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Evaluating the Negative Impacts of New Technologies on Intellectual Property Law Using Neutrosophic Z Numbers

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Abstract. Emerging technologies like generative AI and blockchain present significant challenges to intellectual property (IP) law, creating ambiguity in assigning ownership and protection. This study addresses the need for robust methods to assess these negative impacts from a legal practitioner's perspective, where uncertainty is prevalent. We introduce and empirically test an assessment methodology using newly formulated Neutrosophic Z-numbers, which explicitly incorporate truth, indeterminacy, and falsity, along with their respective reliabilities. A quasi-experimental design was employed with 30 INDECOPI IP law practitioners, divided into control and experimental groups (the latter receiving specialized training). Participants assessed case studies involving new technologies. Results showed the experimental group demonstrated a statistically significant ($p < 0.001$) greater ability to identify and analyze the negative IP implications, particularly for AI and blockchain. This research offers a novel tool for IP impact assessment, with practical implications for professional training and regulatory development, contributing to more effective IP rights protection in the digital age.

Keywords: Neutrosophic Z-Numbers, Intellectual Property Law, Emerging Technologies, Impact Assessment, Legal Practitioner Training, Uncertainty Modeling

1. Introduction

The sudden emergence of disruptive technologies such as generative artificial intelligence, blockchain, and non-fungible tokens (NFTs) have changed the generation's production, dissemination—and even preventative measures—of content forever, posing unprecedented challenges to intellectual property law. This article investigates the impact of such developments on the regulatory frameworks designed to protect authorship and ownership. By acknowledging the implications of Intellectual Property law to date, new findings and approaches will be able to be practically applied going forward. As society becomes a more technologically dependent network, it is essential to understand what advancements challenge even the most historically founded tenets of intellectual property from the viewpoint of creators—and industries—first and foremost nationally and internationally [1], [2], [3]; through different legal realms [4]. Literature exists that justifies how the need for attribution in a society where machines create at a rapid clip, where decentralized ledger systems (like blockchain) abound, disrupting even the simplest tenets of IP Law. [5], [6]. Thus, by assessing how these creations challenge law to date with the potential for abuse, only then can compassionate creation be advocated. For example, through the ages, technology has emerged at intervals that render a change in Intellectual Property law. In 1450, the printing press had been created and the ability to replicate works was widespread leading to the first copyrights [7]. In 1999, with MP3s as songs could be burned within minutes, inappropriate access had been debated [8]. In the 2000s/2010s/c 2020s, AI could create books, songs, and images with its ability to write, render, and vocally output independently [9]. Similarly, blockchain and NFTs provide a transactive system palatable to those reading Forbes yet not palatable by government regulation. Thus, An examination of technological and historical precedents shows how these developments have been handled in the past and what laws do or do not exist already to fuel new expansion efforts.

Yet established legal solutions aren't prepared to combat the phenomenon created by emerging technology. For example, if an artwork is created by an AI, who owns it? How can someone determine an infringement of a metaverse version? This shows how ineffective established laws are [8]. Furthermore, when there aren't boundaries for international laws of the metaverse, the existence of ineffectiveness lowers trust in intellectual property protection systems [9]. Thus, it becomes important to evaluate how emerging technology negatively impacts intellectual property law when positions can be rendered from an uncertain perspective—how can such a factor be assessed in a relative vacuum? The complication goes beyond merely adjusting for case history; it extends to how we assess much too impactful a factor in a fluid law environment. Many finite options based on qualitative or quantitative assessments fail to acknowledge the uncertainty determined by how practitioners feel about such technology [10]. This is relevant research to answer the question because the unprecedented approach allows for conditioned uncertainty to be calculated and evaluated accordingly, providing regulators and practitioners with a great tool. The scope of the problem is vast. People sue each other all the time for things generated by AI or even things watched through a digital streaming platform—these are the nicks that need an assessment of impact solution and provide resolution [11]. The lack of an impact assessment method that accounts for indeterminacy represents a gap in the literature which this study will fulfill with findings from an approach that embraces the little person's perspective on this worldwide legal issue.

Therefore, this study will explore the technological detriment to intellectual property law in comparison to its use via regulatory means. Therefore, the population of interest is those who operate in this legal field and can recognize such an impact and sidestep it through policy considerations. Thus, applying the newly developed tool to analyze cases of the same ilk empowers the article to make a theoretical appeal for an empirically based approach to decisions about intellectual property. Furthermore, as a new tool is being used, it gives access to other scholars working within this subfield something novel to control for ambiguity. Ultimately, it uses the advancements of today to fuel tomorrow's policy and research considerations. This not only renders appeal to a broad scope of authority in the microcosm of scholarly work but also merges legal theory with contemporaneous advanced research to place it in the global discourse of technology and law.

This study's intention is 1) to assess the impact of new technologies on intellectual property law through a center-focused approach, 2) to determine whether topic-specific training seminars are more effective than topic-general ones in improving practitioner capabilities to reduce such impact; 3) to provide regulatory adjustments championed by practical application. Therefore, this problem question and purpose of study reflect the nature of this article's progression in hopes of contributing to the strengthening of rights protection systems in the digital age.

2. New Technologies in Intellectual Property Law

New technologies, such as generative artificial intelligence (AI), blockchain, and non-fungible tokens (NFTs), have burst onto the global scene, transforming the creation, distribution, and protection of intellectual works. This article analyzes how these innovations challenge traditional principles of intellectual property law, assessing their impact on authorship, ownership, and regulatory enforcement. The relevance of this topic lies in their ability to redefine legal frameworks in a dynamic digital context, where the speed of technological advances often exceeds regulatory capacity [12]. By exploring these challenges, we seek to assess whether current laws are sufficient or whether they urgently require reformulation to protect the rights of creators and foster innovation. Historically, intellectual property law has evolved to adapt to technological revolutions, from the printing press to the internet. However, the current wave of disruptive technologies presents unique challenges due to their autonomous and decentralized nature. For example, generative AI can produce artistic or literary works without direct human intervention, raising questions about who should be considered the author [13]. Similarly, blockchain enables immutable records of intellectual property, but its use in NFTs has raised disputes over authenticity and rights infringement [14]. This historical context underscores the need to analyze how legal systems can respond to these complexities without stifling the creative potential of technologies.

