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How AI and Ml Help Service Based Organisations to Resist External Market Shock: Baysian Analysis

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Abstract
The purpose of this research is to investigate the nature of the relationship between artificial intelligence (AI) and machine learning (ML) technologies in service-based organizations on the one hand and organizational resilience on the other, as well as the potential impact of external market shocks on this relationship. A quantitative survey of 171 service-based groups was used to perform the research. The study's findings indicate that using AI and ML technologies in service delivery has a beneficial and substantial effect on organizational resilience. Furthermore, the research discovered that the degree to which external market shocks influence the efficacy of these technologies in improving an organization's resilience moderates the connection between the use of AI and ML technologies and organizational resilience. According to the results, service-based companies can improve their resilience by incorporating AI and ML technologies into their service delivery processes. They must, however, evaluate the possible influence of external market shocks on the efficacy of these technologies in increasing resilience. The research has ramifications for service-based organizations and adds to the body of knowledge on organizational resilience and the application of AI and ML technologies in service delivery.

Keywords: Service organisations, Artificia Intelligence, Machine learning, External shocks, Baysian Analysis

1. Introduction

The application of artificial intelligence (AI) and machine learning (ML) technologies in service-based enterprises has gained popularity in recent years. These innovations might boost consumer satisfaction, cut expenses, and increase organizational effectiveness, as they automate routine tasks, optimize resource management, and enhance fraud detection, lowering costs. Additionally, these technologies facilitate data-driven decision-making, enable predictive maintenance, and refine marketing strategies, thereby boosting overall organizational effectiveness. However, it is unclear to what degree ML and AI technologies help organizations remain resilient in the face of shocks to the external market. The capacity of an organization to endure and adapt to outside shocks, such as economic downturns or natural catastrophes, while continuing to function successfully, is referred to as organizational resilience. Organizational resilience has emerged as a crucial element for long-term success in the quickly evolving corporate environment of today.

The purpose of this study is to examine the connection between organizational resilience in service-based firms and the application of AI and ML technologies. We specifically look at how organizational resilience is impacted by how frequently AI and ML are used in service delivery and if this connection is impacted by outside market shocks. We used an online survey to gather information from a sample of service-based organizations in order to accomplish these goals. We next examined the data and put our theories to the test using Bayesian structural equation modeling (BSEM).

The study's conclusions have significant ramifications for service-based enterprises thinking about implementing AI and ML technology. They contend that although these technologies can increase organizational resilience, the efficiency with which they do so may be impacted by shocks to the external market. Therefore, in light of their particular external environment, companies should carefully examine the possible dangers and advantages of adopting AI and ML technologies.

This study advances previous work by analyzing the effect of AI and ML technologies on organizational resilience while adding to the expanding body of literature on their application in service-based businesses. Our study also emphasizes how crucial it is to take into account external market shocks when evaluating how well AI and ML technologies enhance organizational resilience.

2. Literature Review

2.1. Overview of AI and ML:

Machine learning (ML), natural language processing, robotics, and computer vision are just a few examples of the many subfields that make up the large topic of artificial intelligence (AI), which also includes <u>other</u> related fields, like expert systems, neural networks, fuzzy logic, evolutionary computation, reinforcement learning, knowledge representation, planning, and artificial general intelligence (AGI). The creation of intelligent systems that can carry out activities that traditionally require human intellect, such as sensing, reasoning, learning, and decision-making, is at the heart of artificial intelligence (AI). (Russell & Norvig, 2021).Statistical and computational methods are used in machine learning, a branch of artificial intelligence that enables computers to learn from data and make predictions or judgments without being explicitly programmed. (Alpaydin, 2020). Creating algorithms that can learn from data, get better with time, and make precise predictions or judgments based on fresh data is the aim of machine learning. (Jordan & Mitchell, 2015).

