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The Role of Artificial Intelligence Technology in Predictive Risk Assessment for Business Continuity: A Case Study of Greece

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Abstract: This study examined the efficacy of artificial intelligence (AI) technologies in predictive risk assessment and their contribution to ensuring business continuity. This research aimed to understand how different AI components, such as natural language processing (NLP), AI-powered data analytics, AI-driven predictive maintenance, and AI integration in incident response planning, enhance risk assessment and support business continuity in an environment where businesses face a myriad of risks, including natural disasters, cyberattacks, and economic fluctuations. A cross-sectional design and quantitative method were used to collect data for this study from a sample of 360 technology specialists. The results of this study show that AI technologies have a major impact on business continuity and predictive risk assessment. Notably, it was discovered that NLP improved the accuracy and speed of risk assessment procedures. The integration of AI into incident response plans was particularly effective, greatly decreasing company interruptions and improving recovery from unforeseen events. It is advised that businesses invest in AI skills, particularly in fields such as NLP for automated risk assessment, data analytics for prompt risk detection, predictive maintenance for operational effectiveness, and AI-enhanced incident response planning for crisis management.

Keywords: artificial intelligence (AI); natural language processing (NLP); AI-powered data analytics; incident response planning; predictive risk assessment; business continuity

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1. Introduction

According to Brás et al. (2023b), Le Coze and Antonsen (2023), and van Noordt and Tangi (2023), companies are continuously exposed to a variety of risks that have the potential to disrupt operations, negatively impact profitability, or even jeopardize the organization's existence in today's fast-paced and interconnected business world. Natural disasters, cyberattacks, supply chain interruptions, market volatility, and legislative changes are just a few of the many variables that fall under this broad category of risks. Across all industries, businesses now place a premium on reducing these risks and guaranteeing business continuity. When an organization experiences a disruption—a natural disaster, cyberattack, economic downturn, or other unanticipated event that can possibly affect company operations—business continuity refers to the organization's capacity to continue providing key services and functions both during and after the interruption. According to Biolcheva and Valchev (2022), Le Coze and Antonsen (2023), and Perera et al. (2023), traditional risk assessment techniques frequently fail to adequately handle the complexity and unpredictability of these contemporary concerns. Although risk assessment is a core component of risk management, traditional methods frequently depend on preset models, expert judgment, and historical data. The way hazards are evolving and the speed

with which corporate settings are changing may not be sufficiently considered via these strategies. This shortcoming is especially noticeable when confronted with novel and extraordinary threats, such as the COVID-19 pandemic, which exposed vulnerabilities in many companies' continuity strategies (Drydakis 2022; Perera et al. 2023). Additionally, manual risk assessment procedures are labor-intensive, time-consuming, and subject to human biases. Identifying small trends and patterns that may signal possible threats could prove challenging for these businesses due to their inability to analyze the large amounts of data created by modern enterprises. Rodríguez-Espíndola et al. (2022) assert that there is a critical need for more sophisticated and data-driven approaches to risk assessment that can adjust to changing conditions and offer timely insights.

The current body of research on business continuity and risk assessment has recognized the significance of using new technologies, especially artificial intelligence (AI), to improve risk management's efficacy (Meena and Madan 2023; Galaz et al. 2021). Even though the use of AI in risk assessment has been studied to some extent, further investigation is needed to fully grasp the specific features of AI technology that can make a big difference in predicting risk assessment for business continuity. The promise of AI in risk management is frequently summarized in current research, but a thorough examination of the many AI methods and components that are most useful in various corporate situations is lacking (Meena and Madan 2023). For example, machine learning algorithms, natural language processing (NLP), data analytics, and predictive maintenance systems are just a few of the many technologies that fall under the umbrella of AI. However, the relative impact and effectiveness of these AI components in mitigating various types of risks and ensuring business continuity remain underexplored (Soldatos et al. 2022; Schuett 2023; Božić 2023; Biolcheva and Valchev 2022). Moreover, while recognition of the potential benefits of AI in risk assessment continues to grow, empirical studies quantifying the actual improvements in risk assessment accuracy, efficiency, and overall business continuity resulting from AI adoption are limited. Organizations need concrete evidence to guide their investments in AI technologies for risk management (Zarghami and Dumrak 2021; Yue et al. 2024; Zohuri et al. 2022).

Organizations are continually seeking effective strategies to identify, assess, and mitigate risks that threaten their continuity. According to Jackson et al. (2023), AI has become a transformational force in tackling these issues. Machine learning, NLP, data analytics, predictive maintenance, and other skills are only a few of the many functions of AI technology. With new opportunities to increase readiness and resilience, each of these AI features is vital to the predictive risk assessment for business continuity. According to Brintrup et al. (2023) and Raza (2023), the application of AI-driven predictive maintenance greatly enhances operational continuity. AI is able to forecast when infrastructure and machinery will break down or require maintenance by evaluating sensor data and equipment performance parameters. Preventive measures reduce unscheduled downtime, which is a vital component of business continuity, particularly in the industrial and critical infrastructure industries (Fan et al. 2019; Jiang et al. 2017; Ray 2023; Kagiyama et al. 2019).

One of the most important components of business continuity is incident response planning, which could be improved by AI. Security lapses, hacks, and other incidents could be quickly detected and handled by AI-powered incident response systems. The duration and effect of interruptions could be decreased by using these response systems to automate threat detection, evaluate attack patterns, and recommend response measures (Al-rimy et al. 2019). By undertaking a thorough analysis of the capacity of various AI technology components in predictive risk assessment, this work sought to close the research gap. It aimed to offer empirical insights into the ways in which AI algorithms, natural language processing, data analytics, predictive maintenance, and incident response planning specifically improve risk assessment and, ultimately, guarantee business continuity. The goal of addressing these gaps is to provide useful advice to companies looking to use AI to successfully manage and mitigate risks.

1.1. Purpose of the Study

The primary purpose of this study was to examine the role of various aspects of AI technology in predictive risk assessment and how they contribute to ensuring business continuity.

1.2. Study Objectives

1. To examine the role of natural language processing (NLP) in automating risk assessment processes.
2. To analyze the influence of AI-powered data analytics in identifying emerging risks.
3. To examine the effectiveness of AI-driven predictive maintenance in reducing operational downtime.
4. To assess the integration of AI in incident response planning and its effect on minimizing business disruptions.

1.3. Research Hypotheses

Hypothesis 1. *The integration of natural language processing (NLP) in risk assessment processes leads to more efficient and automated assessments, enhancing business continuity.*

Hypothesis 2. *AI-powered data analytics improve the identification of emerging risks, which enhances business continuity.*

Hypothesis 3. *AI-driven predictive maintenance reduces operational downtime and contributes to business continuity.*

Hypothesis 4. *The incorporation of AI in incident response planning minimizes business disruptions during crises, enhancing business continuity.*

1.4. Significance of the Study

This study holds significance for businesses and organizations aiming to enhance their risk assessment processes and ensure business continuity. By understanding the role of AI in predictive risk assessment, organizations can make informed decisions regarding AI adoption. Additionally, this research contributes to the broader field of AI applications in business by providing empirical evidence of its impact on risk management and continuity planning.