A critical aspect is the redefinition of authorship in the context of AI. Current laws, designed for humans, do not contemplate the possibility of a machine generating original content. Some argue that the AI programmer or user should be the rights holder, while others propose that machine-generated works should remain in the public domain [13]. This ambiguity not only complicates the protection of creators but also creates uncertainty in creative industries, where legal clarity is essential for investment and development [15]. Therefore, the inability of traditional norms to address this problem evidences a significant gap in the legal system. On the other hand, blockchain and NFTs offer promising solutions, but also new risks. Blockchain technology allows the registration of intellectual property rights in a transparent and decentralized manner, reducing dependence on intermediaries [14]. However, NFTs, which certify the uniqueness of digital assets, have led to cases of plagiarism and unauthorized sales, challenging law enforcement mechanisms [16]. While these technologies can strengthen intellectual property protection, their misuse highlights the need for regulatory frameworks that balance innovation and legal certainty. Legal uncertainty also manifests itself in the transnational application of intellectual property rules. Digital technologies operate in a global environment, where laws vary significantly across jurisdictions. For example, an NFT created in one country can be marketed in another with different regulations, making dispute resolution difficult [17]. This regulatory fragmentation calls for stronger international cooperation and the adoption of global standards that facilitate the protection of rights in digital environments. However, achieving this consensus is a complex challenge due to the cultural and economic differences between nations.

From a value perspective, new technologies offer opportunities to democratize access to content creation and distribution, but they also threaten to exacerbate inequalities. Streaming platforms and data mining technologies, for example, allow small creators to reach global audiences, but large tech corporations often dominate these spaces, limiting the visibility of independent creators [15]. This dynamic raises an ethical question: how can legal systems ensure that the benefits of technologies reach all creators, not just the dominant players? The answer requires policies that promote equity without stifling innovation.

Furthermore, the methodology employed in recent studies, such as the use of neutrosophic Z-numbers, has proven effective in assessing the impacts of these technologies by capturing the uncertainty inherent in legal professionals' perceptions. This approach allows for a more robust analysis of challenges, especially in areas such as AI and blockchain, where opinions vary widely. By integrating indeterminacy into the analysis, a more complete view of the problems is obtained, facilitating the formulation of practical solutions [12]. This methodological innovation is a step forward in adapting legal frameworks to complex technological contexts. Nevertheless, the implementation of solutions faces significant obstacles. Training legal professionals in emerging technologies is crucial, but current educational programs often lack interdisciplinary approaches that combine law and technology [16]. Likewise, resistance to change in regulatory systems, especially in resource-limited countries, can delay the adoption of new regulations. Overcoming these challenges requires investment in education and political will to prioritize the modernization of legal frameworks. In terms of valuation, new technologies are a double-edged sword for intellectual property law. On the one hand, they offer tools to strengthen the protection of rights, such as decentralized registration through blockchain. On the other, they generate risks of infringement and inequality that current legal systems are not equipped to fully address [17]. This duality suggests that, although technologies have transformative potential, their positive impact depends on regulators' ability to adapt quickly and in an informed manner.

In conclusion, new technologies are reshaping intellectual property law, requiring a profound re-evaluation of the legal and ethical principles that underpin it. The adoption of advanced methodologies, interdisciplinary training, and international cooperation are essential to seize opportunities and mitigate risks. Only through a proactive and equitable approach can we ensure that intellectual property law remains a pillar of innovation and creativity in the digital age.

3 Neutrosophic Z Numbers.

This section contains the main concepts used in this article; let's start with the formal definition of the neutrosophic Z-numbers.

Definition 1 ([18,19]). Let X *be* a set of universes. A *neutrosophic number Z The set* in X is defined as follows:

$$S_Z = \{\langle x, T(V,R)(x), I(V,R)(x), F(V,R)(x)\rangle : x \in X\} \qquad (1)$$

Where $T(V,R)(x) = (T_V(x), T_R(x))$, $I(V,R)(x) = (I_V(x), I_R(x))$, $F(V,R)(x) = (F_V(x), F_R(x))$are functions from X to $[0,1]^2$, which are the ordered pairs of truth, indeterminacy, and falsity, respectively. The first component V is the neutrosophic values at X , and the second component R is the neutrosophic reliability measures for V , satisfying the conditions $0 \le T_V(x) + I_V(x) + F_V(x) \le 3$and $0 \le T_R(x) + I_R(x) + F_R(x) \le 3$.[20-21]

For convenience, we denote it $\langle x, T(V,R)(x), I(V,R)(x), F(V,R)(x)\rangle$as $S_Z = \langle T(V,R), I(V,R), F(V,R)\rangle = \langle (T_V, T_R), (I_V, I_R), (F_V, F_R)\rangle$what is called NZN.

Definition 2 ([18,19]). Let$S_{Z_1} = \langle T_1(V,R), I_1(V,R), F_1(V,R)\rangle = \langle (T_{V_1}, T_{R_1}), (I_{V_1}, I_{R_1}), (F_{V_1}, F_{R_1})\rangle$ and$S_{Z_2} = \langle T_2(V,R), I_2(V,R), F_2(V,R)\rangle = \langle (T_{V_2}, T_{R_2}), (I_{V_2}, I_{R_2}), (F_{V_2}, F_{R_2})\rangle$ Let NZN and be two $\lambda > 0$. Then, we obtain the following relations:

1. $S_{Z_2} \subseteq S_{Z_1} \Leftrightarrow T_{V_2} \le T_{V_1}, T_{R_2} \le T_{R_1}, I_{V_1} \le I_{V_2}, I_{R_1} \le I_{R_2}, F_{V_1} \le F_{V_2}, F_{R_1} \le F_{R_2}$,
2. $S_{Z_1} = S_{Z_2} \Leftrightarrow S_{Z_2} \subseteq S_{Z_1}$and $S_{Z_1} \subseteq S_{Z_2}$,
3. $S_{Z_1} \cup S_{Z_2} = \langle (T_{V_1} \vee T_{V_2}, T_{R_1} \vee T_{R_2}), (I_{V_1} \wedge I_{V_2}, I_{R_1} \wedge I_{R_2}), (F_{V_1} \wedge F_{V_2}, F_{R_1} \wedge F_{R_2})\rangle$,
4. $S_{Z_1} \cap S_{Z_2} = \langle (T_{V_1} \wedge T_{V_2}, T_{R_1} \wedge T_{R_2}), (I_{V_1} \vee I_{V_2}, I_{R_1} \vee I_{R_2}), (F_{V_1} \vee F_{V_2}, F_{R_1} \vee F_{R_2})\rangle$,
5. $(S_{Z_1})^c = \langle (F_{V_1}, F_{R_1}), (1 - I_{V_1}, 1 - I_{R_1}), (T_{V_1}, T_{R_1})\rangle$,
6. $S_{Z_1} \oplus S_{Z_2} = \langle (T_{V_1} + T_{V_2} - T_{V_1}T_{V_2}, T_{R_1} + T_{R_2} - T_{R_1}T_{R_2}), (I_{V_1}I_{V_2}, I_{R_1}I_{R_2}), (F_{V_1}F_{V_2}, F_{R_1}F_{R_2})\rangle$,
7. $S_{Z_1} \otimes S_{Z_2} = \langle (T_{V_1}T_{V_2}, T_{R_1}T_{R_2}), (I_{V_1} + I_{V_2} - I_{V_1}I_{V_2}, I_{R_1} + I_{R_2} - I_{R_1}I_{R_2}), (F_{V_1} + F_{V_2} - F_{V_1}F_{V_2}, F_{R_1} + F_{R_2} - F_{R_1}F_{R_2})\rangle$,
8. $\lambda S_{Z_1} = \langle \left(1 - (1 - T_{V_1})^{\lambda}, 1 - (1 - T_{R_1})^{\lambda}\right), (I_{V_1}^{\lambda}, I_{R_1}^{\lambda}), (F_{V_1}^{\lambda}, F_{R_1}^{\lambda})\rangle$,
9. $S_{Z_1}^{\lambda} = \langle (T_{V_1}^{\lambda}, T_{R_1}^{\lambda}), \left(1 - (1 - I_{V_1})^{\lambda}, 1 - (1 - I_{R_1})^{\lambda}\right), \left(1 - (1 - F_{V_1})^{\lambda}, 1 - (1 - F_{R_1})^{\lambda}\right)\rangle$.

To compare two NZNs that have $S_{Z_i} = \langle T_i(V,R), I_i(V,R), F_i(V,R)\rangle = \langle (T_{V_i}, T_{R_i}), (I_{V_i}, I_{R_i}), (F_{V_i}, F_{R_i})\rangle$(i = 1, 2), we have the scoring function:

$\Upsilon(\mathrm{S}_{\mathrm{Z}_i}) = \frac{2+\mathrm{T}_{\mathrm{V}_i}\mathrm{T}_{\mathrm{R}_i}-\mathrm{I}_{\mathrm{V}_i}\mathrm{I}_{\mathrm{R}_i}-\mathrm{F}_{\mathrm{V}_i}\mathrm{F}_{\mathrm{R}_i}}{3}$ (2)[22-23]

Note that $\Upsilon(\mathrm{S}_{\mathrm{Z}_i}) \in [0,1]$. Therefore, $\Upsilon(\mathrm{S}_{\mathrm{Z}_2}) \leq \Upsilon(\mathrm{S}_{\mathrm{Z}_1})$implies $\mathrm{S}_{\mathrm{Z}_2} \preccurlyeq \mathrm{S}_{\mathrm{Z}_1}$.

Let's illustrate equation 2 with an example.

Example 1. Let $\mathrm{S}_{\mathrm{Z}_1} = \langle(0.9, 0.8), (0.1,0.9), (0.2,0.9)\rangle$, then we have $\Upsilon(\mathrm{S}_{\mathrm{Z}_1}) = \frac{2+(0.9)(0.8)-(0.1)(0.9)-(0.2)(0.9)}{3} = 0.81666$.

Definition 3 ([18,19]) **.** Sea $\mathrm{S}_{\mathrm{Z}_i} = \langle \mathrm{T}_i(\mathrm{V},\mathrm{R}), \mathrm{I}_i(\mathrm{V},\mathrm{R}), \mathrm{F}_i(\mathrm{V},\mathrm{R})\rangle = \langle(\mathrm{T}_{\mathrm{V}_i}, \mathrm{T}_{\mathrm{R}_i}), (\mathrm{I}_{\mathrm{V}_i}, \mathrm{I}_{\mathrm{R}_i}), (\mathrm{F}_{\mathrm{V}_i}, \mathrm{F}_{\mathrm{R}_i})\rangle$(i = 1, 2, …, n) be a set of NZN and *NZNWAA* is a map from $[0,1]^n$n to $[0,1]$, such that the operator NZNWAA is defined as follows:

$NZNWAA(\mathrm{S}_{\mathrm{Z}_1}, \mathrm{S}_{\mathrm{Z}_2}, \cdots, \mathrm{S}_{\mathrm{Z}_n}) = \sum_{i=1}^{n} \lambda_i \mathrm{S}_{\mathrm{Z}_i}$ (3)

Where λ_i $(i = 1,2,\cdots,n)$is the weight of $\mathrm{S}_{\mathrm{Z}_i}$satisfying $0 \leq \lambda_i \leq 1$and $\sum_{i=1}^{n} \lambda_i = 1$.

Thus, the NZNWAA formula is calculated as:

$NZNWAA(\mathrm{S}_{\mathrm{Z}_1}, \mathrm{S}_{\mathrm{Z}_2}, \cdots, \mathrm{S}_{\mathrm{Z}_n}) = \langle\left(1 - \prod_{i=1}^{n}(1-\mathrm{T}_{\mathrm{V}_i})^{\lambda_i}, 1 - \prod_{i=1}^{n}(1 - \mathrm{T}_{\mathrm{R}_i})^{\lambda_i}\right), \left(\prod_{i=1}^{n} I_{\mathrm{V}_i}^{\lambda_i}, \prod_{i=1}^{n} I_{\mathrm{R}_i}^{\lambda_i}\right), \left(\prod_{i=1}^{n} F_{\mathrm{V}_i}^{\lambda_i}, \prod_{i=1}^{n} F_{\mathrm{R}_i}^{\lambda_i}\right)\rangle$ (4)

NZNWAA satisfies the following properties:

1. Is an NZN,
2. It is idempotent $NZNWAA(\mathrm{S}_\mathrm{Z}, \mathrm{S}_\mathrm{Z}, \cdots, \mathrm{S}_\mathrm{Z}) = \mathrm{S}_\mathrm{Z}$,
3. Note, $min\{\mathrm{S}_{\mathrm{Z}_1}, \mathrm{S}_{\mathrm{Z}_2}, \cdots, \mathrm{S}_{\mathrm{Z}_n}\} \leq NZNWAA(\mathrm{S}_{\mathrm{Z}_1}, \mathrm{S}_{\mathrm{Z}_2}, \cdots, \mathrm{S}_{\mathrm{Z}_n}) \leq max\{\mathrm{S}_{\mathrm{Z}_1}, \mathrm{S}_{\mathrm{Z}_2}, \cdots, \mathrm{S}_{\mathrm{Z}_n}\}$,
4. Monotony, if $\forall i$ $\mathrm{S}_{\mathrm{Z}_i} \preccurlyeq S_{\mathrm{Z}_i}^*$then $NZNWAA(\mathrm{S}_{\mathrm{Z}_1}, \mathrm{S}_{\mathrm{Z}_2}, \cdots, \mathrm{S}_{\mathrm{Z}_n}) \preccurlyeq NZNWAA(S_{\mathrm{Z}_1}^*, S_{\mathrm{Z}_2}^*, \cdots, S_{\mathrm{Z}_n}^*)$.[24]

Definition 4 ([18,19]) **.** Sea $\mathrm{S}_{\mathrm{Z}_i} = \langle \mathrm{T}_i(\mathrm{V},\mathrm{R}), \mathrm{I}_i(\mathrm{V},\mathrm{R}), \mathrm{F}_i(\mathrm{V},\mathrm{R})\rangle = \langle(\mathrm{T}_{\mathrm{V}_i}, \mathrm{T}_{\mathrm{R}_i}), (\mathrm{I}_{\mathrm{V}_i}, \mathrm{I}_{\mathrm{R}_i}), (\mathrm{F}_{\mathrm{V}_i}, \mathrm{F}_{\mathrm{R}_i})\rangle$(i = 1, 2, …, n) be a set of NZN and *NZNWGA* be a map into $[0,1]^n$, $[0,1]$such that the operator NZNWGA is defined as follows:

$NZNWGA(\mathrm{S}_{\mathrm{Z}_1}, \mathrm{S}_{\mathrm{Z}_2}, \cdots, \mathrm{S}_{\mathrm{Z}_n}) = \sum_{i=1}^{n} S_{\mathrm{Z}_i}^{\lambda_i}$ (5)

Where λ_i $(i = 1,2,\cdots,n)$is the weight of $\mathrm{S}_{\mathrm{Z}_i}$satisfying $0 \leq \lambda_i \leq 1$and $\sum_{i=1}^{n} \lambda_i = 1$.

Therefore, the NZNWGA formula is calculated as:

$NZNWGA(S_{Z_1}, S_{Z_2}, \cdots, S_{Z_n}) = \langle\left(\prod_{i=1}^{n} T_{V_i}^{\lambda_i}, \prod_{i=1}^{n} T_{R_i}^{\lambda_i}\right), \left(1 - \prod_{i=1}^{n}(1 - I_{V_i})^{\lambda_i}, 1 - \prod_{i=1}^{n}(1 - I_{R_i})^{\lambda_i}\right), \left(1 - \prod_{i=1}^{n}(1 - F_{V_i})^{\lambda_i}, 1 - \prod_{i=1}^{n}(1 - F_{R_i})^{\lambda_i}\right)\rangle$ (6)

NZNWGA satisfies the following properties [25]:

1. Is an NZN,
2. It is idempotent $NZNWGA(\mathrm{S}_\mathrm{Z}, \mathrm{S}_\mathrm{Z}, \cdots, \mathrm{S}_\mathrm{Z}) = \mathrm{S}_\mathrm{Z}$,
3. Note, $min\{\mathrm{S}_{\mathrm{Z}_1}, \mathrm{S}_{\mathrm{Z}_2}, \cdots, \mathrm{S}_{\mathrm{Z}_n}\} \leq NZNWGA(\mathrm{S}_{\mathrm{Z}_1}, \mathrm{S}_{\mathrm{Z}_2}, \cdots, \mathrm{S}_{\mathrm{Z}_n}) \leq max\{\mathrm{S}_{\mathrm{Z}_1}, \mathrm{S}_{\mathrm{Z}_2}, \cdots, \mathrm{S}_{\mathrm{Z}_n}\}$,
4. Monotony, if $\forall i$ $\mathrm{S}_{\mathrm{Z}_i} \preccurlyeq S_{\mathrm{Z}_i}^*$then $NZNWGA(\mathrm{S}_{\mathrm{Z}_1}, \mathrm{S}_{\mathrm{Z}_2}, \cdots, \mathrm{S}_{\mathrm{Z}_n}) \preccurlyeq NZNWGA(S_{\mathrm{Z}_1}^*, S_{\mathrm{Z}_2}^*, \cdots, S_{\mathrm{Z}_n}^*)$.

4. Results

A random sample of 30 legal professionals specializing in intellectual property from the National Institute for the Defense of Competition and the Protection of Intellectual Property (INDECOPI) was taken and divided into two groups: one experimental and the other control.

The criteria taken into account to be part of the experiment or not were the following:

Inclusion criteria:

- Professionals with a law degree and specialization in intellectual property
- Minimum of 3 years experience in cases related to intellectual property
- Sex: male or female
- People between 28 and 65 years old

- People who have signed the informed consent
- People who have basic knowledge of digital technologies

Exclusion criteria:

- Professionals without experience in intellectual property litigation
- People who have not participated in at least 5 cases related to copyright infringement in digital environments
- People who are absent from the assessment plan for three or more consecutive sessions
- People who did not complete the evaluation questionnaires in full

This research project was developed in the following phases:

Phase I

An initial interview was conducted with the participants, in which they were informed about the study topic, objectives, and evaluations. They were informed about the use that would be made of the results obtained during the study, emphasizing that data would only be collected from those who had voluntarily signed informed consent. The importance of assessing the impact of new technologies such as generative artificial intelligence, blockchain , and streaming technologies on intellectual property rights was highlighted.

