0003				

Conc = concentration of anti-progesterone (Ru486 equivalent), µgram/l; σx = Population Standard Deviation, P = probability; t test statistic =observed value-expected value (control)/σx; S = significance; * = below detection limit for our methods (<0.00096 Ru486 equivalent ug/l); considered as 0 for statistical calculations.

Appendix B

Probability Based on Ranking Method (non-parametric test)

Modified by Elise Rose with additional data using a probability method based on ranking devised by Dr. Michael New.

Summary: Water samples were taken from three cities, Blacksburg, VA, Carbondale, IL, and Austin, TX to measure and compare the amount of anti-progesterone. For each city, six comparisons were made, for a total of 18 comparisons:

1) Between upstream and controls
2) Between downstream and controls
3) Between tap water and controls
4) Between upstream and downstream
5) Between upstream and tap water
6) Between downstream and tap water

Using a non-parametric test, differences in 13 of the 18 comparisons were statistically significant at conventional levels. Importantly, 8 of the 9 comparisons involving control samples achieved conventional levels of statistical significance. That is, the probability was less than 5% that, due to random chance, the control samples were lower than the environmental or tap samples. In other words, we can be 95-99% confident that the environmental or tap samples had more mifepristone than the control samples. The fact that a supermajority of comparisons achieved conventional levels of statistical significance means that we can be statistically confident in the findings.

Blacksburg, VA (5 of 6 comparisons are statistically significant)

1) Upstream (4 Samples) vs. Control (4 Samples)
   All four upstream samples report higher levels of anti-progesterone than all 4 control samples. The likelihood that both control samples would rank last is (4/8)*(3/7)*(2/6)*(1/5) = 1/70 = .01428. This achieves statistical significance at the 98% confidence level.
2) Downstream (4 Samples) vs. Control (4 Samples)
   All four downstream samples report higher levels of anti-progesterone than all 4 control samples. The likelihood that both control samples would rank last is (4/8)*(3/7)*(2/6)*(1/5) = 1/70 = .01428. This achieves statistical significance at the 98% confidence level.
3) Tap water (4 Samples) vs. Control (4 Samples)
   Two tap water samples report higher levels of anti-progesterone than all 4 control samples. Two tap water samples are largely indistinguishable from the control samples. The likelihood that all 4 control samples would rank in the bottom six of 8 samples would be (6/8)*(5/7)*(4/6)*(3/5) = .2143 This result is relatively unlikely, but does not reach conventional standards of statistical significance.
4) Upstream (Four Samples) vs. Tap water (Four Samples)
   All four upstream samples report higher levels of anti-progesterone than the four tap water samples. The likelihood the four upstream samples would all rank in the top four would be (4/8)*(3/7)*(2/6)*(1/5) = 24/1680 = .01428. This is statistically significant at the 98% confidence level.

5) Downstream (Four Samples) vs. Tap water (Four Samples)

All four downstream samples report higher levels of anti-progesterone than the four tap water samples. The likelihood the downstream samples would all rank in the top four would be (4/8)*(3/7)*(2/6)*(1/5)= 24/1680 = .01428. This is statistically significant at the 98% confidence level.

6) Upstream (Four Samples) vs. Downstream (Four Samples)

Analyzing and interpreting these findings is more complicated. The three highest anti-progesterone levels all come from downstream samples. Then there are three samples that are tied (two upstream and one downstream). The two lowest come from downstream samples. The likelihood that the four upstream samples would rank (1, 2, 3, 4), (1, 2, 3, 5) or (1, 2, 3, 6) is: (4/8)*(3/7)*(2/6)*(1/5) + (4/8)*(3/7)*(2/6)*(4/5)*(1/4) + (4/8)*(3/7)*(2/6)*(4/5)*(3/4)*(1/3) .01428 + .01428 + .1428 = .0428. This is statistically significant at the 95% level.

<u>Carbondale, IL</u> (5 of 6 comparisons are statistically significant)

1) Upstream (4 Samples) vs. Control (4 Samples)

All four upstream samples report higher levels of anti-progesterone than all 4 control samples. The likelihood that all 4 control samples would rank last is (4/8)*(3/7)*(2/6)*(1/5) = 1/70 = .01428. This achieves statistical significance at the 98% confidence level.

2) Downstream (4 Samples) vs. Control (4 Samples)

All four downstream samples report higher levels of anti-progesterone than all 4 control samples. The likelihood that all 4 control samples would rank last is (4/8)*(3/7)*(2/6)*(1/5) = 1/70 = .01428. This achieves statistical significance at the 98% confidence level.

3) Tap water (4 Samples) vs. Control (4 Samples)

All four tap water samples report higher levels of anti-progesterone than all 4 control samples. The likelihood that all 4 control samples would rank last is (4/8)*(3/7)*(2/6)*(1/5) = 1/70 = .01428. This achieves statistical significance at the 98% confidence level.

4) Upstream (Four Samples) vs. Downstream (Four Samples)

The means here are close, .0261 vs. .0235. There is not much discernible grouping regarding how the samples are ranked. Thus there is no statistical evidence that there is a difference between the two means.

5) Upstream (Four Samples) vs. Tap Water (Four Samples)

Three upstream samples have the highest level of anti-progesterone. The fourth upstream sample has the lowest. The likelihood of the three upstream samples being the highest is (4/8)*(3/7)*(2/6) = .0716. This achieves statistical significance at the 90% level.

6) Downstream (Four Samples) vs. Tap Water (Four Samples)

Three upstream samples have the highest level of anti-progesterone. The fourth upstream sample has the second lowest. The likelihood of the three upstream samples being the highest and the fourth not being the lowest is (4/8)*(3/7)*(2/6)*(4/5) = .0571. This achieves statistical significance at the 90% level, and approaches the 95% level.

<u>Austin, TX</u> (4 of 6 comparisons are statistically significant)

1) Upstream (4 Samples) vs. Control (5 Samples)
   The three samples with the highest level of anti-progesterone all come from upstream. The fourth upstream sample equals the lowest observed concentration. The likelihood that the three samples with the highest level of anti-progesterone would come from upstream is (3/9)*(2/8)*(1/7) = .0119. This achieves statistical significance at the 98% confidence level.
2) Downstream (4 Samples) vs. Control (5 Samples)
   All four downstream samples report higher levels of anti-progesterone than all 5 control samples. The likelihood that the 4 samples with the highest level of anti progesterone would come from downstream is (4/9)*(3/8)*(2/7)*(1/6) = .0079. The likelihood that all 5 control samples would rank last is the same. This achieves statistical significance at the 99% confidence level.
3) Tap water (4 Samples) vs. Control (5 Samples)
   All four tap water samples report higher levels of anti-progesterone than all 5 control samples. The likelihood that all 5 control samples would rank last is (5/9)*(4/8)*(3/7)*(2/6)*(1/5) = .0079. This achieves statistical significance at the 99% confidence level.
4) Upstream (Four Samples) vs. Downstream (Four Samples)
   Three upstream samples have the highest level of anti-progesterone. The fourth upstream sample has the lowest. The likelihood of the three upstream samples being the three highest is (4/8)*(3/7)*(2/6) = .0716. This achieves statistical significance at the 90% level.
5) Tap water (Four Samples) vs. Downstream (Four Samples)
   The mean levels of anti-progesterone are close here (.0161 vs. .01275). There does not appear to be much clustering in the ranking of samples. This indicates no statistically significant differences.
6) Tap water (Four Samples) vs. Upstream (Four Samples)
   Three of the four samples with the highest level of anti-progesterone come from upstream as does the sample with the lowest level of anti-progesterone. The likelihood that three of the four highest anti-progesterone levels would come from upstream is about 22%. While this is unlikely, it does not reach conventional standards of statistical significance.

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Risk Factors Predictive of Post-abortion Distress Demonstrate That Most Abortions are Contraindicated: A Retrospective Cross-sectional Study

David C. Reardon*, Martha Shuping, Patricia Giebink*****

Abstract

Introduction: The subgroup of women at highest risk of post-abortion distress can be identified using known risk factors. At highest risk are women who feel pressured to undergo unwanted abortions. But abortion providers seldom screen for these, which violates ethical principles of informed consent and of justice. This study examines the effectiveness of an 8-item risk assessment scale.

Materials and Methods: Topic blind surveys were distributed to a random sample of 41- to 45-year-old women. Reproductive histories were assessed, with 22.6% reporting a history of abortion, a rate comparable to national averages. Respondents reporting abortions were queried on risk factors and rated the degree, if any, they attributed any of six negative outcomes to their abortions. Negative outcomes and the maximum harm identified by each respondent were analyzed using correlations, distributions along a constructed risk scale, and Bayesian regression analyses in relation to their self-reported risk factors and abortion decision types.

Results: Risk factors reported as present prior to an abortion were strongly correlated to more negative outcomes. Our 8-item constructed risk scale closely tracked the degree of maximum harm respondents attributed to their abortions. The mean risk scale scores were 2.46 for women whose abortions were wanted, 4.47 for women whose abortions were accepted but inconsistent with their preferences, 5.56 for those whose abortions were unwanted, and 6.68 for those who reported being coerced. Bayesian models revealed that the risk factors explained 50 percent or more of the negative outcomes.

Conclusions: Women considering abortions should be evaluated for risk factors predictive of negative outcomes. Failure to screen for these risk factors constitutes medical negligence. Screening and informing women of their personal risk factors as

required by ethical and legal standards may lead to consideration of alternatives to abortion by women who consider the risks unacceptable.

Keywords: induced abortion; risk factors; decision making; counseling; adjustment disorders; evidence-based practice; pre-abortion screening, informed consent.

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Introduction

For physicians respecting the time-honored Hippocratic Oath, it is clear that induced abortion is a moral evil precisely because it involves the deliberate destruction of a human life. But there is also clear evidence that induced abortion is an independent risk factor for cardiovascular disease (1–4), gestational diabetes mellitus (3,5,6), thyroid-related diseases (6), placenta-related diseases (6), Asherman syndrome (7), increased risk of premature and low birth weight deliveries in subsequent pregnancies (8), and premature death from multiple causes (9,10). Even more common than physical sequelae, abortion is an independent risk factor for the onset or worsening of mental illnesses, as demonstrated in both record linkage studies (11–14) and case-control studies (15–23). These and other studies have firmly established that abortion may trigger, exacerbate, complicate, or otherwise contribute to new or existing mental illnesses. Perhaps more importantly, they consistently demonstrate that there are distinct pre-existing risk factors, and perhaps contributing factors, that can be used to reliably identify the women at greatest risk of the most severe post-abortion sequelae and should be utilized in both pre- and post-abortion counseling (15,16,22–41).