2. Literature Review

2.1. AI Algorithms and Machine Learning Models

AI algorithms and machine learning models have emerged as powerful tools for predictive risk assessment, significantly improving the accuracy and efficiency of risk identification and mitigation processes (Claudino et al. 2019; Galaz et al. 2021). These technologies leverage data-driven approaches to analyze large datasets, identify patterns, and make predictions, making them indispensable for businesses aiming to enhance their risk management and business continuity strategies. According to recent research, AI algorithms and machine learning models have a significant influence on anticipating operational hazards (Radanliev et al. 2020; Drydakis 2022; Perera et al. 2023). Organizations may proactively address possible threats and reduce their impact on business continuity by utilizing AI algorithms and machine learning models in risk assessment (Brás et al. 2023b; Mohamed 2023; Taboada et al. 2023).

The efficiency of machine learning approaches in risk assessment is further enhanced by their scalability and flexibility, as noted by Brintrup et al. (2023). These models make sure that risk assessment procedures are current and sensitive to changing dangers since they can manage enormous amounts of historical data and continually learn from fresh data. This flexibility is especially important in fields where new risks and quick changes are the norm (Tyagi and Bhushan 2023; Calderonio 2023; Taboada et al. 2023; Bibri et al. 2024).

In addition, AI algorithms have shown their predictive modeling abilities in a number of industries, such as manufacturing, healthcare, and finance. For example, machine learning models have been used in the banking sector to predict fraudulent activity, credit risk, and market volatility. These applications have not only improved risk assessment but also facilitated informed decision-making and business continuity planning (Aldrini et al. 2023; Leoni et al. 2022; Nicholas and del Castillo 2023).

Pawel Gmyrek and Berg (2023) noted that while the potential of AI algorithms and machine learning models in predictive risk assessment is vast, there are challenges and ethical considerations that organizations must navigate. AI models rely heavily on high-quality, unbiased data for accurate predictions. If the data used for training is flawed or biased, it can lead to inaccurate risk assessments and potentially detrimental decisions. Another challenge is the "black box" nature of some AI models (Dariush and Pontus 2022). Ethical concerns also arise in the use of AI for risk assessment. Questions about data privacy, fairness, and bias need to be addressed. For instance, if AI models are trained on historical data that reflect biases, they may perpetuate those biases in their predictions, which can lead to unfair outcomes. Organizations must implement robust ethical frameworks and data governance practices to mitigate these concerns (Radanliev et al. 2020; Thekdi et al. 2023; Thekdi and Aven 2023).

Numerous sectors have adopted AI algorithms and machine learning models, each with its own set of benefits and constraints. When it comes to using AI for risk assessment, the financial sector is leading the way (Brás et al. 2023a, 2023b; Radanliev et al. 2020). Credit risk assessment, fraud detection, and market movement prediction are all done through machine learning models. According to Charles et al. (2023) and Zamani et al. (2023), these apps support financial institutions in making well-informed choices, optimizing portfolios, and guaranteeing the provision of financial services. AI is used by retailers for customer customization, inventory control, and demand forecasting. In order to improve supply chains, reduce stockouts, and ensure company continuity during busy shopping seasons, machine learning algorithms examine sales data, consumer behavior, and market trends (Calderonio 2023; Biolcheva and Valchev 2022).

2.2. Natural Language Processing (NLP)

In the context of predictive risk assessment for business continuity, NLP has become a crucial component of AI technology (van Noordt and Tangi 2023; van Noordt et al. 2023; Taboada et al. 2023). Because natural language processing (NLP) algorithms are built to comprehend and interpret human language, they are a vital tool for examining unstructured textual data sources, including event reports, social media posts, news articles, and consumer reviews. With the use of these algorithms, businesses may glean insightful patterns and new details from text data, therefore averting dangers before they arise (Raza 2023). The capacity of NLP to automate the monitoring of massive volumes of textual data is one of the technology's key benefits in risk assessment. As an illustration, a study conducted by Kesa (2023) revealed that more than 80% of the data produced by enterprises is unstructured text data. This type of data, if unanalyzed, might result in lost opportunities and unaddressed hazards. This might be especially crucial for companies whose reputation is paramount. An investigation conducted by A. Kumar et al. (2023), for instance, showed that sentiment analysis methods could reliably categorize product evaluations as either positive or negative, offering insights into consumer satisfaction and any threats to brand reputation.

The significance of NLP in predictive risk assessment is further supported by statistics. The NLP industry is anticipated to expand at a Compound Annual Growth Rate (CAGR) of 20.3% throughout the projection period, from $11.6 billion in 2020 to $35.1 billion by 2026, according to a study by WCO/WTO (2022). This expansion reflects the growing use of NLP technology in a variety of sectors, where risk assessment is essential, such as cybersecurity, healthcare, and finance. The processing of incident reports and textual data pertaining to previous occurrences or near-misses is a crucial use of NLP in risk assessment. NLP

algorithms may assist companies in identifying recurrent trends or incident root causes by evaluating incident reports. This enables them to take proactive steps to stop similar incidents from repeating. The Economic and Social Commission for Asia and the Pacific (ESCAP)—United Nations (UN.ESCAP 2017) conducted research that showed how NLP techniques may be used to improve patient safety and lower the likelihood of medical mistakes in incident reports within the healthcare sector. Sentiment analysis powered by NLP may also be useful for evaluating complaints and client feedback. Organizations can employ NLP in the context of customer relationship management to ascertain consumer sentiment and pinpoint areas of concern (Shah et al. 2023; Kiuchi et al. 2023; Srinivasan et al. 2023).

Additionally, NLP helps to increase the effectiveness of risk reporting and regulatory compliance. Organizations are frequently required by regulatory agencies to provide reports and paperwork, which, if done manually, may be labor-intensive and prone to errors (Calderonio 2023; Tyagi and Bhushan 2023; Apanavičienė and Shahrabani 2023). According to Charles et al. (2023), NLP-based systems may automate the extraction of pertinent information from documents, guaranteeing correctness and compliance while saving time and conserving resources. NLP can help organizations monitor news stories and social media activity during catastrophes in the context of crisis communication. Effective crisis response plans may be established by quickly locating and evaluating pertinent information, potentially minimizing the impact on corporate operations (Chen et al. 2021; De Simone et al. 2023). Additionally, NLP algorithms may be used for social media monitoring, giving businesses the ability to monitor and evaluate public opinion and conversations about their brand or sector (Biolcheva and Valchev 2022; Thekdi et al. 2023; Thekdi and Aven 2023). According to a study by Tan et al. (2022), sentiment analysis using Twitter data could predict stock market movements with an accuracy rate of 87.6%. This finding highlights the potential of NLP in recognizing external variables that may have an influence on company continuity.

2.3. AI-Powered Data Analytics

Tyagi and Bhushan (2023) noted that predictive risk assessment for business continuity has advanced significantly thanks to AI-powered data analytics. Using machine learning algorithms and data processing power, this technology is able to glean insightful information from large datasets. The capacity of AI-powered data analytics to identify new threats is one of its main benefits. Conventional risk assessment techniques frequently depend on predetermined risk variables and historical data (Thekdi et al. 2023; Ghaffarian et al. 2023). On the other hand, new risks might materialize quickly in a constantly changing business environment. AI is particularly good at spotting minute patterns and irregularities in data that might indicate the existence of hazards that have not been previously identified. Unstructured data sources like text, social media posts, and sensor data may include these buried patterns (Biolcheva and Valchev 2022).