Machine learning algorithms come in a variety of forms, such as supervised learning, unsupervised learning, and reinforcement learning. Using labeled data to train a machine learning model for prediction or decision-making is known as supervised learning. A service-based business may, for instance, employ supervised learning to forecast client attrition based on past data. In unsupervised learning, links or patterns are found in unlabeled data. Unsupervised learning, which refers to the process where a service-based company uses machine learning to analyze and group clients based on their behavior patterns without prior labeling, allowing for the discovery of hidden patterns and insights in customer data, may be used by a service-based company to categorize clients according to their behavior. By obtaining feedback on its

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activities, a machine learning model is trained through reinforcement learning to make judgments. For instance, a company that provides services may utilize reinforcement learning to adjust price based on the actions of clients. (Sutton & Barto, 2018).

Numerous industries, including healthcare, banking, manufacturing, transportation, retail, telecommunications, education, energy, and entertainment, have adopted AI and ML. AI and ML may be applied in service-based enterprises to increase corporate operations, optimize resource allocation, and improve customer service. (Davenport &Ronanki, 2018). For instance, a service-based company may utilize machine learning to provide tailored client recommendations, automate repetitive processes, or find fraud.

Despite the potential advantages of AI and ML, there are a number of issues that need to be resolved. The requirement for high-quality data to train machine learning models is one of the major obstacles. Machine learning models may be biased or erroneous in the absence of appropriate and representative data. (Halevy, Norvig, & Pereira, 2009). The interpretability of machine learning models is another difficulty. It can be tricky to explain why a certain choice was taken since certain machine learning algorithms are "black boxes" that are challenging to grasp. (Doshi-Velez & Kim, 2017).

2.2. Service-Based Organizations:

Service-based businesses are ones that focus largely on offering clients intangible services or products rather than tangible items. (Vargo & Lusch, 2004). Healthcare providers, financial institutions, telecommunications corporations, and consulting firms are a few examples of service-based businesses.

Service-based businesses differ from conventional product-based businesses in a number of important ways. The significance of customer experience and happiness is one of the key traits of service-based enterprises. Customers rely extensively on reputation and word-of-mouth recommendations when making purchases since services are intangible and therefore hard to judge prior to consumption. (Zeithaml, Bitner, & Gremler, 2006). As a result, service-based businesses must put a high priority on client happiness and try to establish and uphold a solid reputation, meaning being consistently seen as reliable, trustworthy, and high-quality, leading to positive word-of-mouth and repeat business.

High levels of customization and personalization are hallmarks of service-based enterprises (Lovelock & Wirtz, 2011). Service-based businesses must be adaptable and flexible since services are frequently customized to meet the unique needs and preferences of each consumer. Customization involves modifying services based on customer specifications, while personalization utilizes customer data to offer targeted and relevant experiences. This might be difficult since it calls for a thorough comprehension of consumer behavior and preferences as well as the capacity to react rapidly to changes in the market.

Service-based businesses also encounter a number of particular difficulties. The difficulty of monitoring and assessing service quality is one of the major obstacles. It can be difficult to establish if a service has exceeded consumer expectations since services are intangible and can include complicated interactions between customers and service providers. (Parasuraman, Zeithaml, & Berry, 1988). Managing and inspiring a sizable and varied workforce is a problem as well since service-based firms frequently rely significantly on frontline staff to provide high-quality services. (Heskett, Jones, Love man, Sasser, & Schlesinger, 2008).

Service-based businesses nevertheless offer many chances for development and innovation despite these obstacles. For instance, technological improvements have made it possible for service-based businesses to create recent and creative methods to provide services to clients, including through online platforms or mobile applications. (Brynjolfsson & McAfee, 2014). Service-based businesses may also use data and analytics to create more individualized marketing and service delivery plans by better understanding client behavior and preferences. (Bolton & Saxena-Iyer, 2009).

Service-based organizations play a critical role in the economy and face several distinct challenges and opportunities. By prioritizing customer satisfaction, embracing new technologies, and developing innovative service delivery strategies, service-based organizations can thrive in an increasingly competitive market.