Notably, while the 2008 American Association's Task Force on Mental Health and Abortion (TFMHA) asserted that there was no definitive evidence when, if ever, a single first-trimester abortion of an unwanted pregnancy by an adult woman is the *sole* and *direct cause* of any mental illnesses (42) it is also grudgingly admitted that abortion can *contribute* to emotional and mental health issues (22,42). More importantly, the TFMHA explicitly identified fifteen of the risk factors predictive of more adverse mental health outcomes: "Feelings of commitment to the pregnancy, ambivalence about the abortion decision, low perceived ability to cope with the abortion, history of prior abortion, late term abortion," "terminating a pregnancy that is wanted or meaningful, perceived pressure from others to terminate a pregnancy, perceived opposition to the abortion from partners, family, and/or friends, lack of perceived social support from others, various personality traits (e.g., low self-esteem, a pessimistic outlook, low-perceived control over life), a history of mental health problems prior to the pregnancy, feelings of stigma, perceived need for secrecy, exposure to antiabortion picketing, use of avoidance and denial coping strategies" (42).

Notably, many of these risk factors (such as ambivalence, attachment to the pregnancy, and perceived pressure to abort from others) are markers for abortion decisions which are not consistent with a woman's own preferences. Uta Landy, the former executive director of the National Abortion Federation, has described four common approaches which may lead to more regrets following an abortion. (43). The "spontaneous approach" involves such a rush to act that there is inadequate consideration of underlying feelings, future consequences, and adjustments. The "rational-analytic approach" only considers the practical reasons for an abortion without regard for the emotional considerations. The "denying-procrastinating approach" delays the abortion decision due to ambivalence and conflict. The "no-decision-making approach" cedes the abortion decision to others, often in an effort to deny any responsibility for the decision.

Psychological counseling in the weeks immediately following an abortion can dramatically improve post-abortion adjustments (44). Therefore, identifying the subset of abortion patients who would most likely need and benefit from post-abortion counseling, based on readily identifiable risk factors, should be an important consideration in pre-abortion counseling. In addition,

identification of risk factors is important to enable counselors to provide individualized counseling, including an evidence-based assessment of post-abortion adjustment issues that patients may face who have more or fewer risk factors for more negative outcomes.

Helping women to identify and understand their own individual risk factors during the informed consent process is essential as it may impact the woman's pregnancy decisions. The 2009 textbook of the National Abortion Federation states that "patients with risk factors may require more time to reconsider options" (39). Women who believe that their individual risks are too high may prefer to reconsider alternatives other than abortion to resolve an unintended pregnancy.

The Royal College of Psychiatry in the U.K. stated in 2008 that prior to abortion, healthcare professionals "should assess for mental disorder and for risk factors that may be associated with its subsequent development," pointing out that "consent cannot be informed without the provision of adequate and appropriate information regarding the possible risks and benefits to physical and emotional health." (45).

The principle that a patient's individual risks should be disclosed in the informed consent process was established in the landmark federal appellate court case Canterbury v. Spence, 464 F2d 772 (D.C. Cir. 1972). As discussed in the *AMA Journal of Ethics,* "a physician is now required to disclose all risks that might affect a patient's treatment decisions," and it is also necessary to provide "personalized information about how the treatment might reasonably affect the particular patient," going beyond merely general information (46). Thus, information about individual risk factors is essential for physicians to include in discussions with patients who are considering abortion.

To our knowledge, only one previous study attempted to measure the degree to which risk factors could be used to identify women who required additional pre-abortion counseling or postabortion counseling referrals. That study, led by Elizabeth Belsey, identified five pre-existing criteria that were correlated with more negative emotional adjustments post-abortion (guilt; regret; disturbance of marital, sexual, or interpersonal relationships; or difficulty in coping with day-today activities) during the three-month follow-up period (47). Belsey's team concluded that if pre-abortion screening for these five risk factors had been employed to determine which women would have been referred for more extensive counseling, this screening process would have resulted in both false negatives (missing eighteen percent of the women who did have one or more negative reactions) and false positives (twenty-eight percent of the women identified as higher risk did not have any apparent negative reactions at the three month follow-up interview). But, Belsey concluded, "From the clinician's point of view this result can be viewed as erring on the right side, for a [screening] system that tends to select more women for counseling than is actually necessary is preferable to the reverse" (47).

To our knowledge, no subsequent research has been published to develop a protocol for pre-abortion screening, though clearly such screening should guide referrals for both more extensive pre-abortion and post-abortion counseling. It would also help to identify cases in which abortion may be contraindicated, such as when women are feeling coerced into an unwanted abortion which is contrary to their own maternal preferences. (32,48).

Ideally, all the risk factors for abortion contributing to more adverse emotional and mental effects identified by TFMHA and others should be investigated. Moreover, factor analysis should be employed to eliminate redundant items and to more confidently develop a single, concise instrument for pre- and post-abortion screening.

While that project is outside the scope of our current resources, a subset of these risk factors was included in our national survey investigating the degree to which a random sample of women report facing pressures to abort contrary to their own values and preferences (32,33). The objective of this exploratory study, therefore, is to test whether a subset of known risk factors available in this survey can be meaningfully used to identify abortion patients who are at greater risk of subsequently attributing more emotional outcomes to their abortions in order to provide additional pre- and post-abortion counseling to this higher risk group.

Methods

A topic-blind survey was distributed through the survey panel services of Cint.com, which has over 28 million U.S. residents, to gather 1,000 completed interviews from a random sample of female panelists aged 41 to 45, inclusive. This age group was selected to reduce the confounding effects of time and age and to maximize the proportion of respondents with a history of abortion. Panelists completed the survey on their own electronic devices in exchange for small rewards valued at less than three dollars. The invitation to complete the survey did not describe the survey topic. Additional details about the sample have been previously published in a related analysis of pressures to choose abortion (49).

Developed in consultation with experts in abortion counseling and researchers who have published in this field, the survey included nineteen statements for which respondents rated their agreement on a visual analog scale, electronically coded on a 101-point scale from 0 to 100, inclusive. The statements and scales of agreement are shown in Table 1, along with the abbreviations for each statement as they are used in this study. The first 11 variables in Table 1 were treated as independent risk factors we hypothesized would predict the effects measured in the last 8 variables. Responses were mandatory for every variable, so there was no missing data in any completed surveys.

Table 1: Survey scale abbreviations, text of statements, and scales of agreement with values from 0 to 100

Abbreviation	Complete statement	Scale of Agreement
EmotionalAttachment	My emotional attachment to the pregnancy was…	None at all | Very high
MaternalConflict	The idea of abortion conflicted with my maternal desires.	Not at all | Very much so
MoralConflict	The idea of abortion conflicted with my moral beliefs.	Not at all | Very much so
MalePr	I felt pressure to abort from my male partner.	Not at all | Very much so
FamilyPr	I felt pressure to abort from one or more family members.	Not at all | Very much so
OtherPr	I felt pressure to abort from someone else.	Not at all | Very much so
FinPr	I felt pressure to abort from financial concerns.	Not at all | Very much so
OtherCircPr	I felt pressure to abort from other circumstances.	Not at all | Very much so
MoreSupport	If I had received more support from others, I would have continued the pregnancy.	Not at all true | Very true
MoreFinSecurity	If I had more financial security, I would have continued the pregnancy.	Not at all true | Very true
PersonalPref	Excluding the pressures I faced to have an abortion, in terms of satisfying my own personal preferences the abortion was...	Very Unwanted | Very Wanted
HumanLife	I perceive the pregnancy as being . . .	A clump of cells | A human life
PositiveEmotions	My positive emotions regarding the abortion are . . .	None At all | Very high
NegativeEmotions	My negative emotions regarding the abortion are . . .	None At all | Very high
InterferedwLife	Thoughts and feelings about my abortion have negatively interfered with daily life, work, or relationships.	Not at all true | Very true
Needed Help	I have desired or needed help to better cope with negative feelings or behaviors due to my abortion.	Not at all true | Very true
IntrusiveThoughts	I have had frequent thoughts, dreams, or flashbacks to the abortion.	Not at all true | Very true
FrequentLoss	I have had frequent feelings of loss, grief, sadness about the abortion.	Not at all true | Very true
BetterMentalHlth	Abortion made my mental health . . .	Very much worse | Very much better

An additional independent variable, abbreviated as DecisionType, was the categorical question: "Which best describes your abortion decision?" Respondents were presented with four possible answers: "Wanted and consistent with my values and preferences" (Wanted), "Accepted but inconsistent with my values or preferences" (Inconsistent), "Unwanted and contrary to my values and preferences" (Unwanted), or "Coerced and contrary to my values and preferences" (Coerced). For parametric analyses, these categorical responses were recoded from 1 through 4: Wanted, Inconsistent, Unwanted, and Coerced, respectively. In a previous study, it was found that this variable correlated well with lower or higher rates of negative effects being attributed to an abortion (32). For group comparisons, the group Wanted is treated as the control group since these women represent the most ideal subgroup of women having abortions who, of the four groups, are theoretically predicted to be at lower risk of negative outcomes.

To simplify the analysis, the five scales regarding pressures to abort (MalePr, FamilyPr, OtherPr, FinPr, OtherCircPr) were averaged into a single variable, AvgPr, due to the findings of a previous study, which supported the conclusion that AvgPr provides the best correlation to several outcome measures (49).In addition, after completing a reliability analysis, an overall risk factor scale, RiskScale, with a range from 0 to 8, was constructed for each respondent utilizing eight independent variables. A value of one was added to the RiskScale score for each of the six risk factors (EmotionalAttachment, Maternalconflict, MoralConflict, HumanLife, MoreSupport, MoreFinSecurity) with a score over 50, plus one for a score of PersonPref less than 50 (indicating that the abortion was contrary to the individual's own personal preference, plus one for AvgPr greater than 20 (since an average of 20 over all five individual pressure scales would be equivalent to one score of 100 on at least one of the scales if all other four scores of zero).