According to PwC-GMIS (2020), 74% of firms are utilizing AI for data analytics, and 32% of them believe that AI has greatly enhanced their analytics skills. The increasing use of AI in data analytics highlights how crucial it is for risk assessment and decision-making procedures. Another crucial component of AI-powered data analytics is real-time monitoring. Real-time insights are quite helpful when it comes to risk management and company continuity. For instance, AI in supply chain risk management enables businesses to modify their plans in real-time to minimize any interruptions by tracking variables like weather patterns, geopolitical events, and supplier performance (Meena and Madan 2023; Galaz et al. 2021).

According to a van Noordt and Tangi (2023) report, over 50% of firms will employ real-time data for decision-making by 2024. The move toward real-time analytics is a sign that the importance of AI in guaranteeing business continuity through real-time risk assessments is becoming increasingly apparent. Predictive modeling also benefits from AI-driven data analytics. According to Le Coze and Antonsen (2023) and van Noordt and

Tangi (2023), these models are able to predict possible hazards and their expected effects on business operations. Conventional risk assessment techniques might rely on laborious, human error-prone manual data processing (Pawel Gmyrek and Berg 2023; Tamasiga et al. 2023; Zeng and Yi 2023). Conversely, AI algorithms can quickly handle enormous volumes of data, guaranteeing a more thorough and impartial examination. More accurate risk assessments result from this skill, which lowers the possibility of false positives and negatives (OECD 2020).

Organizations utilizing AI in risk analytics reported a 60% boost in risk detection skills, according to a 2021 European Commission study (European Commission 2021). That study attributed this gain to the automation and scalability of AI-powered analytics. This illustrates how artificial intelligence may improve risk assessment accuracy in a practical way. AI can, for instance, be used in financial risk management to provide a full picture of possible market disruptions by analyzing news articles, trending social media, and economic indicators in addition to traditional financial data (S. Kumar et al. 2023; Alahi et al. 2023; Tyagi and Bhushan 2023).

Cheatham et al. (2019) claim that systems are capable of processing and analyzing big datasets that are too big for human analysis. This scalability is especially useful for worldwide supply chains, where company survival depends on keeping an eye on several suppliers, logistical routes, and market circumstances. More thorough risk evaluations are made possible by AI's capacity to manage large-scale data analysis (van Noordt and Tangi 2023). AI algorithms have the ability to swiftly sort through data, spot irregularities, and initiate automatic reactions or alarms. Preventing such disturbances in their earliest stages is enabled by these quick evaluation and reaction capabilities (Pawel Gmyrek and Berg 2023; L. Chen et al. 2023; Feng and Liu 2023).

Organizations confirm their compliance with standards through certification. ISO 31010:2019 is an international standard that provides guidance on risk management and outlines various risk assessment techniques. The full title of the standard is "ISO 31010:2019—Risk management—Risk assessment techniques." It was published by the International Organization for Standardization (ISO). The standard does not provide a one-size-fits-all approach to risk assessment but rather offers a framework and a set of techniques that organizations can choose from based on their specific needs, context, and objectives. ISO 31010 is intended to be used in conjunction with ISO 31000, which is the overarching standard for risk management (Björnsdóttir et al. 2022).

2.4. Predictive Maintenance

AI-powered predictive maintenance is revolutionizing a number of sectors, especially those that rely significantly on machinery and equipment (Arpilleda 2023; Chen et al. 2021). By minimizing operational disruptions and averting unscheduled downtime, it tackles a crucial component of business continuity. According to Radanliev et al. (2020), this strategy uses sophisticated AI algorithms and data analytics to forecast the likelihood that machinery or equipment may break, enabling businesses to schedule maintenance in advance. Numerous research statistics highlight how predictive maintenance significantly affects company continuity. For instance, predictive maintenance may cut unexpected downtime by 50% and maintenance expenses by up to 40%, according to a study by the International Telecommunication Union—ITU (2022). These figures demonstrate the significant cost savings and increased operational dependability that businesses can obtain by putting AI-powered predictive maintenance solutions into practice. Predictive maintenance also increases the longevity of machinery and equipment, reducing the need for expensive replacements. According to a Claudino et al. (2019) study conducted in the industrial sector, predictive maintenance reduced maintenance expenditures by 25% and breakdowns by 70%.

Gavaghan et al. (2021) noted that traditional maintenance schedules often involve routine checks and replacements based on fixed time intervals, which may not align with actual equipment conditions. AI, on the other hand, assesses the health of equipment in

real-time and can prioritize maintenance tasks based on criticality and impending failures. This targeted approach ensures that resources are allocated where they are most needed, reducing the risk of operational disruptions. Additionally, predictive maintenance contributes to safer work environments. When equipment failures are detected in advance, organizations can plan maintenance activities during scheduled downtime, reducing the need for emergency repairs. This proactive approach minimizes the exposure of maintenance personnel to potentially hazardous situations and improves overall workplace safety (Patil et al. 2023; Charles et al. 2023; Emrouznejad et al. 2023). Figure 1 presents the general stages of risk management from 1900 to our days.

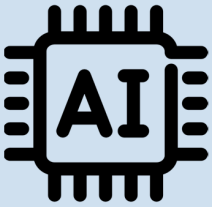
Classical Risk Assessment and Management	Cooperative Risk Management	Business Risk Management	Comprehensive Risk Management	AI Technology in Risk Management
				
1900–1979	1980–1999	2000–2010	2011–2020	2021–AI Era
1900				Our days
Specializing in insurance coverage, finance, and operations with a responsive approach to risk management.	Integrated risk management into the process of strategic planning, taking into account functioning, ethical, and strategic concerns.	The strategy was comprehensive, including new threats such as cyber risk, and placed particular emphasis on the role of corporate culture in risk management.	The wider implications of risks include the integration of risk management with business tasks such as environmental responsibility, administration, and regulation.	AI technologies are proven to be invaluable in quickly identifying and controlling dangers. AI response planning becomes critical for minimizing business disruptions during crises, particularly in the realm of cybersecurity.

Figure 1. The Stages of Risk Management from 1900 to our days.

2.5. AI in Incident Response Planning

The integration of AI in incident response planning has become increasingly critical for minimizing business disruptions during crises, particularly in the realm of cybersecurity (Tan et al. 2022). In today's digitally connected world, organizations face a growing number of cyber threats that can jeopardize business continuity. According to Charles et al. (2023), AI technologies are proven to be invaluable in quickly identifying and controlling these dangers. The increasing number of cybersecurity incidents could have serious repercussions. Over 1100 data breaches were reported in the United States alone in 2020, exposing millions of records, according to an OECD assessment from (OECD 2022). Data loss, financial losses, reputational harm, and operational interruptions are all possible outcomes of these catastrophes. These difficulties are intended to be addressed by AI-powered incident response systems (Le Coze and Antonsen 2023).