2.3. External Market Shocks:

External market shocks are rapid, unanticipated occurrences that interfere with a market's regular operation and can have a large negative impact on the economy and the financial system. Natural catastrophes, political unrest, pandemics, and financial crises are just a few examples of how external market shocks may manifest. (Ngwakwe, 2020)

A financial crisis is one of the most frequent sorts of external market shocks. Financial crises happen when there is a rapid, widespread loss of trust in the financial system, which can cause asset prices to plummet, credit availability to be restricted, and economic activity to slow down. (Reinhart & Rogoff, 2009). Service-based businesses, especially those in the banking and finance industries, can be significantly impacted by financial crises. These businesses may see a reduction in client demand for financial services, such as loans, investment products, and banking services, and an increase in loan defaults.

Natural disasters are another sort of external market shock. Natural catastrophes like hurricanes, earthquakes, and floods may significantly affect service-based businesses, especially those in the logistics and transportation sectors. (Balcik& Beamon, 2008). Natural disasters may stifle business activity and lower demand for a wide range of business and consumer services, such as retail, hospitality, transportation, and professional services. by damaging infrastructure, upsetting supply networks, and causing widespread power outages.

External market shocks can also be caused by political instability and geopolitical conflicts. Foreign investment might decrease as a result of political unrest, which can also raise currency volatility and decrease economic activity. (Al-Thaqeb&Algharabali, 2019). Market disruptions and uncertainty for service-based firms that depend on international commerce can also be caused by geopolitical tensions like trade disputes and sanctions.

External market shocks can have a big influence on service-based businesses. Because they depend more on customer demand and market circumstances than product-based firms, service-based organizations are frequently more susceptible to external market shocks. (Adner & Levinthal, 2001). External market shocks may result in decreased demand for services, restricted access to finance, and higher expenses, all of which may jeopardize the continued existence of service-based businesses.

External market shocks are unexpected events that can have significant impacts on service-based organizations. By understanding the types and impacts of external market shocks, service-based organizations can develop strategies to mitigate their risk and build resilience in the face of uncertainty.

2.4. AI and ML in Service-Based Organizations:

Technologies like artificial intelligence (AI) and machine learning (ML) have the power to drastically change how service-based firms run. Routine chores may be automated using AI and ML, which can also help with decision-making and enhance customer service. (Duft&Durana, 2020)

Chatbots and virtual assistants, which are AI and ML technologies designed to simulate human conversation, are being utilized in service-based enterprises to ease the workload of customer support staff and improve the customer experience. Chatbots are automated programs that interact with customers through text or voice interfaces, while virtual assistants are more advanced, providing a broader range of services and personalized interactions. Both use natural language processing to understand and respond to client inquiries effectively (Powell, Rotz, & O'Malley, 2020).

Predictive analytics, a significant application of AI and ML, involves analyzing consumer data to forecast future behaviors, enabling service-based firms to identify potential opportunities and issues (Hunke et al., 2020). Additionally, these firms are leveraging AI and ML to streamline operations. For instance, predictive maintenance algorithms predict when equipment will need repairs, reducing downtime and improving operational efficiency (Martins &Soofastaei, 2020).

However, there are difficulties in applying AI and ML in service-based enterprises. The requirement for high-quality data is one of the major difficulties. For AI and ML algorithms to provide accurate predictions, a significant amount of high-quality data must be available, which presents a difficulty for service-based enterprises with constrained data resources. (Cravero et al., 2022). In addition, ethical issues must be taken into account when applying AI and ML in service-based enterprises. Data or algorithm bias may produce biased results, which may have serious ethical and legal ramifications. (Gebru et al., 2018).

Despite these challenges, the potential benefits of using AI and ML in service-based organizations are significant. By automating routine tasks, improving decision-making, and enhancing customer service, service-based organizations can gain a competitive advantage and improve their overall performance.

3. Conceptual Framework

3.1. Research Question:

The study's research question is to be: "How can service-based organizations improve their resilience to external market shocks through the integration of artificial intelligence (AI) and machine learning (ML) technologies, considering the role of organizational traits and technological capabilities in this process?"