The final independent variable utilized was the age at which respondents reported having their first abortion (Age1stAbortion), with any responses under 10 and over 45 set to the average age reported by all other respondents.

To better accommodate our focus on evaluating risk factors predictive of negative outcomes, four additional outcome variables were also calculated. The first was an assessment of the net negative emotions (if any) (NetNegEmotions), calculated by subtracting the score for PositiveEmotions from NegativeEmotions, yielding a possible range from -100 to +100. Second, the net negative mental health effect (NetNegMHeffect) was calculated using the formula (BetterMentalHlth-50)*(-2), yielding a range from -100 to +100, such that a positive value indicated that the respondent attributed negative mental health effects to her abortion and a negative value indicated an attribution of positive effects. Third, we created the variable MaxHarm which represented the highest value reported for any of the other negative outcome variables (NegativeEmotions, InterferedwLife, NeededHelp, IntrusiveThoughts, FrequentLoss, NetNegEmotions, NetNegMHeffect).

Our constructed RiskScale and MaxHarm scales were tested for reliability using Cronbach's α analyses. The independent and dependent variables were further tested for their interactions

using Pearson's r correlations and examined for their relationship to DecisionType and RiskScale and to determine whether the single-item DecisionType could predict negative outcomes as well as the multi-item RiskScale Decisiontype and RiskScale, representing an experimental sum of all the risk factors, were then tested for their predictive values in regard to the highest degree of negative outcomes women attributed to their abortions as measured in MaxHarm.

Finally, Bayesian regression analyses were conducted to identify which combinations of risk factors were best fitted to predict each measure of negative outcomes that respondents directly attributed to their abortions. Unlike ordinary least squares (OLS) regression—which imposes a priori assumptions that can bias results and fail to detect associations not fitting those assumptions—Bayesian regression treats parameters as random variables, incorporates weakly informative priors, and derives posterior probabilities directly from the data. This eliminates assumption-driven distortions and allows identification of risk–outcome relationships that OLS might miss.

Analyses and figures were conducted using R-Studio (Build 576) and JASP 0.16.4. The study design was approved by the Sterling Institutional Review Board (ID:10225). Participants signed informed consent agreements with the survey distributor, Cint.com.

Results

Figure 1 shows a flow chart of study participation. A total of 248 (23.7%) of 1,039 qualified respondents who began the topic blind survey reported a history of one or more abortions. Of those reporting a history of abortion, 226 (91%) completed the survey after the word "abortion" was first used. Women who reported a history of abortion were four times more likely to drop out before completing the survey than those who had not (OR=4.43, 95% CI=2.31-8.49). The percentage of women reporting abortions closely matches the Guttmacher Institute's estimated lifetime rate (23.67%) for a history of induced abortions among American women over 40 years of age (50). The average age at the time of first abortion was 22.6. A previously published analysis indicates that the sample is reasonably representative of the national population overall demographics (49), but that the identified rate of abortions among blacks and lower-income women may be lower than what would be expected based on other reports (51)

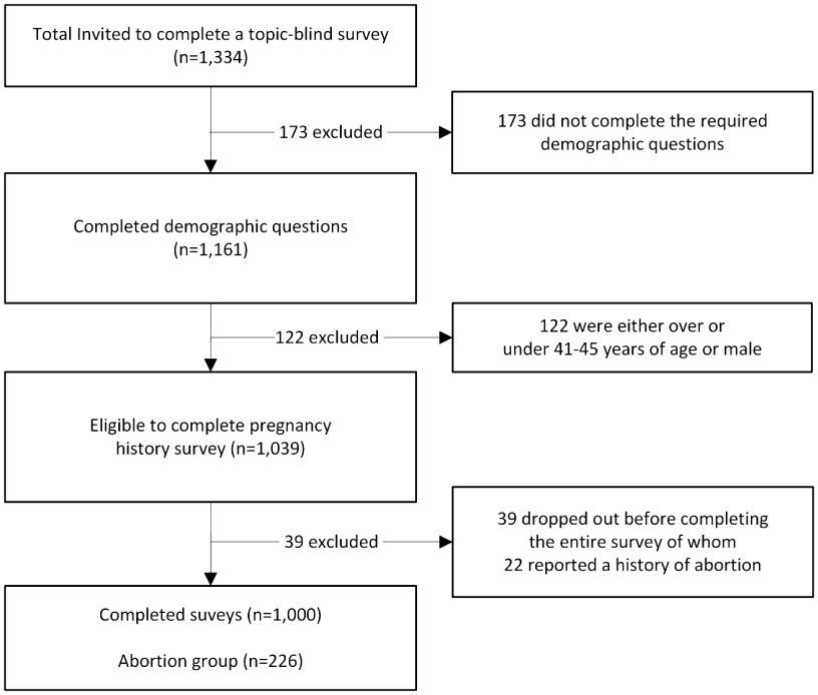


Figure 1: Study Participation

Additional details regarding the study population, sources of pressure to abort, and DecisionType have been previously reported (32,33) and are not replicated here. In summary, 33% of the sample reported their abortions as wanted and consistent with their values and preferences, 43% reported that their abortions were accepted but inconsistent with their values and preferences, 14% reported that their abortions were unwanted and contrary to their values and preferences, and 10% reported that their abortions were coerced.

As described in the methods section, an overall risk scale, RiskScale, was constructed from the eight risk factor scales included in our survey, and a scale measuring the greatest degree of adverse effects, MaxHarm, was constructed from seven scales measuring the degree of adverse effects that respondents directly attributed to their abortions. Unidimensional reliability tests yielded Cronbach's α values of 0.874 (95% CI: 0.847 to 0.896) for the RiskScale and 0.880 (95% CI: 0.854 to 0.902) for MaxHarm. These high α values indicate good reliability and internal consistency for both the items in RiskScale and MaxHarm.

Descriptive statistics of the key variables are shown in Table 2. Additional descriptive statistics of the dependent and independent variables used for any constructed variables are included in the supplement (52). Notably, across the six scales for individual negative outcomes (0 to 100), the most frequent single response was 0, and approximately a fourth of all responses

were above the midpoint of severity. This reflects the S-shaped response curves of these scales, with significant numbers of respondents reporting values at each extreme.

Table 2: Descriptive Statistics of Key Variables

Scale (minimum to maximum)	Mode	Median	Mean	Std. Deviation	25th percentile	50th percentile	75th percentile
DecisionType (1 to 4)	2	2	2	0.93	1	2	2
RiskScale (0 to 8)	4	4	4.18	2.42	2	4	6
NegativeEmotions (0 to 100)	0	51	50.65	32.97	23.00	51.00	78.00
InterferedwLife (0 to 100)	0	30	35.71	32.98	3.00	30.00	58.50
NeededHelp (0 to 100)	0	28	33.95	32.72	2.00	28.00	61.00
IntrusiveThoughts (0 to 100)	0	22	33.20	33.61	1.25	22.00	59.75
FrequentLoss (0 to 100)	0	35	39.30	34.49	3.25	35.00	67.00
NetNegEmotions (-100 to 100)	-100	0	0.28	55.65	-35.75	0.00	37.00
NetNegMHeffect (-100 to 100)	-2	0	1.94	46.74	-21.50	0.00	30.00
MaxHarm (0 to 100)	100	61.50	59.69	31.58	40.00	61.50	87.00

[a] The mode is computed assuming that variables are discreet.

Table 3 shows positive correlations between all the variables. The Pearson's *r* correlations between the negative outcome scales and Decision Type were of medium strength (0.3 to 0.5). However, using the standard conversion formula ($d= 2r/\sqrt{1-r^2}$), a Pearson's *r* correlation of 0.30 roughly corresponds to a Cohen's d of approximately 0.63, which most guidelines would classify as a medium-to-large effect. RiskScale was more strongly correlated (r ~ 0.6 to 0.7) to all of the outcome variables except NetNegMHeffect. Additional descriptive statistics and all correlations between all the predictor variables and outcome variables are included in a separate supplement (52). These results indicate that RiskScale is a better predictor for both individual types of negative effects that women attribute to their abortions as well as for an overall measure of the highest degree of negative effects, MaxHarm, than DecisionType.

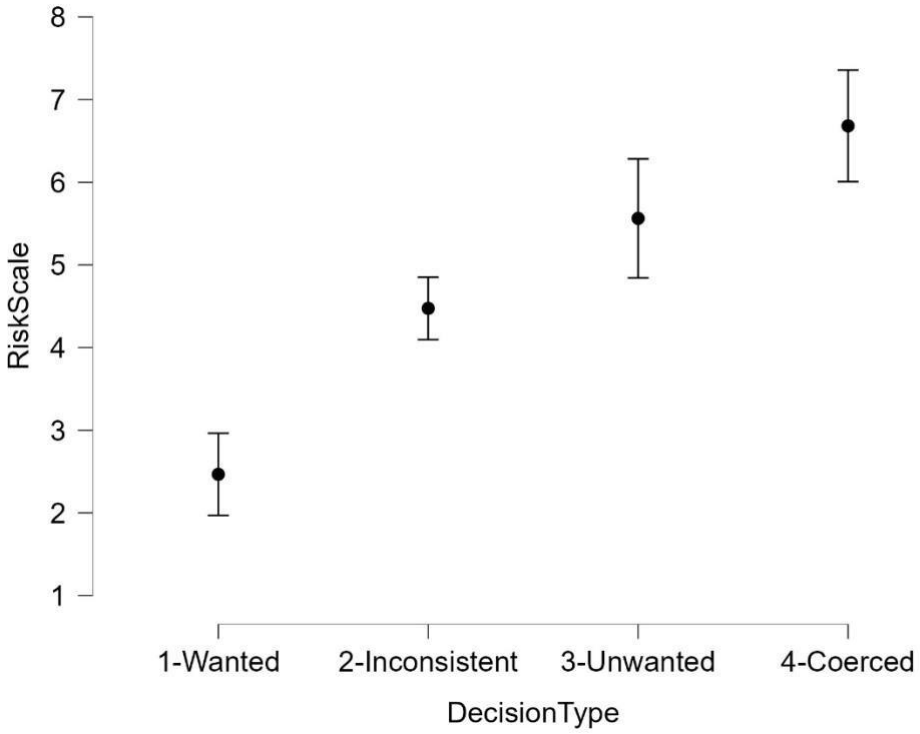
Table 3: Correlations Between DecisionType and RiskScale and All Outcome Variables