AI is useful in incident response planning, according to (Cheatham et al. 2019) research by Cheatham, Javanmardian, and Samandari. Their study discovered a noteworthy decrease in the mean time to detect (MTTD) and the mean time to respond (MTTR) to security issues in firms utilizing AI-driven incident response systems. Measuring an organization's ability to detect and neutralize threats rapidly is what makes MTTD and MTTR crucial metrics for evaluating the quality of the incident response. AI is able to evaluate past

event data in order to continuously refine incident response tactics, according to the World Economic Forum (2023). AI helps businesses create more effective defenses and proactive security measures by recognizing typical attack patterns and weaknesses. In the face of changing cyberthreats, this adaptable strategy makes sure incident response procedures continue to work.

Kaur et al. (2023) noted that the speed at which AI can evaluate enormous volumes of data is another important feature for incident response applications. Large-scale datasets containing logs, network traffic information, and event recordings can be produced by security incidents. It might be difficult for human analysts to manually go through this data, which would cause delays in recognizing serious risks (Z.-S. Chen et al. 2023). These data are well processed and correlated by AI-driven systems, freeing analysts to concentrate on strategic decision-making rather than data mining. AI may also provide security occurrences context, which is essential for a successful response (Taboada et al. 2023; Barcaui and Monat 2023). AI may distinguish between an isolated incident and a part of a broader, coordinated operation by examining the behavior of threats over time. Effective resource allocation and incident response effort prioritization depend heavily on this contextual data. The capacity of AI to draw lessons from previous events is a crucial component in crisis response (Jackson et al. 2023; Zarghami and Dumrak 2021; Feng et al. 2023). By identifying patterns and trends in past event data, machine learning models may assist businesses in optimizing their security posture. For example, AI can recommend taking specific preventive actions to lessen the chance of a recurrence if a certain kind of assault has happened before. AI can also improve threat intelligence's accuracy (Soldatos et al. 2022; Meena and Madan 2023).

3. Results

This section presents an interpretation and explanation of the findings of this study.

3.1. Demographic Characteristics

In terms of gender, the sample is predominantly male, constituting 60% of the respondents (Table 1). Females represent 40% of the sample. This distribution reflects a gender imbalance in the sample, with a notable predominance of males. This could be indicative of the demographic trends in the field of AI or the specific sectors from which the sample was drawn. The age distribution of the respondents is skewed toward the middle-aged group.

Table 1. Demographic information of the respondents.

Item	Categories	Frequency	Percentage
Gender	Male	216	60.0%
	Female	144	40.0%
	Total	360	100%
Age bracket	Below 25 years	18	5.0%
	25–35 years	99	27.5%
	36–45 years	182	50.6%
	Above 45 years	61	16.9%
	Total	360	100%
Education level	Certificate	5	1.4%
	Diploma	40	11.1%
	Degree	310	86.1%
	Master's and above	5	1.4%
	Total	320	100%
Experience in AI	Below 2 years	16	4.4%
	2–10 years	215	59.7%
	More than 10 years	129	35.8%
	Total	320	100%

Source: Authors' elaboration.

The largest group, 50.6%, falls within the 36–45 years age bracket, indicating a mature and likely experienced cohort. The next significant group, 27.5%, is within the 25–35 years age bracket, representing the younger professionals in the field. Regarding educational qualifications, the overwhelming majority, 86.1%, hold a degree. This high percentage underscores the importance of advanced education in the field of AI, where diploma holders constitute 11.1%, while only a small fraction holds either a certificate or a master's degree. The low representation of master's degree holders could be due to various factors, including the recent growth of AI as a field of study or the sample's specific professional contexts. In terms of experience with AI, the majority of respondents, 59.7%, have 2–10 years of experience, suggesting a significant presence of professionals who have a substantial but not extensive background in AI. Those with more than 10 years of experience account for 35.8%, indicating a significant proportion of highly experienced individuals in the field.

3.2. Descriptive Results

The results concerning the role of NLP in automating risk assessment processes are presented in Table 2.

Table 2. Results on the role of natural language processing (NLP) in automating risk assessment processes.

Statement	%	SD	D	NS	A	SA
NLP significantly speeds up the risk assessment process in my organization.	%	0.0	6.5	23.4	58.5	11.7
The use of NLP leads to more accurate identification of risks compared to traditional methods.	%	2.6	6.5	11.7	79.2	0.0
NLP technology effectively interprets unstructured data for risk assessment purposes.	%	0.0	23.4	5.2	15.6	55.8
I trust the results provided by NLP in risk assessment over manual analysis.	%	1.3	2.6	11.7	72.7	11.7
NLP has been cost-effective in automating risk assessment processes in my organization.	%	0.0	2.6	11.7	74.0	11.7
NLP tools are user-friendly and easy to integrate into our existing risk assessment processes	%	3.9	6.5	11.7	61.0	16.9
The integration of NLP has improved the consistency of risk assessments in our business.	%	2.6	1.3	13.0	62.3	20.8

Key: SD = Strongly disagree, D = Disagree, NS = Not sure, A = Agree, and SA = Strongly agree. Source: Authors' elaboration.

Table 2 shows that a high percentage (70.2%) agree or strongly agree, indicating that most respondents believe NLP has a positive impact on the speed of risk assessment processes. A substantial majority (79.2%) agree, suggesting that NLP is perceived to enhance the accuracy of risk identification. The absence of strongly agree responses might indicate some reservations or the need for further improvements. A total of 71.4% either agree or strongly agree, highlighting NLP's effectiveness in handling unstructured data, a critical aspect of risk assessment. The majority (84.4%) trust NLP over manual analysis, indicating a high level of confidence in NLP's capabilities in risk assessment. A majority (85.7%) agree or strongly agree that NLP is cost-effective, which is a vital factor for technology adoption in business. Most respondents (78.9%) find NLP tools user-friendly and easy to integrate, suggesting good usability and compatibility with existing systems. A combined 83.1% agree or strongly agree, indicating that NLP contributes positively to the consistency of risk assessments.

This study analyzed the influence of AI-powered data analytics in identifying emerging risks and the results are presented in Table 3.

Table 3. Results on the influence of AI-powered data analytics in identifying emerging risks.

Statement	%	SD	D	NS	A	SA
AI-powered data analytics enables quicker identification of emerging risks in the business environment.	%	0.0	7.8	22.1	58.4	11.7
Data analytics driven by AI enhances the accuracy of predicting potential risks.	%	2.6	15.6	10.4	48.1	23.4
The use of AI in data analytics has improved our organization's responsiveness to unforeseen risks.	%	5.8	5.2	24.7	2.6	61.7
AI-driven analytics tools are integral to our strategic risk management planning.	%	1.3	7.8	13.0	66.2	11.7
The insights provided by AI-powered data analytics are highly valued in our risk assessment process.	%	0.0	1.3	3.9	51.9	42.9
AI data analytics has led to more comprehensive risk identification compared to traditional methods.	%	0.0	6.5	23.7	50.6	19.2
The use of AI in data analytics supports a proactive approach to risk management in my organization.	%	9.0	0.0	5.2	52.9	41.9

Key: SD = Strongly disagree, D = Disagree, NS = Not sure, A = Agree, and SA = Strongly agree. Source: Authors' elaboration.