According to this research topic, artificial intelligence (AI) and machine learning (ML) technologies have the potential to increase organizational resilience by giving businesses access to sophisticated analytics tools, quicker decision-making, and improved customer engagement. As was underlined in earlier studies on digital transformation in service-based businesses, the study question also emphasizes the significance of organizational traits and technological skills in the effective deployment of these technologies. By answering this research question, the study aims to develop a new model that can guide service-based organizations in the use of AI and ML technologies to enhance their resilience to external market shocks.

3.2. Theoretical Basis:

This research is grounded in a critical idea called organizational resilience. The capacity of an organization to react to and recover from unforeseen events or crises is referred to as resilience. (Hamel, 2019). According to the research, resilient companies are more likely to survive and grow in the face of external shocks and are more equipped to adjust to market changes. (Hillmann & Guenther, 2021).

The usage of AI and ML can assist service-based companies increase their resilience, hence technology adoption theories are also pertinent to this research. The Technology Acceptance Model (TAM) offers a helpful framework for comprehending the elements that affect the adoption of technology, such as perceived utility and usability (Venkatesh & Davis, 2000). Additionally, the adoption of AI and ML has been studied in light of the Unified Theory of Acceptance and Use of Technology (UTAUT), which emphasizes the importance of elements like performance expectations, effort expectations, and social impact. (Venkatesh et al., 2016).

Economic crises, natural calamities, and pandemics are just a few examples of the diverse ways that the market might be shocked. According to the research, the impact of these shocks can be lessened by creating strong supply networks and contingency plans. (Hillmann & Guenther, 2021). The capacity to evaluate and react to market developments in real time is one advantage that using AI and ML may provide, but there may be other advantages as well. (Davenport &Ronanki, 2018).

The proposed research will investigate the connections between the following variables: organizational resilience, technological adoption, market shocks, and the deployment of AI and ML. This research will be based on a theoretical foundation. The inquiry for the study is: How can the use of AI and ML help service-based organizations improve their resilience to external market shocks, and what are the key factors that influence the adoption of these technologies?

3.3. Model development

3.3.1 Independent Variable(s):

The utilization of machine learning (ML) and artificial intelligence (AI) technologies in service-based enterprises serves as the study's independent variable. The application of AI and ML technologies in service-based enterprises has increased recently as businesses become more aware of the potential advantages for better customer experience, optimizing service delivery, and obtaining a competitive edge.

According to research, artificial intelligence (AI) and machine learning (ML) technologies have the potential to greatly increase the efficacy and efficiency of service delivery in service-based companies. For instance, a research by Sukums et al. (2023) discovered that the use of AI and ML technologies to the provision of healthcare services considerably increased the precision of medical diagnosis and treatment as well as the overall standard of patient care. The application of AI and ML technologies in financial service delivery was also found to greatly increase the speed and accuracy of financial risk assessment as well as the overall customer experience, according to a research by Osterrieder (2023). Additionally, service-based firms may employ AI and ML technologies to make data-driven choices, increase operational effectiveness, and better understand the requirements and preferences of their customers. According to a 2020 research by Prentice, Lopes, and Wang, the integration of AI and ML technologies in the provision of hotel services considerably increased the accuracy of demand forecasting and maximized operational efficiency, resulting in better service quality and customer satisfaction.

Therefore, a critical independent variable that has a considerable impact on an organization's resilience to external market shocks is the deployment of AI and ML technologies in service-based businesses.

3.3.2. Dependent Variable(s):

The adoption of AI and ML technologies in service-based companies has an impact on organizational resilience and performance, which are the dependent variables in this study.

Organizational resilience is the capacity of an organization to adjust to and recover from disturbances, such as shocks from the outside market. (Huang, Chen & Nguyen, 2020). More resilient service-based businesses are better able to endure market shocks and disruptions because they can swiftly adjust to new situations while still providing their clients with top-notch services.