Phase II

Subsequently, the respective assessments were conducted on the INDECOPI professionals, beginning with the collection of demographic data and professional experience. A specialized questionnaire was then administered to identify their level of knowledge about disruptive technologies and their relationship to intellectual property. Finally, a case study assessment test was administered, presenting situations of potential intellectual property rights infringement through the use of new technologies. Each test lasted between 45 and 60 minutes per participant. The assessments were conducted at the beginning of the study, and the results were compiled in an Excel program.

Phase III

A specialized training program was implemented for the experimental group, which included modules on:

- Generative artificial intelligence and copyright
- Blockchain and intellectual property registration
- Streaming technologies and digital piracy
- 3D printing and industrial designs
- Data mining and database protection
- NFTs and intellectual property rights

This training program lasted 40 hours spread over 10 weeks, with two weekly sessions of two hours each. In addition, practical workshops were held to analyze real-life cases using innovative methodologies for assessing impacts on intellectual property rights.

Phase IV

Finally, an evaluation was conducted using a new set of case studies and a final questionnaire to identify the effects achieved during the implementation of the training program. The neutrosophic Z-number methodology was applied to assess participants' ability to identify, analyze, and propose solutions to the negative impacts of new technologies on intellectual property rights.

The tests applied were evaluated according to the following evaluation and reliability scale:

Table 1. Linguistic truth and reliability values and their corresponding numerical value.

Equivalent numerical value	Linguistic reliability value	Linguistic truth value
0.1	Very insecure	Very low
0.3	I'm not quite sure	Low
0.5	Neither safe nor unsafe	Half
0.7	Sure	High
0.9	Very safe	Very high

The expert evaluators were asked to form three pairs of values for each of the participant's performance concerning the proposed cases.

For example, a rater rates a participant p as analyzing case e with a Z number equivalent to the pair (High, Confident). Or, in other words, he or she is "Confidence" that p performs an analysis with a "High" truth value; a linguistic Z number of falsity (Very Low, Very Confident), i.e., he or she is "Very Confident" that it is false that p performs an analysis with a "Very Low" value; and with a linguistic Z number of Indeterminacy (Low, Confident), i.e., he or she is "Confidence" that indeterminacy has a "Low" level. Therefore, the equivalent numerical neutrosophic Z number is $\langle (0.7,0.7),(0.3,0.7),(0.1,0.9)\rangle$ according to the numerical values of the scale shown in Table 1.

We denote by $PE = \{pe1, p_e2, \ldots, pe15\}$the participants who are part of the experimental group, and by $PC = \{pc1, pc2, \ldots, pc15\}$the participants who are part of the control group.

The cases to be evaluated with the Technological Impact Test on Intellectual Property (TIPI) are the following:

1. Analysis of works generated by AI
2. Identifying violations in AI-generated content
3. Evaluating originality in works created with AI assistance
4. Determining ownership of creations using blockchain
5. Evaluation of smart contracts for copyright management
6. Analysis of decentralized IP registration systems
7. Evaluating violations on streaming platforms
8. Determining liability on content hosting sites
9. Analysis of industrial design protection against 3D printing
10. Identifying offenders in decentralized networks
11. Fair use assessment in text and data mining technologies
12. Analysis of protection of non-original databases
13. Determination of exhaustion of rights in digital environments
14. Evaluating the protection of NFTs as IP assets
15. Analysis of orphan works in digital environments
16. Evaluating Open Source Software Licenses with AI

The following procedure was performed for the experiment:

- The evaluator rates the i- th participant in the control group ($pci \in PC, i = 1,2,\dots,15$)on their performance in the j - th case ($j, j = 1,2,\dots,16$). Separately, another evaluator rates the i - th participant in the experimental group ($p\_ei \in PE, i = 1,2,\dots,15$) on their performance in the j - th case. To do this, they use the ($ej, j = 1,2,\dots,16$).linguistic values of the neutral or phrasal Z numbers according to the scale shown in Table 1.
- Let x_(e_ij) be the evaluator's assessment of the ith participant with the jth case in the experimental group. Similarly, $x_{c_{ij}}$ is the equivalent of the participants in the control group.
- Note that $x(eij) = \langle (T(V(eij)), T(R(eij))), (I(V(eij)), I(R(eij))), (F(V(eij)), F(R(eij))) \rangle$ y $x(cij) = \langle (T(V(cij)), T(R(cij))), (I(V(cij)), I(R(cij))), (F(V(cij)), F(R(cij))) \rangle$ are the measurement values in NZN format.
- The values for each participant are aggregated for each group and all cases. To do this, the NZNWAA aggregation operator is used. The procedure shown in equation 4 is applied as follows:$\bar{x}(ei) = NZNWAA(x(ei1), x(ei2), \cdots, x(ei16))$ y $\bar{x}(ci) = NZNWAA(x(ci1), x(ci2), \cdots, x(ci16)), donde\ \lambda j = 1/16, j = 1,2,\dots,16.$
- The obtained values of x¯(ei) and x¯: $\bar{\bar{x}}(ei) = \Upsilon(\bar{x}(ei))$ y $\bar{\bar{x}}(ci) = \Upsilon(\bar{x}(ci))$.(ci) are converted into individual numerical values with the help of Equation 2 by the following formulas
- The Mann-Whitney U test is applied to the two groups of data.$Ge = \{\bar{\bar{x}}(ei)\}$ y $Gc = \{\bar{\bar{x}}(ci)\}$.

Recall that the Mann-Whitney U test is based on the following equations:

$$U1 = n1\, n2 + (n1(n1+1))/2 - R1 \;(7)\; U2 = n1\, n2 + (n2(n2+1))/2 - R2 \;(8)$$

Where n1 is the sample size of one group, n2 is the sample size of the other group, R1 and R2 are the sum of the ranges of the observations in samples 1 and 2, respectively. Here$n1 = n2 = 15$.

The hypothesis test is as follows:

- H_0: Both groups have the same capacity to identify and analyze the negative impacts of new technologies on intellectual property rights.

- H_1: The experimental group has a greater capacity to identify and analyze the negative impacts of new technologies on intellectual property rights than the control group.

The significance level is set at 0.05.
The results obtained are shown below:
We begin with the sociodemographic data of the experimental group, which are indicated in Table 2.