Pearson's r - all findings p<.001

Variable	1	2	3	4	5	6	7	8	9
1. DecisionType	—								
2. RiskScale	0.558	—							
3. NegativeEmotions	0.476	0.714	—						
4. InterferedwLife	0.370	0.627	0.621	—					
5. NeededHelp	0.365	0.640	0.592	0.838	—				
6. IntrusiveThoughts	0.327	0.629	0.560	0.681	0.707	—			
7. FrequentLoss	0.355	0.708	0.585	0.669	0.689	0.805	—		
8. NetNegEmotions	0.493	0.617	0.886	0.559	0.523	0.496	0.505	—	
9. NetNegMHeffect	0.318	0.401	0.472	0.453	0.426	0.391	0.468	0.588	—
10. MaxHarm	0.443	0.689	0.802	0.689	0.662	0.684	0.748	0.704	0.509

Despite the superiority of RiskScale in predicting negative outcomes, it is also strongly correlated to Decisiontype. Figure 2 shows that the RiskScale mean scores increase with each DecisionType further from the ideal, “Wanted and consistent with my values and preferences.” The mean RiskScale scores were 2.46 for women whose abortions were wanted, 4.47 for women whose abortions were accepted but inconsistent with their preferences, 5.56 for those whose abortions were unwanted, and 6.68 for those who experienced coerced abortions. Similarly, as shown in a separate supplement (52), distinct differences relative to DecisionType were observed across all predictor and outcome variables [34].

Figure 2: Mean RiskScale scores, with 95% confidence intervals, by DecisionType



However, RiskScale was more strongly correlated to MaxHarm (Pearson's r = .689; 95% CI 0.614 to 0.752) than DecisionType ((Pearson's r = .443; 95% CI 0.332 to 0.542). Figure 3 shows the mean and confidence intervals for each point in the RiskScale (range 0 to 8) relative to the MaxHarm value (range 0 to 100) The figure shows a good progression suggesting that higher RiskScale values show a proportional relationship to higher levels of MaxHarm.

Figure 3: Mean MaxHarm scores with 95% CI relative to RiskScale Scores

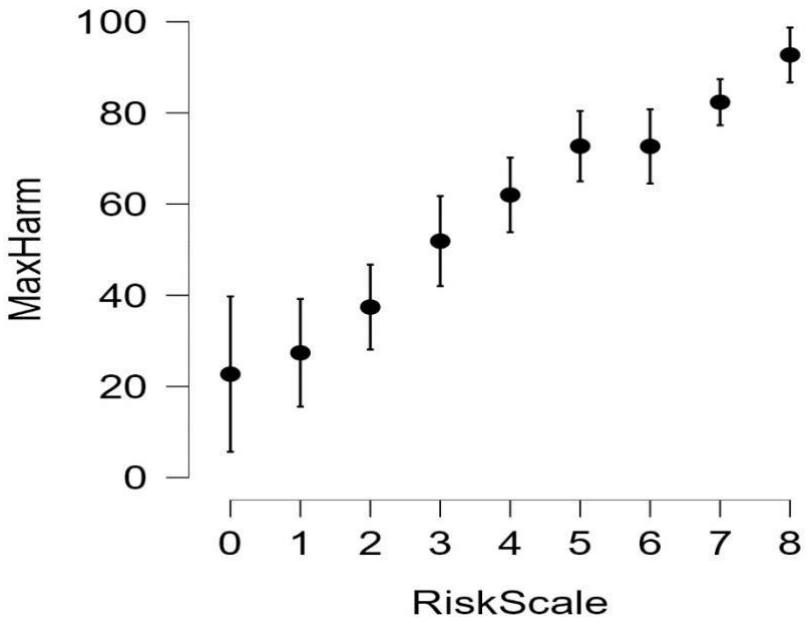


Table 4 shows the distribution of MaxHarm scores, segregated by the RiskScale scores, with the percentage of respondents above and below three MaxHarm cut-off scores (20, 50, and 80). Overall, 15.9% of the women attributed little to no harm to their abortions (MaxHarm<21), 84.1% reported moderate to severe negative reactions (MaxHarm> 20) attributed to their abortions, 64.2% attributed significant to severe reactions (MaxHarm> 50) to their abortions, and 32.3% rated one or more negative effects as severe (MaxHarm> 80). Among the latter group, one of the 73 women (1.3%) reporting MaxHarm>80 had a RiskScale of 0. Given the small number of women in many cells (n<10), our sample size is too small to establish reasonable confidence intervals for all cells in the tables. Still, the results are sufficient to identify general trends while also demonstrating that there will likely always be some outliers, especially among women with few or no identified risk factors.

Table 4: Distribution of women by RiskScale score and by MaxHarm threshold scores disaggregated by RiskScale scores

			Respondents below or above various MaxHarm score thresholds							
RiskScale	**Total**		**<21 (little or no harm)**		**>20 (moderate to severe)**		**>50 (significant to severe)**		**>80 (severe)**	
	n	**%**	**n**	**%**	**n**	**%**	**n**	**%**	**n**	**%**
0	13	5.8%	9	69.2%	4	30.8%	3	23.1%	1	7.7%
1	27	11.9%	16	59.3%	11	40.7%	6	22.2%	3	11.1%
2	27	11.9%	8	29.6%	19	70.4%	8	29.6%	1	3.7%
3	24	10.6%	3	12.5%	21	87.5%	11	45.8%	3	12.5%
4	33	14.6%	0	0.0%	33	100.0%	21	63.6%	8	24.2%
5	28	12.4%	0	0.0%	28	100.0%	26	92.9%	13	46.4%
6	21	9.3%	0	0.0%	21	100.0%	18	85.7%	8	38.1%
7	31	13.7%	0	0.0%	31	100.0%	31	100.0%	17	54.8%
8	22	9.7%	0	0.0%	22	100.0%	21	95.5%	19	86.4%
Total	226		36		190		145		73	
% of Total	100.0%		15.9%		84.1%		64.2%		32.3%	

Bayesian linear regressions were run for each outcome variable using all of the significantly associated predictor variables. Age1stAbortion was not significantly correlated to the outcome variables and was therefore excluded from the Bayesian modeling. Only the highest of 512 models tested for each outcome variable are shown in Table 5. The top ten models and posterior summary results for each outcome variable are shown in a separate supplement (52). In most cases, R^2 was near or above 0.5, indicating that the model of risk factors tested explains 50 percent or more of the variance in the outcome variable. They also reveal that the different risk factors have greater

predictive value for different outcome variables. This finding underscores the importance of evaluating a comprehensive list of risk factors.

Table 5: Bayesian Linear Regression results identifying the combination of predictor variables that most accurately model each negative outcome variable

Outcome	Top Model	P(M)	P(M|data)	BF_M	R^2
MaxHarm	EmotionalAttachment + MoralConflict + MoreFinSecurity + HumanLife	0.0008	0.086	118.339	0.555
NetNegMHeffect	PersonalPref + HumanLife	0.003	0.149	62.654	0.216
NetNegEmotions	MoralConflict + MoreFinSecurity + PersonalPref	0.001	0.373	498.734	0.535
FrequentLoss	EmotionalAttachment + MoralConflict + AvgPr + MoreSupport	0.0008	0.092	127.307	0.562
IntrusiveThoughts	EmotionalAttachment + AvgPr + MoreSupport + HumanLife	0.0008	0.273	473.262	0.495
NeededHelp	EmotionalAttachment + MoralConflict + AvgPr + MoreSupport	0.0008	0.124	178.429	0.480
InterferedwLife	EmotionalAttachment + MoralConflict + MoreSupport	0.001	0.139	134.906	0.494
NegativeEmotions	MaternalConflict + MoralConflict + AvgPr + MoreFinSecurity + PersonalPref	0.0008	0.127	183.315	0.627

Discussion

Main Findings

This survey of a national random sample of women who had abortions, on average, 20 years earlier, indicates that 84.1% of the women attributed moderate to severe negative reactions (MaxHam >20) to their abortions. Most women also reported multiple risk factors (average RiskScale = 4.18). if abortion had been flagged as contraindicated for anyone with more than one risk factor (RiskScale > 1), 82.3% of these abortion patients would have been flagged as at risk of moderate-to-severe psychosocial harm.

The results in Table 4 also suggest that even allowing women with a RiskScale score under two to proceed with an abortion (n= 40) would have resulted in 37.5% (n=15) subsequently

reporting moderate to severe negative reactions and 10% (n=4) reporting severe negative reactions (>80) on one or more of the outcome scales.

Conversely, regarding false positives, using the same threshold (RiskScale>1), only 4.9% (n=11) with a RiskScale score over one would have been denied an abortion or referred for additional counseling, which in retrospect may have been unnecessary, since they would later attribute little or no harm to their abortions (MaxHarm<21).

If the threshold for referral was the presence of any risk factor (RiskScale>0), the percent of false positives would rise to 12.0%. Still, the risk of false negatives (failure to refer for additional counseling) would drop to 7.7% for severe reactions, 23.1% for significant-to-severe reactions, and 30.8% for moderate-to-severe reactions. Our relatively small sample size demands caution regarding these preliminary estimates, but the trends in the data are sufficient to support the general conclusion, as previously stated by Belsey, that the benefits of referring for additional counseling more often than necessary are most likely to outweigh the inconveniences associated with unnecessary referrals (47). Additional research is clearly necessary to improve and refine both the measures of pre-existing risk factors and the extent of negative outcomes they predict.

In our analysis, each of the 11 risk factors investigated was meaningful. But future research is necessary to investigate the prevalence and significance of additional risk factors reported elsewhere. (48,53–55). This should include better prospective, longitudinal studies with nationally representative samples of women across all age groups and validated scales for psychiatric assessments. More evidence-based screening practices will contribute to better pre-abortion counseling and decision-making, which reduce the incidence rate of coerced, unwanted, unsafe, and unnecessary abortions.