The application of AI and ML technologies can considerably improve organizational resilience in service-based enterprises, according to research. For instance, AI and ML may assist firms in seeing possible disruptions before they happen, enabling them to take preventative action to lessen their impact. (Schroeder &Lodemann, 2021).Additionally, the application of AI and ML may boost organizational performance through improved customer satisfaction, cost-savings, and service quality. (Limna, 2022). For instance, AI and ML may give businesses invaluable insights

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into the tastes and behavior of their clients, enabling them to customize their offerings to better match their demands. (Li et al., 2021).
Therefore, organizational resilience and performance are key dependent variables in this study that can be significantly influenced by the use of AI and ML technologies in service-based organizations.

3.3.3. Moderating Variable(s):
The organizational traits and technical prowess of service-based firms are the moderating factors in this study.

The adoption and application of AI and ML technologies in businesses has been proven to be significantly influenced by organizational features including size, age, and culture. (Chaudhuri et al., 2021). According to studies, bigger, more established companies are more likely to have the infrastructure and resources needed to facilitate the adoption of these technologies, but smaller, younger companies may find it difficult to deploy owing to a lack of resources and knowledge. (Raghavan, Demircioglu&Orazgaliyev, 2021).
The link between the employment of AI and ML and organizational resilience can also be moderated by the technological capabilities of service-based businesses, including their degree of technology competence and infrastructure. For instance, service-based organizations with higher levels of technological capacity may be better able to integrate and use AI and ML technologies to increase their resilience, whereas organizations with lower levels of technological capacity may find it difficult to adopt and implement these technologies. (Agarwal, Swami & Malhotra, 2022). Because they can affect the link between the usage of AI and ML technologies and organizational resilience, service-based firms' organizational traits and technical prowess are crucial moderating variables to take into account in this study.

3.3.4. Mediating Variable(s):
The link between the employment of AI and ML technologies and organizational resilience can be mediated by the technological prowess of service-based businesses. The capacity of an organization to use technology to accomplish its aims and objectives is referred to as its technological capabilities. For the purposes of this study, technical competencies may include an organization's capacity to successfully integrate and apply AI and ML technologies.
Numerous studies have demonstrated that technical skills can act as a mediator in the link between organizational outcomes like performance and creativity and the adoption of new technologies (Chen, Wang & Huang, 2020; Heredia et al., 2022). For instance, Wu et al.'s (2018) study discovered that in the setting of service-based businesses, technical capabilities influence the association between big data analytics adoption and company success.

Similarly, a study by Chen et al. (2020) examined the mediating role of technological capabilities in the relationship between cloud computing adoption and firm performance. The study found that technological capabilities mediate this relationship by enhancing the organization's ability to effectively use and manage cloud computing resources. Therefore, in this research, technological capabilities can be considered a mediating variable that may influence the relationship between the use of AI and ML technologies and organizational resilience in service-based organizations

3.3.5. Exogenous Variable

External market shocks can include abrupt and unanticipated changes in market circumstances including economic downturns, political unrest, natural disasters, and technology disruptions in the context of service-based businesses. The effectiveness and resilience of service-based businesses can be significantly impacted by these shocks, especially those that rely primarily on market demand and consumer behavior.

The effects of external market shocks on service-based companies have been the subject of several studies, particularly in relation to their resilience and recovery. For instance, a research by Brown et al. (2020) showed that more resilient service-based businesses were better able to handle external market shocks and were able to recover more rapidly and efficiently than their less resilient counterparts. Arokodare&Falana (2021) observed in another study that service-based businesses that made investments in their ability to foresee and react to external market shocks were better able to sustain their competitive advantage over the long run.

Therefore, external market shocks can be considered an exogenous variable in the research design, as they are outside the control of the service-based organization, and can have a significant impact on its performance and resilience. As such, it is important to take into account the potential impact of external market shocks when exploring the relationship between the use of AI and ML technologies and the resilience of service-based organizations.