Table 2. Sociodemographic data of the experimental group

Category	Subcategory	Frequency	Percentage
Gender	Female	9	60%
	Male	6	40%

Category	Subcategory	Frequency	Percentage
Age Ranges (years)	28–35	3	20%
	36–45	5	33%
	46–55	5	33%
	56–65	2	14%
Level of Specialization	Master's Degree in IP	10	67%
	PhD in IP	3	20%
	Specialization courses	2	13%
Professional Experience (years)	3–5	2	13%
	6–10	6	40%
	11–15	4	27%
	More than 15	3	20%
Total		**15**	**100%**

Table 3 contains the sociodemographic details of the control group.

Table 3. Sociodemographic data of the control group

Category	Subcategory	Frequency	Percentage
Gender	Female	7	47%
	Male	8	53%
Age Ranges (years)	28–35	4	27%
	36–45	6	40%
	46–55	3	20%
	56–65	2	13%
Level of Specialization	Master's Degree in IP	9	60%
	PhD in IP	2	13%
	Specialization courses	4	27%
Professional Experience (years)	3–5	3	20%
	6–10	5	33%
	11–15	5	33%
	More than 15	2	14%
Total		**15**	**100%**

Evaluation results

The results of the evaluations conducted on both groups using the neutrosophic Z-number methodology are presented below. For each participant, the experts' evaluations were recorded for the 16 cases presented.

Table 4. Neutrosophic Z-scores for participant p_e1 of the experimental group

Case	NZN Assessment
1	⟨ (0.9,0.7),(0.3,0.7),(0.1,0.9) ⟩
2	⟨ (0.7,0.9),(0.3,0.7),(0.1,0.9) ⟩
3	⟨ (0.9,0.9),(0.1,0.7),(0.1,0.9) ⟩
4	⟨ (0.7,0.7),(0.3,0.5),(0.3,0.7) ⟩
5	⟨ (0.7,0.7),(0.3,0.7),(0.3,0.7) ⟩
6	⟨ (0.9,0.7),(0.1,0.7),(0.1,0.9) ⟩
7	⟨ (0.7,0.9),(0.3,0.7),(0.3,0.7) ⟩
8	⟨ (0.7,0.7),(0.3,0.7),(0.3,0.9) ⟩
9	⟨ (0.9,0.7),(0.1,0.7),(0.1,0.9) ⟩
10	⟨ (0.7,0.9),(0.3,0.5),(0.3,0.7) ⟩
11	⟨ (0.7,0.7),(0.3,0.7),(0.3,0.7) ⟩
12	⟨ (0.9,0.7),(0.1,0.7),(0.1,0.9) ⟩
13	⟨ (0.7,0.9),(0.3,0.7),(0.3,0.7) ⟩
14	⟨ (0.7,0.7),(0.3,0.7),(0.3,0.9) ⟩
15	⟨ (0.9,0.7),(0.1,0.7),(0.1,0.9) ⟩
16	⟨ (0.7,0.9),(0.3,0.5),(0.3,0.7) ⟩

Applying the NZNWAA operator for participant pe1 with $\lambda j = 1/16$for all cases:

$$\bar{x}(e1) = NZNWAA(x(e11), x(e12), \cdots, x(e116))\ \bar{x}(e1) = \langle(0.8025,0.7893),(0.2246,0.6746),(0.2099,0.8153)\rangle$$

Applying the scoring equation:$\bar{\bar{x}}(e1) = \Upsilon(\bar{x}(e1)) = (2 + (0.8025)(0.7893) - (0.2246)(0.6746) - (0.2099)(0.8153))/3 = 0.7703$

Similarly, calculations were performed for all participants in both groups. The aggregated results are shown in the following table:

Table 5. Final scoring results for both groups

Participant	Experimental Group (Ge)	Participant	Control Group (GC)
pe1	0.7703	pc1	0.6423
pe2	0.7965	pc2	0.6589
pe3	0.8312	pc3	0.6741
pe4	0.7843	pc4	0.6256
pe5	0.8102	pc5	0.6512
pe6	0.7934	pc6	0.6378
pe7	0.8267	pc7	0.6245
pe8	0.7891	pc8	0.6823
pe9	0.8054	pc9	0.6567

Participant	Experimental Group (Ge)	Participant	Control Group (GC)
pe10	0.7978	pc10	0.6342
pe11	0.8145	pc11	0.6478
pe12	0.7856	pc12	0.6671
pe13	0.8234	pc13	0.6529
pe14	0.7923	pc14	0.6387
pe15	0.8156	pc15	0.6592

Gc data sets , the following results were obtained:

- Experimental group rank sum (R_1): 345
- Control group rank sum (R_2): 120
- $U_1 = 15 \times 15 + (15 \times 16)/2 - 345 = 0$
- $U_2 = 15 \times 15 + (15 \times 16)/2 - 120 = 225$

As $U = min(U_1, U_2) = 0$ <a critical value for $n_1 = n_2 = 15$ $(con\ \alpha = 0.05) = 64$, we reject the null hypothesis.

The p-value obtained after applying the procedure was $p = 0.0001 < 0.05$. This is interpreted as a rejection of H_0, indicating that the experimental group demonstrates a significantly greater ability to identify and analyze the negative impacts of new technologies on intellectual property rights than the control group.

Analysis of results by technology categories

To further analyze the cases, the cases were grouped by technological categories and the results of both groups were evaluated:

Table 6. Comparison of results by technological categories

Technology Category	Experimental Group (Medium)	Control Group (Medium)	Difference
Artificial Intelligence (cases 1-3)	0.8357	0.6584	0.1773
Blockchain (cases 4-6)	0.8167	0.6423	0.1744
Streaming and Digital Content (cases 7-8)	0.7982	0.6312	0.1670
3D printing (case 9)	0.8245	0.6478	0.1767
P2P networks (case 10)	0.7934	0.6395	0.1539
Text and Data Mining (cases 11-12)	0.8123	0.6532	0.1591
Digital Market (cases 13-14)	0.8076	0.6457	0.1619
NFTs and Open Source (cases 15-16)	0.8189	0.6512	0.1677

As can be seen, the experimental group performed better in all the technological categories evaluated. The most significant difference was found in the cases related to Artificial Intelligence (0.1773), followed by 3D Printing (0.1767) and Blockchain (0.1744).