Strengths and Limitations

A strength of our study is its high participation rate in a sample reasonably representative of the national population of women aged 41-45 years. On average, this population had their abortions 20 years earlier, which gives them both greater perspective about their experience and greater distance, which may have improved response rates among those who would have been more likely to refuse to participate in a follow-up shortly after their abortions. In addition, we were able to assess the degree to which each outcome variable that respondents directly attributed to their abortions. On the other hand, the limitation of the sample to women in this narrow age group introduces the possibility that self-assessments of both the risk factors and outcome variables may be significantly different among younger women and women who are interviewed closer to their abortion experiences.

A weakness of the study, however, is that it is entirely retrospective and limited to a sample of women who had their abortions, on average, about 20 years ago. Memories and feelings may change over time and may introduce recall bias, including the influence of subsequently developed personal, political, or ideological beliefs. Ideally, the variables examined in this study should be used in longitudinal studies, such as the National Longitudinal Study of Adolescent to Adult

Health, to evaluate how responses and participation rates may vary over time. In addition, this study is limited to U.S. residents. Future investigations should explore if there are any cultural influences on risk factors.

Another limitation is that our study examined a relatively small portion of all the risk factors that have been identified in the literature (48,53–56). Additional research should be conducted to investigate both other known risk factors and a larger variety of the negative outcomes (including both self-assessments and validated assessments of affective disorders, traumatic reactions, substance use, and suicidal behaviors) that have been reported elsewhere (55,57).

Additional limitations apply to terminology used in the questionnaire, which may be interpreted differently by respondents. For example, the word "coerced" may have different practical, social, or legal meanings to different respondents. Therefore, those who described their abortions as coerced may not have had abortions which would meet the standards defined for "coercion" under various state statutes. Readers should be aware that this term, like many terms used in the questionnaire, may be interpreted differently by respondents.

Finally, the eight items used to construct RiskScale do not include all the TFMHA-identified risk factors, much less all the additional risk factors identified by other reviewers. Additional investigations, including factor analyses, should be conducted to optimize a risk assessment scale. The scale developed and tested here has excellent internal consistency (Cronbach's $\alpha = 0.874$), but it may still be missing other items that are more important than the eight selected for this experiment. Additional testing and validation are highly recommended.

Interpretation

In our experience providing abortion services (PKG) and pre-abortion counseling (MS), screening for risk factors was not part of any training protocol. This lack of screening is consistent with what is reported in research examining counseling practices at 27 U.S. abortion clinics, which revealed that while the following components were "always" included: "1) Provide information about the procedure (96%), 2) assess the certainty of patients' abortion decisions (92%), 3) assess patients' feelings and provide emotional support (74%), and 4) provide contraceptive health education (92%)…"(58), screening for risk factors predictive of negative emotional reactions was not mentioned. Yet systematic screening for risk factors is certainly warranted and even indicated in the National Abortion Federation's textbook on abortion (59), which identifies 18 risk factors, including "commitment and attachment to the pregnancy," and "perceived coercion to have the abortion." While the authors, experienced abortion counselors, suggest that "patients with risk factors may require more time to reconsider options," it is unclear if there is adequate training and implementation of this recommendation. Similarly, the American Psychological Association's Task Force on Mental Health and Abortion identified 15 risk factors predictive of more negative outcomes (53) and analyses of these indicate that the majority of women undergoing abortions are likely to report multiple risk factors (55).

Research on how abortion counseling has evolved in the decades since 1973 gives insight into possible reasons why more attention to predictive risk factors may be lacking (60). In her report, Joffe, a former board member of the National Abortion Federation, concluded that politicization of abortion has negatively impacted abortion counseling practices. One counselor told her: "I think we fought so hard to protect abortion rights that there was a real hesitation on anybody's part to address that [for] some women, abortion might be hurting them" (60). In addition, Joffe reported that administrative pressures to process patients through the intake process rapidly, often preventing counselors from taking the time they need to provide true individualized counseling to their patients.

Evidence-based pre-abortion screening of known risk factors is necessary for several reasons. First, screening is necessary to develop an evidence-based recommendation of whether the risks of abortion outweigh the benefits for each individual patient. Second, screening is necessary to properly personalize disclosures of risks to each patient that are relevant to her own risk profile as required by medical ethics and case law (46). Third, screening is necessary to identify pressures women may face to submit to abortions that are contrary to their own personal preferences and values. In such cases, health care professionals should be prepared to offer referrals, additional counseling, or other assistance that might ameliorate these pressures and to assist the patient in finding resources that will help her to achieve her own reproductive preferences. Indeed, the American College of Obstetricians and Gynecologists has published committee opinions recommending that women should be screened for intimate partner violence (61) and reproductive coercion (62) at the first pregnancy visit and at least once a trimester during pregnancy. Such screening provides an opportunity to educate women and offer resources which can help to prevent coerced abortion.

Notably, prior research indicating that women who anticipate negative reactions to their abortions are more likely to experience negative reactions (37) has been used to advance an argument for censoring pre-abortion risk disclosures. The proponents of this view believe that withholding information "that stresses the negative aftereffects of abortion" is justified because exposure to these facts "may have a harmful effect on their adjustment to the abortion experience" (28). But this is purely speculation. Even the proponents of this hypothesis' own study of different pre-abortion counseling methods revealed that counseling designed to bolster self-efficacy and confidence in one's abortion decision resulted in only a small reduction in the incidence and degree of negative feelings, which lasted for only a few weeks after an abortion (63). Despite this failure, they hold that "Longer and more extensive counseling sessions might be expected to have longer-lasting effects" (28). But is it not more likely that the women who are most ambivalent about their abortion decisions, or feel pressured into abortions that are contrary to their own values and preferences (all TFMHA risk factors), quite rightly and accurately anticipate more negative feelings in the aftermath precisely because of their ambivalence and compromised decision-making? The best evidence suggests they are correct in their self-assessments. To pretend they are mistaken in their expectations is deceptive and unethical, representing an injustice and a failure of informed consent.

Medical ethics literature and court cases have addressed the issue of physicians withholding information about treatment risks when it is anticipated that knowledge of those risks might cause the patient to decline a treatment the physician believes would be beneficial. Murray, citing *Carr vs. Strode*, states that "a physician must disclose information that a reasonable person would want to have for decision making, even though that information may cause the patient to refuse treatment that the physician believes is in the patient's best interest" (46,64). The World Medical Association (of which the A.M.A. is a member organization) points out that under the "medical paternalism" of the past, it was acceptable for a physician to decide what was best for the patient and make treatment decisions with limited communication, but those days are long past. Today, "a mentally competent adult patient has the right to give or withhold consent to any diagnostic procedure or therapy" and "has the right to the information necessary to make his/her decisions" (65).

Ethics literature and the courts do recognize a "therapeutic privilege" to withhold information about risks of treatment only very rarely, in extreme circumstances 1) if the person is unconscious and may need emergency treatment or he benefit of the treatment clearly outweighs any harm or 2) if the person would be seriously harmed by disclosure of risk, for example if the patient were so emotionally upset that they might become incapable of making a rational decision. But information about risks may not be withheld merely because it could cause someone to decide not to undergo the treatment the physician prefers (25,46,65–67). This is especially true regarding abortion decisions, since there have been cases where abortion providers have exhibited racist or eugenic mindsets driving them to encourage and facilitate abortions that might be contraindicated purely to advance their own social engineering preferences (25).

Although there are multiple theories regarding the ethical principle of "justice," it can be understood as "fairness" (68). Carr v. Strode, citing Bernard v. Char, states "since the patient must suffer the consequences, and since he or she bears all the expenses of the medical treatment, fundamental fairness requires that the patient be allowed to know what risks a proposed treatment entails." (64). The Belmont Report also considers justice as fairness in the distribution of burdens and benefits. (69). When a physician fails to disclose individualized risk factors, a high-risk individual may be forced to bear a greater burden of risk without their knowledge or consent.

Moreover, by providing accurate evidence-based information confirming to these women that they will likely face more post-abortion adjustment issues can serve several good purposes. First, it is an essential right of patients, especially when undergoing an elective procedure, to be informed of all risks associated with the procedure so that they can make their own informed decision about whether any hoped-for benefits are likely to outweigh the possible risks (25,70). Second, our data reveal that approximately one in four abortion patients may be at risk of feeling pressured to undergo unwanted or coerced abortions. In these and other cases, providing women with evidence-based information confirming their expectations of being at higher risk of negative emotional reactions may arm them with the information they need to explain and convince those pushing them into unwanted abortions as to why an abortion, in their unique personal circumstances, may lead to lasting harms. Third, if abortion is chosen, it prepares them for the possibility and likelihood that they may need and benefit from post-abortion counseling. Fourth,

if abortion is chosen, it will help to dispel the idea that there is "something wrong with me" because "everyone says I should be able to get over my abortion quickly."[25,70]. In short, women are ill-served by the false impression that abortion is risk-free. It is not a panacea. Nor will it turn back the clock so that their lives will go on as if they had never been pregnant. In at least some cases, women are looking for reasons to *not* have an abortion, precisely so they can use that information to convince loved ones who are pressuring them for an abortion why it simply isn't for them (25,71).

In short, the suggestion that women should be shielded from information about emotional risks associated with abortion precisely to reduce the incidence rate of emotional problems is both ill-conceived and a violation of patients' rights to full disclosure of all risks associated with a medical procedure, even when causal paths have not yet been determined (70). We strongly disagree with this policy. Women deserve evidence-based screening and risk-versus-benefit assessments, as supported by the medical ethics literature and case law.

Indeed, there is no evidence of any physical or psychosocial benefits that are directly attributable to induced abortion, medical or procedural (22,23,25,72). Indeed, even the proabortion researchers who led the Turnaway Study have admitted that there is no psychological harm to being denied an abortion (73,74). Therefore, with no proven benefits and many substantial risks, it would seem clear that it is medically unethical to provide abortions (72,75).

For abortion proponents, these concerns about the negative effects of abortion on women may be secondary to the higher ideal of women being free to choose abortions, and to control their own bodies, including the risks that may follow (11,15,25).