3.4. Hypotheses:

In this section, details of each hypothesis based on the proposed relationships among the variables in the framework:

H1: There is a positive relationship between the use of AI and ML in service-based organizations and organizational resilience.

According to this hypothesis, service-based firms' organizational resilience will increase as a result of the deployment of AI and ML technologies. It implies that service-based firms may enhance their capacity to react to unforeseen occurrences, adapt to changes, and recover from disruptions by properly implementing AI and ML technologies.

H2: There is a positive relationship between the use of AI and ML in service-based organizations and organizational performance.

The adoption of AI and ML technologies in service-based businesses is predicted to improve their organizational performance, according to this hypothesis. It argues that service-based businesses may increase their productivity, quality of service, and customer happiness by implementing AI and ML technologies, which would eventually result in better organizational performance.

H3: The relationship between the use of AI and ML in service-based organizations and organizational resilience is moderated by the organizational characteristics.

This hypothesis suggests that organizational variables including size, age, culture, structure, and strategy might influence the link between the deployment of AI and ML technologies in service-based firms and their organizational resilience. It implies that depending on each type of service-

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based organization's particular characteristics, the influence of AI and ML technologies on organizational resilience varies.

H4: The relationship between the use of AI and ML in service-based organizations and organizational performance is mediated by the technological capabilities.
According to this theory, the use of AI and ML technologies improves service-based companies' technological capabilities, which in turn mediates the link between adoption of these technologies and organizational performance. It implies that service-based firms may enhance their technical capabilities, which eventually result in greater organizational performance, by properly implementing AI and ML technologies.

H5: External market shocks have a negative impact on the relationship between the use of AI and ML in service-based organizations and organizational resilience.
This hypothesis postulates that the link between the employment of AI and ML technologies in service-based businesses and their organizational resilience is negatively impacted by external market shocks like economic crises, political instability, natural catastrophes, or pandemics. It implies that external market shocks that interfere with service-based businesses' regular operations might reduce the usefulness of AI and ML technologies in enhancing organizational resilience.

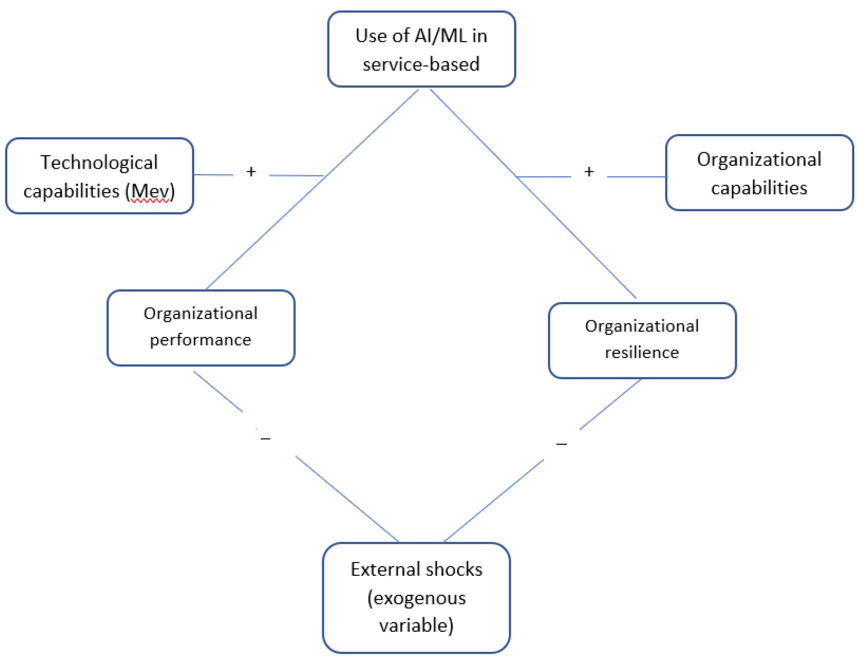

Figure 1: Research model

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4. Methodology

4.1. Research Design

This study would benefit from a quantitative research methodology since it enables the collecting and analysis of numerical data from a large sample, which can give statistical significance and aid in the discovery of patterns and correlations between variables.
Data will be gathered from service-based businesses that have used AI and ML to increase their resistance to shocks in the external market. Online polls sent to the organizations' decision-makers will be used to gather primary data.