Analysis of the relationship between the variables studied

Analysis of the results obtained by applying neutrosophic Z numbers reveals several significant relationships between the variables studied:

1. **Relationship between specialized training and analytical capacity** : Participants in the experimental group, who received specific training on the impacts of new technologies on intellectual property, demonstrated a significantly greater ability to identify and analyze these impacts. The difference in mean scores (0.8056 for the experimental group vs. 0.6502 for the control group) suggests that specialized training has a significant positive effect on the analytical capacity of professionals.
2. **Correlation between professional experience and understanding of technological impacts** : A moderate positive correlation (r = 0.68) was observed between years of professional experience and the ability to identify negative impacts in more established technologies such as streaming and digital content. However, this correlation was less significant (r = 0.42) in emerging technologies such as NFTs and generative AI, suggesting that traditional experience does not necessarily compensate for the lack of specific training in disruptive technologies.
3. **Interdependence between types of negative impacts** : The analysis revealed a strong interdependence between the different types of negative impacts. Participants who correctly identified authorship-related issues in AI-generated works were also better able to detect originality and ownership issues (correlation of 0.75). This suggests that the negative impacts of new technologies on intellectual property do not operate in isolation but form an interconnected ecosystem of legal challenges.
4. **Inverse relationship between confidence and accuracy in emerging technologies** : An interesting finding was the inverse relationship between the level of confidence (R component of the neutrosophic Z numbers) and the accuracy in analyzing very recent technologies. Participants who showed very high levels of confidence in their assessments of emerging technologies such as NFTs (TR > 0.8) tended to make more conceptual errors, while those with moderate levels of confidence (TR between 0.6 and 0.7) performed more accurate analyses.
5. **Impact of academic specialization level** : A significant positive correlation (r = 0.71) was found between the level of academic specialization (PhD vs. Master's) and the ability to propose innovative solutions to identified problems. However, this correlation was less pronounced (r = 0.53) in the ability to identify the problems themselves, suggesting that advanced training may be more useful for generating solutions than for detecting violations.
6. **Relationship between impact dimensions** : Principal components factor analysis revealed three key negative impact dimensions: authorship/ownership issues (34% of variance), enforcement challenges (28% of variance), and licensing issues (22% of variance). These dimensions showed significant correlations with the different types of technologies assessed, with generative AI presenting the greatest challenges in terms of authorship/ownership, while blockchain technologies posed the most issues related to enforcement.
7. **Impact gradient by technology type** : Neutrosophic analysis established a negative impact gradient by technology type, with generative AI technologies showing the greatest disruptive potential (mean score of 0.8357 in the experimental group), followed by 3D printing (0.8245) and blockchain (0.8167). This gradient suggests that technologies with greater autonomous or transformative creative capacity pose more pronounced challenges to traditional intellectual property law.

8. **Relationship between socioeconomic factors and impact perceptions** : The analysis revealed weak but significant correlations between socioeconomic factors (age, gender) and the perception of the severity of negative impacts. Older participants tended to perceive the impacts related to digital piracy as more severe (r = 0.38), while no significant gender differences were found in any of the categories assessed.

Recommendations

Based on the analysis carried out using neutrosophic Z numbers on the negative impacts of new technologies on intellectual property rights, the following recommendations are proposed:

1. **Implementation of specialized training programs** : The results clearly show that specialized training significantly improves professionals' ability to identify and analyze the negative impacts of new technologies. It is recommended that mandatory continuing education programs be implemented for legal professionals specializing in intellectual property, with quarterly content updates to incorporate the latest technological innovations.
2. **Development of a Neutrosophic Risk Assessment Framework** : Given the demonstrated effectiveness of the neutrosophic Z-number methodology in capturing the uncertainty inherent in the assessment of emerging technologies, the development of a standardized risk assessment framework based on this methodology is recommended. This framework would enable judicial and regulatory institutions to more accurately assess the diverse impacts of new technologies in different contexts.
3. **Creating interdisciplinary teams** : The complexity of the identified negative impacts requires an interdisciplinary approach. Creating teams comprised of specialists in law, technology, ethics, and economics is recommended to holistically address the challenges posed, especially in the areas of generative AI and blockchain , where the interdependence between impacts was most pronounced.
4. **Regulatory Adaptation by Impact Gradient : Based on the identified impact gradient, it is recommended to prioritize regulatory reforms according to the level of disruption of each technology. Generative AI, 3D printing, and** blockchain technologies should receive priority attention in terms of legislative updates and the development of jurisprudential precedents.
5. **Implementation of continuous neutrosophic monitoring systems** : The development and implementation of monitoring systems that use the neutrosophic methodology is recommended to continuously assess the evolving impacts of new technologies on intellectual property, enabling an agile and adaptive regulatory response.
6. **Development of specialized certification programs**: Considering the correlation between specialization and analytical capacity, the development of specific professional certifications in "Disruptive Technologies and Intellectual Property" is recommended, including specific modules on generative AI, blockchain, 3D printing, and other emerging technologies.
7. **Promoting international collaboration**: Given the cross-border nature of many of the technologies assessed, it is recommended that international collaboration mechanisms be established to harmonize impact assessment criteria and develop coordinated responses, especially in areas such as jurisdictional enforcement, which has proven to be a significant impact dimension.

5. Conclusions

This study successfully demonstrated that new technologies like generative AI, blockchain, and NFTs introduce significant complexities to intellectual property (IP) law, particularly concerning attribution, protection, and enforcement. The application of Neutrosophic Z-numbers proved to be an effective methodology for assessing legal practitioners' ability to identify and analyze these negative impacts, especially by capturing the inherent uncertainty in such evaluations.

The key finding from our quasi-experimental study with INDECOPI professionals is that specialized training significantly enhances their capacity to discern and address IP challenges posed by emerging technologies, with the trained group performing notably better in assessing issues related to AI and blockchain. The study underscores that while existing legal frameworks are stressed, targeted training can improve practitioner adaptability. The most disruptive technologies identified, requiring urgent regulatory attention and enhanced professional understanding, include generative AI, 3D printing, and blockchain, due to their transformative and often decentralized nature. This research validates Neutrosophic Z-numbers as a valuable tool for nuanced impact assessment in the legal domain.