Conclusion

There is general agreement that pre-existing risk factors can be used to identify those women at greatest risk of negative mental health outcomes, which they attribute to their abortions (28,48,53–56). While limited to retrospective data, the risk scale developed in this study appears to offer an efficient means of identifying the subsets of women who may benefit from additional pre-abortion counseling, referrals for post-abortion counseling, and other interventions that may alleviate the pressures to submit to unwanted, coerced, or otherwise contraindicated abortions.

Most abortions are sought with the hope for psychosocial benefits. But in fact, there is no research demonstrating any measurable psychosocial benefits from abortion, for women in general or in specific subsets of women. Even the Turnaway Study, which was designed with the anticipation of proving psychological harms resulting from women being denied abortions, failed to find any such harms. Indeed, women who were denied abortions reported being overwhelmingly happy to have had their babies, with only 4% still wishing, five years later, that they might have had an abortion. According to the lead author: "I expected that raising a child one wasn't planning to have might be associated with depression or anxiety. But this is not what

we found over the long run. Carrying an unwanted pregnancy to term was not associated with mental health harm. Women are resilient to the experience of giving birth following an unwanted pregnancy, at least in terms of their mental health" (73).

Our findings confirm what common sense and traditional medical ethics suggest: a failure to screen for risk factors predictive of adverse reactions to abortion is medical negligence. Nowhere else in medicine would the failure to screen for such strongly correlated risk factors be tolerated.

Physicians respecting the time-honored Hippocratic Oath should be aware of these risk factors in order to be in a position to provide evidence-based counseling to women and families facing problematic pregnancies. They should also be aware of these risk factors so that they can provide expert testimony regarding the failure of abortion providers to provide evidence-based medical recommendations, screening, and risk disclosures.

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Viewing D&E Abortion Procedure Promotes Negative Emotions

Anna Cecilia Gessler*, Dominic Zak*, Isabella Dammeyer*, Peter Patelli*, Rachel Vander Woude*, Cole Stull*, Rylie Severson*, Derek M Doroski**

Abstract: Induced abortion, "an intervention intended to terminate a pregnancy so that it does not result in a live birth"[1], is a highly contentious procedure, with varying comprehension of actual abortion procedures used. The comprehension of the actual abortion procedure used in the second trimester may affect the various levels of support or lack thereof for abortion after the first trimester. The most common second trimester surgical abortion procedure is Dilation and Evacuation (D&E). Many commonly available descriptions of the D&E lack sufficient detail and may not be sufficient for patients or the public to understand the procedure. Little is known about the public's understanding of D&E abortion procedures. This pilot study investigates how viewing an animated D&E procedure impacts participants' perceived understanding of the procedure, emotional responses, and pro-life/prochoice affiliations.

Researchers conducted a 14-item pre- and post- intervention survey in the Ohio Valley region (n=50). While participants' pro-life/pro-choice position on abortion did not immediately change after watching the video, participants' perceived understanding of the procedure increased ($p<0.05$, $d=0.45$). Furthermore, both prolife and pro-choice cohorts reported a high frequency (70%) of negative emotion when considering abortion after viewing the procedure. Notably, participants who perceived themselves to have a greater knowledge of abortion felt more negative emotion ($p<0.05$, $r=-0.49$).

In conclusion, the results of this pilot study suggest animated depictions of a D&E abortion procedure increased participants' perceived understanding of abortion, which may demonstrate a lack in current public understanding. In addition, those who are knowledgeable about abortion procedures were found to be more likely to report negative feelings toward the use of D&E procedures and to identify as prolife. Although participants' pro-life/pro-choice position on abortion did not immediately change after watching the video, it is possible that comprehension of the details of a D&E procedure may promote a pro-life identity in the long term. Further

long-term research is needed to confirm whether greater abortion knowledge and negative emotional responses promote a long-term pro-life affiliation.

Keywords: abortion perception, dilation and evacuation, D&E, dilation and extraction, second trimester abortion, abortion video

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Ethics Approval and Consent to Participate: The survey was approved by the Franciscan University of Steubenville Institutional Review Board.

Introduction

Induced abortion, an intervention intended to terminate a pregnancy so that it does not result in a live birth[2], is a common procedure in the United States. While the term 'abortion' can be used medically to refer to both induced abortion and spontaneous abortion (i.e., miscarriage), the use of the term 'abortion' typically refers to induced abortion. Therefore, in this paper, 'abortion' refers to 'induced abortion' unless indicated otherwise. It is estimated that between 613,400 [3] and 1,038,000 [4] abortions are performed annually in the US alone. The dilation and evacuation procedure (D&E) is performed in the 14th through the 27th week of pregnancy (menstrual age) and is the third most common abortion procedure performed in the United States, with approximately 60,000 cases annually.[5] To perform a D&E, the cervix will be dilated over the course of 1-2 days. Cervical dilation is typically accomplished using either osmotic dilators, such as laminaria, or mechanical dilators, such as a balloon catheter. Once dilated, the woman is sedated before a speculum, a tool to hold the vagina open in order to visualize the cervix, is inserted. A tenaculum is then used to grasp the cervix to allow a vacuum cannula to be inserted through the cervix. The vacuum cannula is used to remove the amniotic fluid surrounding the fetus. A grasping forceps is then used to apply traction to the fetal limbs for the purpose of separation and removal of the fetal legs and arms from the fetal torso. The torso is then removed with similar traction by grasping forceps. If the fetal skull is too large to be removed with the torso, the skull is crushed and removed in pieces[6]

Prominent descriptions of the D&E procedure may not be sufficient for patients or the public to comprehend the operation. For example, Planned Parenthood, the largest abortion provider in

the United States, describes D&E procedures as a "combination of medical tools to remove the pregnancy tissue out of your uterus",[7] but gives little detail that would be useful for fully informed consent. Similarly, the National Abortion Federation uses terms such as "removal of the pregnancy" and "emptying the uterus" that lack specificity.[8]

Since 96% of biologists agree that fertilization is the moment human life begins, referring to a human fetus as "pregnancy tissue" or omitting descriptions of fetal limb removal withholds important information that patients may reasonably desire when making decisions about medical procedures and may violate the principles of informed consent and thus become a significant issue for patient care.[9]

An accurate understanding of abortion procedures can also be important for making informed political decisions. Many surveys have been conducted to evaluate people's positions regarding abortion and the circumstances under which they should be performed.[10] The impact information has on a person's emotions, understanding, and affiliation can aid in understanding pro-life/prochoice rationales. There have been no studies examining how individuals' perception of abortion changes when educated on the details of abortion procedures or how these perceptions may change in different demographics. The goal of this pilot pre-post intervention survey study was to determine how exposure to the details of a D&E procedure might affect understanding of second trimester abortion, pro-life/pro-choice ideological affiliation, and emotions toward abortion.

Materials and Methods

A 14-item survey was created to assess individuals' understanding of second trimester abortion, pro-life/pro-choice ideological affiliation, and emotions toward abortion before and after watching an animated depiction of a dilation and evacuation abortion procedure.[11] Subjects younger than 18 were excluded from the survey. The survey was approved by the Franciscan University of Steubenville Institutional Review Board. Participants were not asked to define abortion or to discuss their personal experience with abortion, and no explicit definition of abortion was provided. All surveys completed in their entirety were included in the analysis. Exclusion criteria for surveys included those that were not fully completed by subjects, or that could not be read or had their data transcribed by the researchers. A total of 50 surveys were collected, and none met the exclusion criteria.

The data were collected using a convenience sample collected in eastern Ohio and western Pennsylvania, a region known as the Ohio Valley (n=50). In pairs, researchers visited houses in select neighborhoods using a prewritten script to minimize the potential for a priming effect. When a potential subject answered a knock, the subject was asked to participate in a study conducted by students at Franciscan University. The researcher conducting the interview was randomly selected for each house. An incentive of free food and drink was offered to all subjects. A consent form was obtained from participants, and both the survey and form were placed in a sealed envelope by the

participant. No names or other identifying information were included in the data, and researchers were unable to view or access the surveys until they were sealed in an envelope. The survey consisted of a series of questions using semantic differential scales, affiliation scales, and demographic information, and was divided into two major sections, pre-video and post-video (Fig. S1). Between the two survey sections, participants watched a brief animated video depicting a D&E.12 The only parts of the video shown were those depicting the actual procedure. Participants were informed that they could stop the video at any time. Participants were unable to access or view the post-video portion of the survey until the depiction was finished.

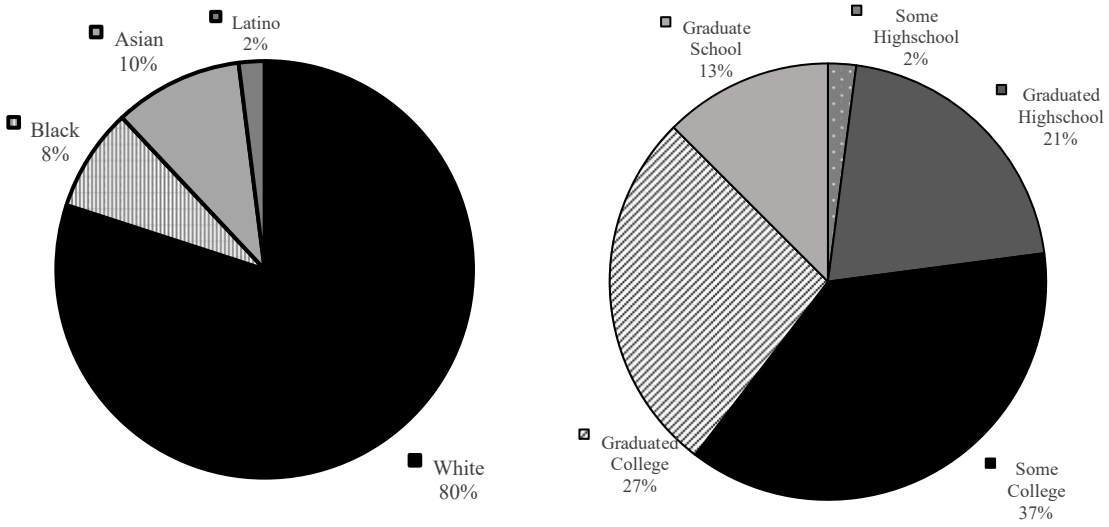
Pro-life/pro-choice affiliation was evaluated by self-report on a sliding scale. Subjects were coded as pro-life if they rated themselves from 0 to 3 on the pro-life/pro-choice scale, moderate if they rated themselves 4 to 6, and pro-choice if they rated themselves 7 to 10.