The results in Table 3 show that a significant 70.1% of respondents (agree and strongly agree combined) believe that AI-powered data analytics enables quicker identification of emerging risks. This suggests that AI's speed and efficiency in processing and analyzing large datasets are highly valued in a business environment where a rapid response to changing conditions is critical. Furthermore, 71.5% of respondents agree or strongly agree that AI enhances the accuracy of predicting potential risks. This reflects the advanced capabilities of AI in pattern recognition and predictive modeling, which are essential for accurate risk forecasting. A notable 64.3% (agree and strongly agree) feel that AI in data analytics has improved their organization's responsiveness to unforeseen risks. This underscores AI's role in enabling organizations to react swiftly and effectively to unexpected challenges, enhancing resilience and adaptability. A majority of 77.9% view AI-driven analytics tools as integral to their strategic risk management planning. This indicates a strong reliance on AI for strategic decision-making, underlining its importance in long-term risk management and business planning. An overwhelming 94.8% of respondents value the insights provided by AI-powered data analytics in their risk assessment process. This demonstrates the trust and reliance placed on AI's analytical capabilities to guide risk assessment and management strategies. Also, 70.4% believe that AI data analytics has led to more comprehensive risk identification compared to traditional methods. This suggests that AI's extensive data processing capabilities are crucial for identifying a broader range of potential risks, thus enhancing overall risk management. Finally, 93.5% agree or strongly agree that the use of AI supports a proactive approach to risk management. This reflects a significant shift from reactive to proactive risk management, facilitated by AI's predictive capabilities.

This study further examined the effectiveness of AI-driven predictive maintenance in reducing operational downtime and the results are presented in Table 4.

Table 4. Results on the effectiveness of AI-driven predictive maintenance in reducing operational down time.

Statement	%	SD	D	NS	A	SA
AI-driven predictive maintenance has noticeably reduced the frequency of operational downtime.	%	1.3	7.8	11.7	62.3	16.9
The predictive alerts provided by AI systems are accurate and timely.	%	2.6	11.7	9.1	64.9	11.9
The use of AI for maintenance has led to cost savings in equipment repair and replacement.	%	7.8	7.7	2.1	70.8	11.7
AI-driven maintenance strategies have improved the lifespan of our critical equipment.	%	9.1	9.9	2.1	47.3	31.7
Predictive maintenance using AI is more efficient than traditional maintenance approaches.	%	5.2	18.2	15.6	44.2	16.9
The implementation of AI in maintenance has improved overall operational efficiency	%	5.2	14.7	4.5	58.3	17.4
I am satisfied with the role of AI in predictive maintenance within our organization.	%	0.0	8.2	5.6	19.4	66.9

Key: SD = Strongly disagree, D = Disagree, NS = Not sure, A = Agree, and SA = Strongly agree. Source: Authors' elaboration.

Table 4 shows that a significant majority (79.2%) of respondents agree (agree and strongly agree combined) that AI-driven predictive maintenance has notably reduced operational downtime. This high percentage underscores AI's effectiveness in identifying potential equipment failures before they occur, thereby minimizing unexpected breakdowns and production halts. Furthermore, 76.8% of participants acknowledge the accuracy and timeliness of AI-generated predictive alerts. This reflects the advanced capabilities of AI systems in analyzing vast amounts of data to provide reliable predictions and alerts, enabling proactive maintenance actions. A substantial 82.5% of respondents agree that AI in maintenance leads to cost savings. This highlights AI's role in preventing costly repairs and replacements by timely identifying issues that can be addressed before they escalate into major problems. Consequently, 79% of respondents agree that AI-driven maintenance strategies have enhanced the lifespan of critical equipment. AI's ability to provide precise maintenance schedules and identify minor issues before they turn major contributes to prolonging equipment life and ensuring optimal performance. The responses vary more regarding efficiency in comparison to traditional maintenance approaches, with 61.1% agreeing that AI-based predictive maintenance is more efficient than traditional methods. This indicates a positive reception, yet also suggests room for improvement or a need for wider understanding and adoption of AI-based methods. Furthermore, 75.7% agree that implementing AI in maintenance has boosted overall operational efficiency. This reflects the broader impact of AI in optimizing not just equipment maintenance, but also streamlining various operational processes. An overwhelming 86.3% express satisfaction with AI's role in their organization's predictive maintenance. This high level of satisfaction demonstrates the perceived value and effectiveness of AI in this domain.

This study evaluated the integration of AI in incident response planning and its effect on minimizing business disruptions and the results are presented in Table 5.

Table 5. Integration of AI in incident response planning and its effect on minimizing business disruption.

Statement	%	SD	D	NS	A	SA
AI integration in incident response planning has significantly reduced business disruptions.	%	0.0	1.6	9.9	76.9	11.8
The use of AI in incident response contributes to quicker recovery from unexpected incidents.	%	0.0	37.7	1.9	21.8	38.7
AI tools aid in accurately predicting the impact of potential incidents on business operations.	%	3.1	9.9	2.1	27.9	51.7
The integration of AI has improved the coordination and management of incident responses.	%	5.2	18.2	15.6	44.2	16.9
AI-enhanced incident response plans are more comprehensive and effective than traditional plans.	%	3.9	36.4	18.2	29.9	11.7
The use of AI in incident response planning has increased the resilience of our business.	%	7.8	4.7	6.2	71.7	9.7
I am confident in the ability of AI-integrated plans to handle future business disruptions effectively.	%	9.1	3.4	9.2	67.8	10.6

Key: SD = Strongly disagree, D = Disagree, NS = Not sure, A = Agree, and SA = Strongly agree. Source: Authors' elaboration.

According to Table 5's results, the majority of respondents (76.9%) agree, with a minority (11.8%) strongly agreeing that the use of AI in incident response planning has significantly decreased business disruptions. Given the high degree of agreement, it appears that AI tools can effectively reduce the impact of accidents on company operations, resulting in an environment that enables businesses to be more resilient. Regarding AI in incident response helping with quicker recovery, opinions are divided; notable numbers of 38.7% strongly agree and 21.8% agree that AI helps with quicker recovery from incidents. Nonetheless, a sizable 37.7% are indifferent, suggesting some ambiguity or no discernible influence in this field. This suggests that although AI has advantages, its ability to expedite recovery may not be consistently evident in all contexts or industries. With another 27.9% in agreement, more than half of the respondents (51.7%) strongly think that AI helps in precisely forecasting the consequences of probable incidents. In order to effectively manage risks and plan for business continuity, proactive risk management requires a strong conviction about the accuracy of AI's predictive powers. Here, the answers are more divided: 44.2% agree and 16.9% strongly agree that the integration of AI has enhanced management and coordination. Nonetheless, a total of 23.4% (5.2% strongly disagree and 18.2% disagree) voice doubt, indicating that variables like organizational preparedness, incident complexity, and the quality of implementation may have an impact on how beneficial AI is in this area. A balanced opinion is shown in the responses, with 29.9% agreeing and 11.7% strongly agreeing that plans enhanced by AI are more thorough and efficient. Nonetheless, a noteworthy 18.2% disagree and 36.4% neither agree nor disagree, indicating a split view on the superiority of AI-enhanced plans over conventional techniques. This may be the result of organizational context differences or variances in the quality of AI integration. The use of AI in crisis response planning has boosted corporate resilience according to a substantial majority (71.7%), with 9.7% strongly agreeing. This high degree of agreement emphasizes how AI may strengthen company operations' overall resilience to disturbances. Similarly, 10.6% strongly agree and the majority (67.8%) agree that they are confident in AI-integrated plans' capacity to manage upcoming business challenges. There is a widespread sense of confidence regarding AI's ability to handle

issues in the future, but there are still some misgivings, as evidenced by the 9.1% of respondents who disagree and the 9.2% who are neutral.