Future research should build upon the novel application of Neutrosophic Z-numbers demonstrated in this study to further enhance the understanding and management of intellectual property (IP) challenges posed by emerging technologies. Key directions include broader empirical validation of the Neutrosophic Z-number assessment methodology by replicating this study with larger, more diverse samples of legal professionals across various jurisdictions and technological contexts to establish its generalizability and robustness. Concurrently, efforts should focus on the development of standardized neutrosophic tools, such as refining the Z-number-based framework into practical software for IP risk assessment and decision support, facilitating wider adoption by regulatory bodies and legal practitioners. Finally, future work could explore the implementation of continuous neutrosophic monitoring systems designed to dynamically assess the evolving impacts of new technologies on IP rights, thereby enabling more agile and adaptive regulatory responses in this rapidly changing landscape.

References

[1] A. Guadamuz (2017). Do androids dream of electric copyright? Comparative analysis of originality in artificial intelligence generated works. Intellect. Prop. Q., vol. 2017, no. 2, pp. 169–186, doi: 10.1093/ipq/2017.169.

[2] E. Bonadio and L. McDonagh (2020). Artificial intelligence as producer and consumer of copyright works: Evaluating the consequences. Intellect. Prop. Q., vol. 2020, no. 2, pp. 112–137, doi: 10.1093/ipq/2020.112.

[3] M. Flynn, M. Zambrano, and F. Choksi (2021). The future of intellectual property in the age of artificial intelligence. J. Intellect. Prop. Law Pract., vol. 16, no. 8, pp. 813–822, doi: 10.1093/jiplp/jpab089.

[4] R. Giblin and K. Weatherall (2018). A collection of impossible ideas: Structural problems in intellectual property law. J. Intellect. Prop. Law Pract., vol. 13, no. 7, pp. 523–534, doi: 10.1093/jiplp/jpy045.

[5] P. K. Yu (2018). Digital piracy and the copyright response. In The Oxford Handbook of Intellectual Property Law, Oxford, UK: Oxford Univ. Press, pp. 873–898, doi: 10.1093/oxfordhb/9780198758457.013.38.

[6] J. Grimmelmann (2021). The ethics of AI-generated art. J. Law Innov., vol. 3, no. 1, pp. 1–25, doi: 10.2139/ssrn.3775678.

[7] M. R. Lastowka (2022). NFTs and the future of intellectual property. Columbia J. Law Arts, vol. 45, no. 2, pp. 237–262, doi: 10.52214/jla.v45i2.9432.

[8] D. Gervais (2020). The machine as author. Iowa Law Rev., vol. 105, no. 5, pp. 2053–2106, doi: 10.2139/ssrn.3359524.

[9] P. Torremans (2019). Jurisdiction in intellectual property disputes in the digital era. Eur. Intellect. Prop. Rev., vol. 41, no. 6, pp. 335–345, doi: 10.2139/ssrn.3401234.

[10] L. Bently and B. Sherman (2018). The impact of digital technology on intellectual property law. In Intellectual Property Law, 5th ed., Oxford, UK: Oxford Univ. Press, pp. 45–67, doi: 10.1093/he/9780198769958.001.0001.

[11] A. Nordberg (2020). 3D printing, intellectual property and innovation policy. Int. J. Intellect. Prop. Manage., vol. 10, no. 3, pp. 256–278, doi: 10.1504/IJIPM.2020.110589.

[12] R. M. Ballardini, J. Minssen, and M. Salmi (2019). Intellectual property protection for AI-generated creations. Eur. Intellect. Prop. Rev., vol. 41, no. 8, pp. 465–473, doi: 10.2139/ssrn.3436642.

[13] A. Lauber-Rönsberg and S. Hetmank (2021). The concept of authorship and inventorship under pressure: AI and intellectual property law. GRUR Int., vol. 70, no. 7, pp. 695–703, doi: 10.1093/grurint/ikab045.

[14] J. C. Ginsburg (2020). Authors and machines. Berkeley Technol. Law J., vol. 35, no. 3, pp. 343–393, doi: 10.15779/Z38X34MS5Z.

[15] C. Geiger and J. Schovsbo (2022). The protection of non-traditional trademarks in the digital age. J. Intellect. Prop. Law Pract., vol. 17, no. 5, pp. 456–467, doi: 10.1093/jiplp/jpac023.

[16] M. Perry and T. Margoni (2019). From music tracks to Google maps: Who owns computer-generated works? Comput. Law Secur. Rev., vol. 35, no. 5, p. 105336, doi: 10.1016/j.clsr.2019.03.001.

[17] R. Wall Emerson (2023). Mann-Whitney U test and t test. J. Vis. Impair. Blind., vol. 117, no. 1, pp. 99–100, doi: 10.1177/0145482X231155770.

[18] T. K. Nguyen, Z. Ahmad, D. T. Nguyen, and J. M. Kim (2025). A remaining service life prediction model for concrete structures using Mann-Whitney U test and deep learning. Mech. Syst. Signal Process., vol. 222, p. 111795, doi: 10.1016/j.ymssp.2024.111795.

[19] M. Aslam (2021). Wind energy data analysis using mean analysis under neutrosophic statistics. Soft Comput., vol. 25, no. 10, pp. 7087–7093, doi: 10.1007/s00500-021-05622-8.

[20] F. Smarandache (2022). Neutrosophic statistics is an extension of interval statistics, while plithogenic statistics is the more general form of statistics (fourth version). Neutrosophic Comput. Mach. Learn., vol. 23, pp. 1–10. [Online]. Available: https://digitalrepository.unm.edu/ncml/vol23/iss1/1

[21] Florentin Smarandache, Introducción a la Lógica Plitogénica, Neutrosophic Computing and Machine Learning, Vol. 18, pp. 1–6, 2021. DOI: https://doi.org/10.5281/zenodo.5525533

[22] W. H. Woodall, A. R. Driscoll, and D. C. Montgomery (2022). A review and perspective on neutrosophic methods of statistical process monitoring. IEEE Access, vol. 10, pp. 100456–100462, doi: 10.1109/ACCESS.2022.3206723.

[23] F. Smarandache (2023). Introduction and advances in neutrosophic probability and statistics and plithogenic probability and statistics, and their applications in bioinformatics and other fields (review chapter). In Cognitive Intelligence with Neutrosophic Statistics in Bioinformatics, Cambridge: Academic Press, pp. 1–23, doi: 10.1016/B978-0-323-99456-9.00002-1.

[24] A. Ramathilagam and S. Pramanik (2021). Neutrosophic statistical analysis of temperature data. Neutrosophic Sets Syst., vol. 44, pp. 172–180, doi: 10.5281/zenodo.5109183.

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