The data were assessed for normality using the Shapiro-Wilk test. Non-parametric data containing two groups of discrete and continuous variables were analyzed using the MannWhitney test and the Kruskal-Wallis Test. Continuous nonparametric data were analyzed using dummy-coded multiple regression models. Discrete nonparametric data were analyzed using the Levene Test. Vargha and Delaney's A,[13] η^2, and Pearson's correlation coefficient were used to measure the effect size of ordinal data. Parametric data with discrete and continuous variables were analyzed using two-sided t-tests. Parametric data containing continuous variables were analyzed using multiple regression models. Parametric data with two discrete variables were analyzed using ANOVA. Effect sizes for parametric variables were measured using Cohen's d and Pearson's correlation coefficient. Effect sizes were interpreted using Cohen's 1988 heuristic thresholds.[14] Vargha and Delaney's A was interpreted using the heuristic thresholds suggested in their paper. Bimodality of distributions was evaluated using Sarle's bimodality coefficient[15] at a kurtosis of $\kappa 3$. p-values of less than 0.05 were considered statistically significant. The R software environment and Excel's native statistical analysis programs were used for all analyses.

Results

The racial composition of survey participants was 80% White, 10% Asian, and 8% Black. 2% of our population was Latino, and 8% said they were Hispanic (Fig. 1). A chi-squared test of goodness of fit showed no differences between the demographic distribution across race and sex in our study compared to the US Census Bureau statistics for the Steubenville-Weirton region ($p=0.2646$).[16]

Figure 1. Distribution of Race and Education Level of Subjects (n=50).



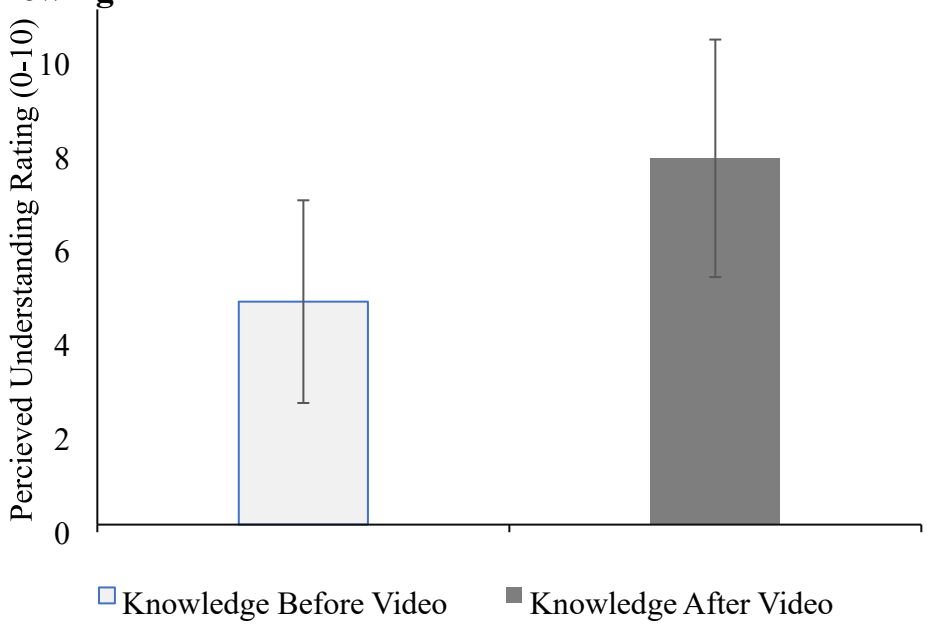
Survey results yielded equal numbers of men (n=25) and women (n=25), with a mean age of 35.17 $\pm$1 8.5 years, and most participants had college-level education (Fig. 1).

Participants' Perceived Knowledge of Abortion Before and After Video Viewing

When asked to rank their understanding of abortion on a 0-10 scale, most participants (84%) perceived themselves to have moderate to high levels (5-10) of understanding of an actual abortion procedure before watching the video. In fact, 16% of participants perceived themselves to have a full understanding of abortion. Males were significantly more likely to harbor higher perceived levels of understanding about abortion than females ($p=0.0300$, $A=0.3456$). Regarding participants' affiliation with abortion, the results were bimodal ($BC=0.73$), with 38% of respondents selecting 0 (pro-life), and 28% 10 (pro-choice). In the analysis, pro-life and pro-choice individuals were defined as reporting between 0 and 3 and 7 and 10 on the abortion affiliation scale. Among the pro-life cohort, the average abortion affiliation score was 0.34, with a standard deviation of 0.93. Among the pro-choice cohort, the average abortion affiliation score was 9.13, with a standard deviation of 1.25. There was a statistically significant difference ($p=0.0044$, $\eta^2=0.48$) in the variances between pro-life affiliation and pro-choice affiliation. Subjects who had

received a graduate school level of education were significantly more likely to affiliate with prolife ideology than subjects who had received less education (p=0.0207, A=0.2159). Other demographic factors, like race and age, did not have a significant impact on perceived understanding or abortion affiliation.

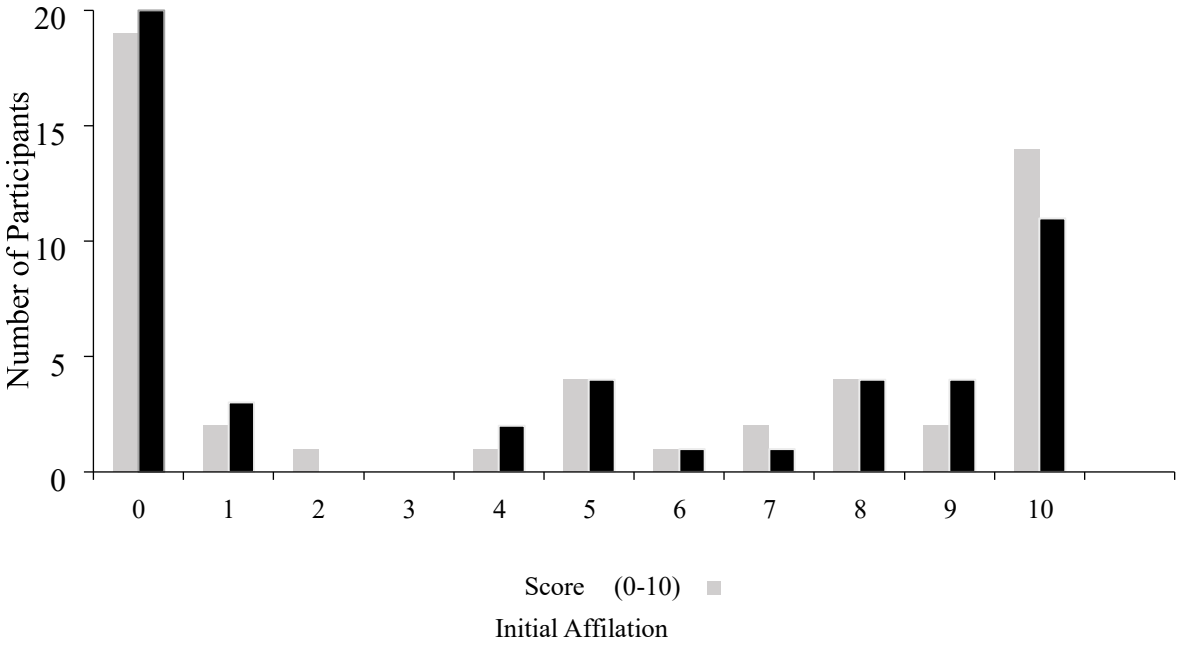
Figure 2: Participants' Perceived Knowledge of Abortion Before and After Video Viewing



Participants reported their understanding of an actual abortion procedure on a scale of 0 to 10. 10 was the highest. 0 was the lowest.

Watching an animated depiction of a D&E abortion significantly increased perceived understanding of an actual abortion procedure (Fig. 2, p=0.0003, d=0.45), but did not have a statistically significant impact on abortion affiliation (Fig. 3, p=0.42). Increased levels of perceived understanding of abortion before and after watching the animated depiction of a D&E abortion were associated with a decrease in pro-choice views (p=0.0138, r=0.2567).

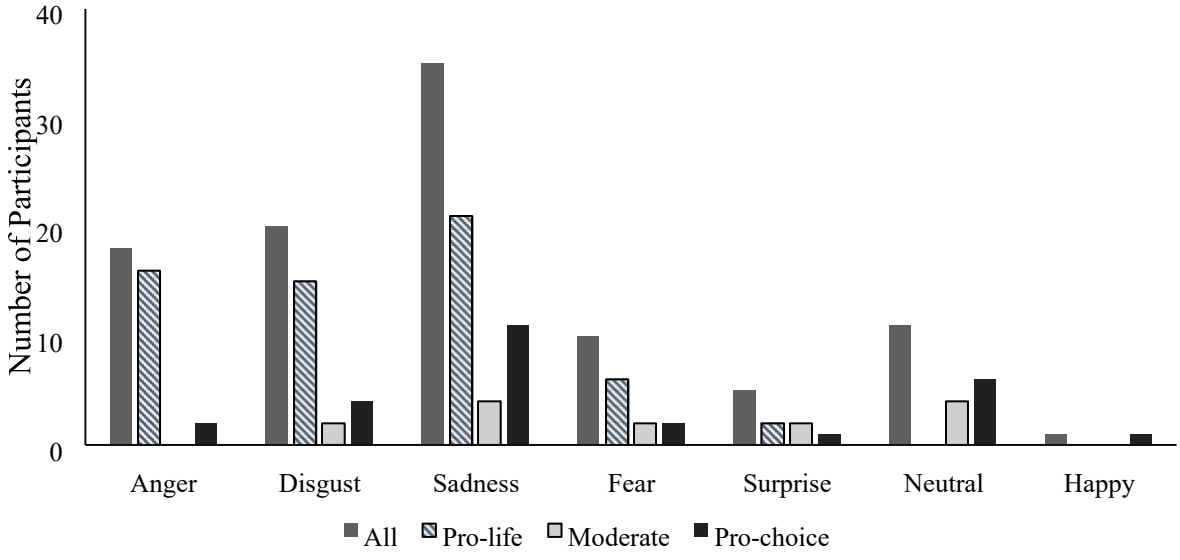
Figure 3: Affiliation with abortion after watching the abortion video



Participants' pro-life/pro-choice identification on a scale of 0 to 10. 10 was pro-choice. 0 was pro-life.