This study also identified the different outcomes of business continuity, and the results are presented in Figure 2.

Figure 2. Results about the different outcomes of business continuity.

Figure 2 shows that the majority of the respondents (28.8%) indicated that the most significant outcome of effective business continuity is the continued improvement of revenue generation. This suggests that businesses that focus on maintaining uninterrupted operations are more likely to experience sustained or increasing revenue streams. This was followed by 21.6% of respondents who highlighted improved agility and adaptability abilities as key outcomes. This reflects the importance of being able to quickly adjust to changing circumstances, such as market shifts or emergencies, which is a crucial aspect of maintaining business continuity. Agile and adaptable businesses are better positioned to navigate unpredictable situations, thereby securing their operations and future. Furthermore, 16.3% of respondents chose improved risk management to achieve effective business continuity. Effective business continuity planning inherently involves identifying and mitigating various risks, thus enhancing the overall risk management capabilities of the organization. This could include risks related to financial, operational, technological, and reputational factors. Better employee safety and morale was cited by 11.3% of the respondents. This confirms the human element in business continuity, highlighting that safeguarding employees and maintaining high morale is not just an ethical obligation but also a business strategy that can lead to more resilient and effective operations. An improved competitive advantage was noted by 9.7% of respondents. This suggests that companies that are able to maintain continuous operations, especially in the face of disruptions that affect competitors, can gain an edge in the market. A smaller proportion of respondents, 7.6%, indicated improved regulatory compliance as a significant outcome. This is likely due to the fact that many business continuity strategies align with regulatory requirements, ensuring that companies are not only resilient but also compliant with legal and industry standards. The smallest portion of respondents (4.7%) mentioned other benefits, such as improved customer confidence and improved reputation. These are critical but often indirect benefits of business continuity, where consistent and reliable operations lead

to increased trust among customers and stakeholders, thereby enhancing the company's reputation in the market.

3.3. Regression Analysis

Table 6 presents the results of a multiple regression analysis that aimed to assess the cumulative impact of various AI technologies on business continuity.

Table 6. Multiple Regression Analysis results.

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
(Constant)	61.35	8.13		6.14	0.003
Natural language processing (NLP) in automating risk assessment processes	0.114	0.152	0.146	1.104	0.002
AI-powered data analytics in identifying emerging risks	0.341	0.038	0.650	5.03	0.001
AI-driven predictive maintenance in reducing operational downtime	0.174	0.112	0.046	1.17	0.011
Integration of AI in incident response planning	0.361	0.038	0.370	11.03	0.000
Model	**R Square**	**Adjusted R Square**	**F**	**Sig.**	
	0.584	0.501	63.01	0.001	

Dependent Variable: Business continuity.

From the regression results, the R square value is 0.584, and the adjusted R square is 0.501. This indicates that approximately 58.4% of the variance in business continuity can be explained by the independent variables in the model. The adjusted R square value, which accounts for the number of predictors in the model, is slightly lower but still significant. This suggests that the model has a good fit. Furthermore, the F statistic (63.01) and its associated significance value (0.001) indicate that the overall regression model is statistically significant.

The constant (intercept) value of 61.35 with a standard error of 8.13 and a significant T-value of 6.14 ($p = 0.003$) suggests that when all of the independent variables are at zero, the expected value for business continuity is notably high. This indicates other factors not covered in the model could also be influencing business continuity.

NLP shows a small positive unstandardized coefficient (0.114) and a standardized coefficient of 0.146, with a T-value of 1.104 ($p = 0.002$). This suggests that while NLP in automating risk assessment processes has a positive effect on business continuity, its impact is relatively moderate. While NLP does contribute to more efficient and automated risk assessments, its impact on business continuity is not as strong as some other factors. Hypothesis one is accepted but with a caveat that NLP's influence is significant yet not dominant.

The AI-powered data analytics variable shows a significant positive impact on business continuity, with an unstandardized coefficient of 0.341 and a high standardized coefficient of 0.650. The T-value of 5.03 ($p = 0.001$) indicates a strong positive relationship, suggesting that using AI for data analytics in identifying emerging risks is highly beneficial for business continuity. Therefore, hypothesis two is strongly accepted, indicating a critical role of AI in risk identification.

AI-driven predictive maintenance has an unstandardized coefficient of 0.174 and a lower standardized coefficient of 0.046, with a T-value of 1.17 ($p = 0.011$). AI-driven predictive maintenance does contribute to reducing operational downtime and thus aids in business continuity. However, its impact is comparatively less pronounced. Hypothesis three is accepted but indicates a lesser impact than in the other AI applications.

Integration of AI in Incident response planning shows the highest impact with an unstandardized coefficient of 0.361 and a standardized coefficient of 0.370. The T-value of 11.03 (p = 0.000) is highly significant. This suggests that integrating AI into incident response planning is critically beneficial for maintaining business continuity. Therefore, hypothesis four is strongly accepted, highlighting the critical role of AI in effective incident response planning for business continuity.

4. Materials and Methods

4.1. Study Design

This study adopted a quantitative research design, employing a cross-sectional approach to examine the role of AI technology in predictive risk assessment for business continuity. This design was selected because it was efficient in collecting a lot of data in a short amount of time, which made it easier to compare and analyze the effects of various AI technologies on business continuity. Because the survey was cross-sectional, it provided an overview of the thoughts and experiences of technology specialists at a particular moment in time.

4.2. Target Population

This research's population of interest was categorized as technology specialists with knowledge of AI applications across a range of Greek sectors. This group of experts was chosen as an essential source of data due to their in-depth understanding of and expertise with AI technology (3.5% of persons with tertiary education and employed in science and technology) (Eurostat 2022). Because Greece has a distinct economic and technical environment that may have an impact on the uptake and application of AI technologies, focusing on Greek industries gave this research a regional character that deepens it.

4.3. Sample Size

This study selected a sample size of 360 technology experts. The Krejcie and Morgan table, a commonly used technique for estimating sample sizes in research, was used to arrive at this figure (Krejcie and Morgan 1970). It was determined that the selected sample size would adequately give a representative overview of the viewpoints and experiences of Greek IT professionals with relation to AI applications in the business continuity and predictive risk assessment. Considering the time and resources available for the investigation, a sample size of 360 individuals was deemed enough to strike a compromise between statistical power and practicality.