Participants' affiliation with abortion was not significantly different after watching the abortion video (Mann-Whitney Wilcoxon, $p>0.05$).

Figure 4: Number of participants recording basic emotions, grouped by affiliation with abortion according to a self-rating on a 10-point scale.



Ratings of 0-3 were categorized as pro-life, 4-6 were moderate, and 7-10 were pro-choice.

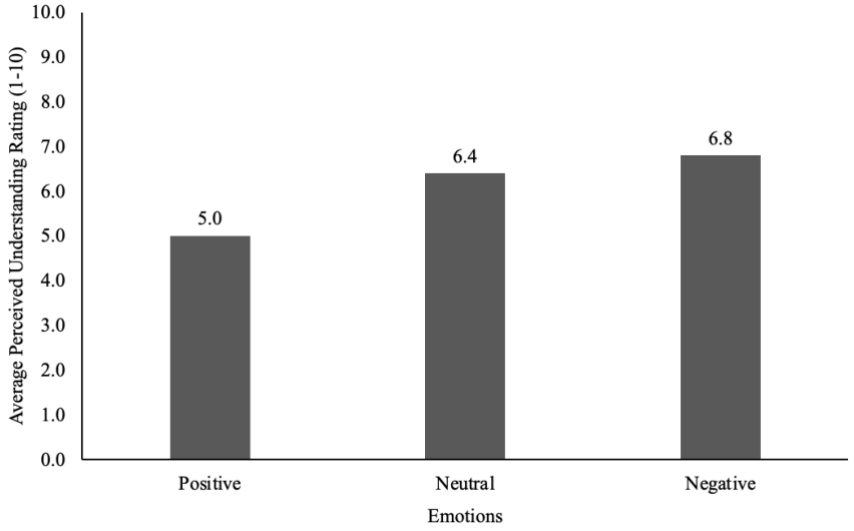
Subjects' feelings about abortion after watching the video were almost entirely negative (Fig. 4). The most common negative feeling was sadness, with 70% of subjects reporting feelings of sadness when thinking about abortion after watching the video, including over 50% of prochoice identifying subjects and over 90% of pro-life identifying subjects. By contrast, 2% of participants reported feelings of happiness.

Subjects were significantly more likely to report negative emotions if they reported higher levels of abortion understanding after watching the video ($p=0.0000$ $r=-0.49$), reported a greater increase in understanding ($p=0.0000$ $r=-0.43$), or were black ($p=0.0008$, $D=0.5890$).

Discussion

This novel pilot study examines how a person's ideological affiliation, emotion, and understanding are affected by viewing an animated video on the D&E procedure in a second-trimester abortion. Despite high levels of perceived understanding of abortion, participants generally reported an increase in understanding after watching the animated abortion procedure (Fig. 2). Higher levels of perceived understanding of abortion were associated with higher levels of negative emotion (Fig. 5). This data suggests that most people dislike D&E abortion procedures when they view the details of the D&E procedure. Negative emotion when thinking about abortion was predominant in both pro-life and pro-choice participants (Fig. 4), suggesting that dislike of D&E abortion procedures is not confined to pro-life individuals.

Figure 5: Average perceived understanding rating grouped by participant's emotion, according to a self-reported scale.



Higher perceived understanding was associated with a greater likelihood of negative emotion (multiple regression, $p<0.0001$).

In addition, those with a higher perceived understanding of abortion were more likely to have negative opinions about the procedure (Fig. 5). However, the video had no significant impact on short-term abortion affiliation (Fig. 3). It is possible that people do not associate D&E abortion with abortion as a whole. In the surveying process, a few people stated that D&E abortion is uncommon or is one of the worst procedures despite the fact that[17] approximately 60,000 D&E abortions are performed annually. Further research would be useful in examining whether participants are against D&E procedures while still supporting abortion as a whole.

Notably, higher levels of perceived understanding were not correlated with changes in affiliation ($p<0.001$, Fig. 1) but were associated with greater pro-life affiliation. These results, combined with high levels of negative emotion, may suggest that a person's affiliation with abortion is not based on their emotions or perceived understanding regarding an abortion procedure in the short term. This contradicts the assumption that ideological alignment is predicated on emotional reaction and perceived comprehension. If ideological affiliation was based on emotion, it might be expected that most pro-choice participants would feel positive or neutral emotions after watching the video. If ideological affiliation was based on perceived understanding, it might be expected that a change in understanding would result in a change in affiliation. It is possible that pro-life individuals with a greater understanding of abortion are experiencing prolonged negative emotions about abortion over time. If true, the sustained negative emotions about abortion might promote pro-life affiliation in the long-term, but not in the short-term. Long-term studies of how individuals' views on abortion evolve, given increased levels of understanding about the procedure, may provide greater insight into these results.

A previous study found that those with higher education levels tend to identify as prochoice.[18] However, the results of this experiment showed no correlation between education and affiliation. In fact, those who had received a graduate-level education or more tended towards prolife identification ($p=0.0207$). This discrepancy could be explained if educational institutions in this region provide students with more education about the abortion procedure, more pro-life arguments, or fewer pro-choice arguments in general and may reflect regional differences in education about abortion.

Pro-life identifying subjects were more likely to identify as 0, which is fully pro-life, compared to how likely pro-choice subjects were to identify as 10, fully pro-choice, on the abortion affiliation ($p=0.044$). This suggests pro-life individuals may be less willing to change their beliefs about abortion compared to pro-choice individuals, or perhaps that they are more confident in their beliefs, given their statistically higher levels of knowledge.

Strengths

Our study has several strengths. While in-person interviewing could expose the study to priming effects, these effects were mitigated by randomly assigning survey administrators within the research group and following a script. Furthermore, participants were informed that the survey was being conducted by students from Franciscan University, which may suggest a pro-life affiliation among participants and introduce social desirability bias. The risk of bias was limited

by researchers avoiding communicating any views on abortion in their interactions with subjects. No control group was employed in the study design, which prevents us from concluding the D&E procedure video was the sole cause of the negative emotional response. Covariates, such as the at-home study environment or viewing of any graphic medical procedure, may have contributed to the observed increase in negative emotion. Strengths of the in-person survey, as opposed to online, include the guarantee that every participant is human (e.g., not a bot), completes the survey only once, and watches the video to completion. Another strength of the in-person survey is that the subject can ask clarifying questions, which can reduce errors.

Limitations

A weakness of this study is the geographical restriction of the sample population to the Ohio Valley, which makes it difficult to generalize the results to a wider geographic area. Post hoc power analysis revealed that, with the detected effect size of 0.45 in the bivariate analysis, the study's statistical power was approximately 0.93. Results with effect sizes smaller than this were likely underpowered for the study design. These strengths and the mitigation of the weaknesses support the significance of our results.

Conclusions

The results of this pilot study suggest that watching an animated depiction of a D&E abortion is likely to induce negative emotion and increase a person's understanding of abortion but is unlikely to change ideological affiliation immediately. Further studies and experiments should be performed to confirm these results and elucidate the causes of pro-life/pro-choice affiliation, determine how understanding impacts abortion views, and what role emotion plays in a person's decision to support or reject abortion policies could be valuable.

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Appendix 1:_Full Survey

Survey number: _____

1. What is your age? ____

2. Which of the following best describes you? *(check all that apply)*

   ☐ White ☐ Black ☐ Asian

   Other *(please specify):* _____

3. Are you Hispanic? *(please check one)* ☐ Yes ☐ No

4. What is your sex? *(please check one)* ☐ Male ☐ Female

5. What is the highest level of education have you completed?

   ☐ Attended some high school
   ☐ Graduated high school
   ☐ Attended some college
   ☐ Graduated college
   ☐ Attended graduate school
   ☐ Attended medical/ dental/ veterinary school

6. How would you rate yourself on a scale of 0 to 10, with 10 being the most "pro-choice," 0 being the most "pro-life", and 5 being "neutral"? *(please circle)*

   0 1 2 3 4 5 6 7 8 9 10
   Pro-life Neutral Pro-choice

7. What are your reasons for this rating?

   _____
   _____
   _____

8. On a scale of 0 to 10 how would you rate your understanding of an actual abortion procedure, with 0 being the lowest and 10 being the highest level of understanding? *(please circle)*

   0 1 2 3 4 5 6 7 8 9 10
   Lowest Highest

9. Informative Video (3-5 minutes) – you may stop the video at any time

10. After viewing the video, how would you rate your <u>previous</u> understanding of an actual abortion procedure, with 0 being the lowest and 10 being the highest level of understanding? *(please circle)*

    0 1 2 3 4 5 6 7 8 9 10
    Lowest Highest

11. After viewing the video, how would you rate your <u>current</u> understanding of an actual abortion procedure, with 0 being the lowest and 10 being the highest level of understanding? *(please circle)*

    0 1 2 3 4 5 6 7 8 9 10
    Lowest Highest

12. After viewing the video, how would you rate yourself on a scale of 0 to 10, with 10 being the most "pro-choice," 0 being the most "pro-life", and 5 being "neutral"? *(please circle)*

    0 1 2 3 4 5 6 7 8 9 10
    Pro-life Neutral Pro-choice

13. After viewing the video, what emotions come to mind when thinking about abortion? *(check all that apply)*

    ☐ Anger ☐ Fear ☐ Sadness ☐ Neutral
    ☐ Disgust ☐Happiness ☐ Surprise

14. Do you have any other comments that you would like to share regarding this survey, the video, or thoughts on abortion?

    _____
    _____
    _____

If you desire to provide more detailed thoughts, please request a separate form from the interviewer.

Substance Abuse & Mental Health Administration hotline: 1-800-662-HELP

Project Rachel Help with grieving and healing after abortion: 1-888-456-HOPE