4.4. Sampling Technique

A stratified random sampling technique was employed to ensure a representative sample of the target population. To apply this approach, the population was divided into discrete industry-based groupings, or strata, from which participants were chosen at random. More broadly applicable conclusions were made possible by the method's guarantee that the sample fairly represented the variety found among Greece's technology experts.

Another method exists for determining the sample, which gives a smaller sample, but this method was not used since the offer from the respondents in this research was large (Kalfas et al. 2020, 2022; Kalogiannidis et al. 2022, 2023a).

4.5. Data Collection

A structured questionnaire was employed to gather quantitative information on the viewpoints and experiences of the participants regarding the application of AI technology in risk assessment and business continuity. With items ranging from "Strongly Disagree" to "Strongly Agree", the questionnaire used a Likert scale approach. Because of its capacity to gauge participants' thoughts or attitudes about certain claims about AI technology and its uses in a range of commercial settings, this format was selected. The questionnaire was mostly distributed online, using email lists, industry forums, and professional networks to

reach the target group of technology professionals in Greece's many industries. A larger audience, responder convenience, and a greater response rate were all guaranteed by online dissemination. It also made the process of gathering replies faster, which is crucial for preserving the data's relevance in a rapidly evolving field like AI. To ensure a high response rate and quality of responses, ethical considerations were adhered to whereby participants were informed about the importance of the study and its potential impact on understanding AI's role in business continuity. Clear instructions were provided on how to complete the questionnaire, and participants were assured of the confidentiality of their responses to encourage candidness in their answers. Follow-up reminders were also sent to participants who did not respond initially, to maximize the response rate.

4.6. Measurement of Variables

The primary variables of interest in this study were the perceived effectiveness and impact of different AI technologies (like NLP, AI-powered data analytics, AI-driven predictive maintenance, and AI integration in incident response planning) on business continuity. These variables were measured using a Likert scale, providing a quantitative measure of participants' attitudes and perceptions. A Likert scale allowed for a nuanced analysis of the degree to which participants agreed or disagreed with statements regarding the effectiveness of AI technologies in various aspects of business continuity.

4.7. Data Analysis

The questionnaires underwent preliminary processing after being collected, which involved verifying their uniformity and completeness. To preserve the integrity of the data, any incomplete or inconsistently filled-out questionnaires were either corrected (where feasible) or left out of the analysis. This first screening made sure that the data used for the subsequent study were correct and comprehensive. The data collected through the questionnaires were analyzed using SPSS (Statistical Package for the Social Sciences). The analysis primarily involved regression analysis to investigate the relationships between the different AI technologies and their impact on business continuity. Regression analysis was chosen (Equation (1)) base on its ability to determine the strength and direction of these relationships, providing insights into which AI technologies have the most significant impact on predictive risk assessment and business continuity (Kalfas et al. 2023; Kalogiannidis et al. 2023b).

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \varepsilon \ldots\ldots\ldots\ldots\ldots\ldots 1 \quad (1)$$

where

Y = Business continuity
β_0 = Constant (coefficient of intercept)
X_1 = Natural language processing (NLP) in automating risk assessment processes
X_2 = AI-powered data analytics in identifying emerging risks
X_3 = AI-driven predictive maintenance in reducing operational downtime
X_4 = Integration of AI in incident response planning
ε = Represents the error term in the multiple regression model

The different hypotheses of this study were tested based on the obtained regression results at the 0.05 level of significance.

5. Discussion

This study's findings indicate a strong perception of NLP as a positive force in speeding up and enhancing the accuracy of risk assessment processes. The high percentage of respondents agreeing that NLP significantly speeds up risk assessment and leads to more accurate identification of risks (van Noordt and Tangi 2023; Brás et al. 2023b; Mohamed 2023) underscores the efficiency and effectiveness of NLP in handling unstructured data. This is in line with the insights provided by Drydakis (2022) and A. Kumar et al. (2023), who noted the capability of NLP in automating and streamlining risk assessment. This

study also shows that when compared to conventional approaches, NLP results in a more accurate identification of dangers. Because NLP algorithms are skilled at understanding the subtleties of human language, they may extract insights and clues that could be missed by manual analysis. This increased precision is essential for spotting emerging hazards that might have serious consequences in addition to evident ones. van Noordt and Tangi (2023), for example, pointed out how NLP's capacity to sift through enormous datasets might reveal hidden correlations and patterns, boosting the scope and depth of risk assessment. The ability of NLP technology to comprehend unstructured data is revolutionary for risk assessment. The majority of the data created in the current digital era is unstructured data, which might range from text documents to audio recordings. Over 80% of an organization's data are unstructured, as Kesa (2023) noted, and NLP's ability to interpret these data effectively is priceless. This enables more sophisticated and informed decision-making in addition to giving firms a more complete picture of potential threats.

This study also shows that findings from NLP are more trusted compared to those from manual analysis. This confidence is proof of the dependability and sophistication of contemporary NLP systems. According to Biolcheva and Valchev (2022), the accuracy and dependability of NLP have been greatly improved by advances in AI and machine learning, making NLP a reliable tool in the risk assessment toolbox. Furthermore, these results imply that NLP is an affordable option for automating risk assessment procedures. In a time when companies are constantly searching for budget-friendly alternatives, NLP offers a workable option that lowers the time and personnel costs related to manual analysis while simultaneously improving the overall caliber of risk assessment. Budget restrictions are a major factor for small and medium-sized firms (SMEs) in Greece, as Soldatos et al. (2022) has noted. This makes this feature of NLP especially essential in their environment. It has been discovered that incorporating NLP into risk assessment procedures increases consistency. While human error and biases are common in manual risk assessments, natural language processing (NLP) provides a standardized method of data analysis. Perera et al. (2023) also pointed out that maintaining consistency is essential to guaranteeing the validity of risk assessments and their ability to be repeated over time. Regression research, however, suggests that NLP has a moderate influence on business continuity, suggesting that while NLP is helpful, it is not the only factor that determines business continuity.

This study's focus on AI-powered data analytics in identifying emerging risks reveals a critical area where artificial intelligence significantly contributes to predictive risk assessment and business continuity. AI-powered data analytics harnesses machine learning algorithms and advanced data processing to uncover valuable insights from extensive datasets, enabling organizations to foresee potential risks and adapt strategies proactively. One of the standout findings is the role of AI-powered data analytics in expediting the identification of emerging risks. Traditional risk assessment methods are often constrained by their reliance on historical data and predefined risk factors, which may not capture the evolving nature of the business landscape where new risks can surface rapidly. AI-driven analytics, however, excels in detecting subtle patterns and anomalies in data that could indicate the emergence of previously unrecognized risks. This capability is highlighted in PwC-GMIS (2020) report, which underscores the widespread adoption and the significant improvement in analytics capabilities brought about by AI in various organizations.

The advanced capabilities of AI in pattern recognition and predictive modeling are crucial for accurate risk forecasting. AI algorithms can analyze large datasets to identify trends that human analysts might overlook. This aspect is particularly important given the dynamic nature of risk factors in modern business environments. Studies like those by Galaz et al. (2021) and Meena and Madan (2023) have demonstrated the substantial impact of AI in predicting operational risks, affirming its indispensable role in enhancing risk management strategies (Meena and Madan 2023; Galaz et al. 2021). These findings resonate with the study's observation of a strong positive relationship between AI-powered data analytics and business continuity, as indicated by the high standardized coefficients in the regression analysis. AI algorithms can continuously analyze data streams, allowing

organizations to respond promptly to changing conditions. This feature is crucial in areas like supply chain risk management, where factors like weather patterns, geopolitical events, and supplier performance need constant monitoring. The real-time monitoring capability of AI is also echoed in the 2020 report by PwC-GMIS, emphasizing AI's role in enhancing organizational responsiveness to unforeseen risks (PwC-GMIS 2020). This study's findings corroborate the research by van Noordt and Tangi (2023), indicating that AI-powered data analytics leads to more comprehensive risk identification compared to traditional methods (van Noordt and Tangi 2023). This comprehensive approach to risk identification, enabled by AI, is vital for organizations to develop a thorough understanding of the potential threats they face.

The effectiveness of AI-driven predictive maintenance in reducing operational downtime is well-recognized among respondents (Arpilleda 2023; Chen et al. 2021). This finding corroborates the reports by the International Telecommunication Union (ITU 2022) and Claudino et al. (2019), which highlight the cost savings and operational reliability achieved through predictive maintenance. However, the regression analysis suggests that its impact, while positive, is less pronounced compared to other AI applications. The integration of AI in incident response planning shows a high impact on minimizing business disruptions (Charles et al. 2023; Tan et al. 2022). This is consistent with OECD's (2022) findings on rising cyber threats and the need for AI-driven incident response systems. The regression analysis strongly supports the critical role of AI in effective incident response planning for business continuity, underlining its significant contribution in maintaining operational resilience during crises.

This study's findings provide valuable insights into how different AI technologies can be strategically leveraged for predictive risk assessment and business continuity. While each AI aspect contributes uniquely, the integration of AI in incident response planning stands out as particularly impactful. These insights are essential for businesses in Greece and beyond, as they navigate an increasingly complex and risk-prone business environment. This study, therefore, not only fills the identified research gap but also offers practical guidance for organizations aiming to harness AI for effective risk management and business continuity.

6. Conclusions

This study presented a comprehensive analysis of the role of AI in predictive risk assessment for the business continuity, with a particular focus on the Greek business landscape. The results show how different AI technologies may significantly improve risk management and guarantee the ongoing operations of businesses. NLP has proven to be a rather successful tool for automating risk assessment procedures. NLP has a generally mild effect on business continuity, even though it greatly expedites the risk assessment process and produces more accurate risk identification compared to older techniques. This shows that, even while NLP may help automate and streamline risk assessment procedures, it is only one piece of the puzzle when it comes to guaranteeing business continuity. On the other hand, emerging risk identification is more significantly impacted by AI-powered data analytics. AI's capacity to analyze massive amounts of data quickly and spot patterns has proven to be quite helpful in quickly identifying new threats. This capacity enables an organizational response to unanticipated hazards and increases the accuracy of risk prediction. This study provides compelling evidence for the application of AI in data analytics as a vital instrument for strategic risk management and predictive risk assessment.

This study discovered that, despite having a less noticeable effect than other AI applications, AI-driven predictive maintenance helps to reduce operational downtime. AI-powered predictive maintenance lowers the cost of equipment replacement and repair while extending the life of crucial equipment, both of which are essential for business continuity. However, the efficacy of AI varies in this field and is probably affected by the particular environment in which it is used.

One especially important use for business continuity that has evolved is the incorporation of AI into incident response planning. AI plays a critical role in event detection, management, and response, particularly with regard to cybersecurity concerns. This study discovered that incident response plans with AI enhancements are more thorough and efficient than conventional plans, boosting firms' resistance to interruptions. These results were further supported by the regression analysis, which showed that AI applications, especially in data analytics and incident response planning, significantly improved business continuity. The regression analysis's high R square value highlights the significant amount of business continuity variance that these AI solutions can account for.

This study's overall findings emphasize how AI is revolutionizing risk assessment and business continuity planning. It highlights how important it is for companies, particularly those in Greece, to incorporate AI technology into their risk management plans. This integration will better equip them to anticipate and handle risks as well as bounce back from setbacks with agility, which will provide them with a competitive advantage in the market. These results also imply that although AI technologies have a lot to offer, how well they are implemented and the particular corporate environment in which they are used will determine how beneficial they are. Thus, companies have to develop a comprehensive strategy, including several AI technologies in a way that suits their unique requirements and difficulties. Furthermore, in order to stay up to date with the changing business environment and developing dangers, these technologies must be continuously evaluated and adjusted.

6.1. Implications of This Study

This study highlights how crucial NLP is to the automation of risk assessment procedures. Although NLP has little effect on business continuity, it greatly expedites the risk assessment procedure, which results in quicker and more accurate detection of possible hazards. Businesses may use NLP to handle enormous volumes of unstructured data quickly by incorporating it into their risk assessment frameworks. Risk assessments become more regular and dependable as a result of this automation, which also increases productivity and lowers the possibility of human error. It is crucial to remember that, even considering NLP's advantages, a complete risk management strategy should incorporate other AI technologies as well.

One of the most important aspects of business continuity is the impact of AI-powered data analytics in spotting new threats. Based on this study, it can be concluded that AI-driven data analytics greatly increases the speed and accuracy of risk prediction. This ability is crucial in a constantly changing corporate environment. Businesses should leverage AI to process and analyze large datasets, enabling them to identify subtle trends and emerging risks that traditional methods might miss. This proactive approach to risk management is crucial for staying ahead of potential disruptions and ensuring business agility.

AI-driven predictive maintenance's role in reducing operational downtime, although less pronounced than other AI applications, is still notable. Predictive maintenance minimizes the frequency and impact of equipment failures, thereby ensuring uninterrupted operations. This aspect is particularly relevant for industries reliant on machinery and equipment. By adopting AI-driven predictive maintenance, businesses can extend the lifespan of their assets, reduce maintenance costs, and enhance their overall operational efficiency.

6.2. Areas for Future Research and Limitations of This Study

Future research may focus on more sophisticated AI methods like deep learning, even though this paper covers AI algorithms and machine learning models in great detail. Investigations into how deep learning, with its advanced pattern recognition skills, may offer even more detailed insights into risk assessment and management and may be necessary. Future research should also address the ethical and regulatory implications of using AI in risk assessment. This includes exploring data privacy concerns, the potential

for bias in AI algorithms, and how different regulatory frameworks impact the adoption of AI technologies.

The present research primarily emphasizes the use of AI technology in predicting risk assessment. Nevertheless, there is a lack of emphasis on business continuity management (BCM) as a means to mitigate the effects of artificial intelligence. Subsequent study should prioritize the development of inventive systems that can effectively tackle both business continuity management and the business consequences of AI. Merging BCM with risk assessment may cause confusion among readers due to their distinct disciplinary domains.

Furthermore, this research had methodological constraints. Although it examined the whole nation of Greece, the information used was only gathered from Greece, which might have compromised the generalizability of the findings. To overcome this constraint, we selected Greek IT experts as a representative sample and extrapolated their findings to include other regions worldwide, rather than only focusing on Greece.

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