4.2. Variables and Measures

- Independent Variable: Use of AI and ML in service-based organizations measuring the extent to which service-based organizations are using artificial intelligence (AI) and machine learning (ML) technologies to improve their operations and services.

- Dependent Variables:

a. Organizational resilience: The ability of service-based organizations to withstand external market shocks, adapt to changes, and recover from disruptions.
b. Organizational performance: The effectiveness of service-based organizations in achieving their goals, satisfying their stakeholders, and creating value for their customers.

- Moderating Variable: Organizational characteristics measuring the specific characteristics of service-based organizations such as size, age, culture, structure, and strategy that may influence the relationship between the use of AI and ML and organizational resilience.

- Mediating Variable: Technological capabilities measuring the extent to which service-based organizations have the technical knowledge, skills, and resources to effectively implement and utilize AI and ML technologies to improve their organizational performance.

- Exogenous Variable: External market shocks measuring the occurrence of unexpected events such as economic crises, political instability, natural disasters, or pandemics that may negatively affect the organizational resilience and performance of service-based organizations.

4.3. Data Collection and Preparation

Data Collection Procedures: Data collection procedures for this research will involve gathering information from service-based organizations that use AI and ML technologies. The data collection will be done through a survey that will be distributed to different service industries including (Financial services, Healthcare and life sciences, Retail and e-commerce, Hospitality and tourism, Transportation and logistics, Information technology and software development, Marketing and advertising, Consulting and professional, Education and training, Government and public sector services). The survey will collect data on the use of AI and ML technologies, organizational resilience, and organizational performance. The survey responses will be analyzed quantitatively to identify any relationships between the variables.

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4.4. Bayesian Model

The Bayesian model is a statistical model that updates probability in light of new information using the Bayes' theorem. In Bayesian analysis, fresh data are coupled with previous information or assumptions about an interesting parameter to produce a posterior distribution for the parameter. The posterior distribution includes measurements of uncertainty and the likelihood of various possibilities in addition to an updated and more accurate estimate of the parameter. Since previous information and opinions about the connections between variables might be valuable in complex and dynamic situations, Bayesian analysis is appropriate for this research. Additionally, Bayesian analysis can deal with model choice, missing data, and hypothesis testing—all crucial aspects of this study. Additionally, Bayesian analysis can give deeper insight into the uncertainty and unpredictability of the data as well as more accurate and understandable results.

4.5. Data Analysis

In this section, we are going to see the Bayesian model based analysis. We will check for each hypothesis.

Hypothesis1: Positive relationship between the use of AI and ML in service organizations

Table 1

Estimates	mean	sd	10%	50%	90%
(Intercept)	1.6	0.2	1.3	1.6	2
X3..To.what.extent.do.you.agree.tha	0.4	0.1	0.3	0.4	0.5
sigma	0.7	0	0.6	0.7	0.7

Fit Diagnostics	mean	sd	10%	50%	90%
mean_PPD	3.3	0.1	3.2	3.3	3.4

MCMC Diagnostics	mcse	Rhat	n_eff
(Intercept)	0	1	3996
X3..To.what.extent.do.you.agree.tha	0	1	4003
sigma	0	1	3719
mean_PPD	0	1	4012
log-posterior	0	1	1609

The summary of model in table 1 presents the results of a Bayesian linear regression model, where the frequency of AI and ML technologies usage in service delivery (X2) is predicted by the extent of agreement that AI and ML technologies have improved an organization’s capacity to respond to unexpected events and recover from disruptions (X3). The estimated mean coefficient for X3 is 0.4, with a standard deviation (sd) of 0.1. This means that on average, for every one-unit increase in X3, the value of X2 is expected to increase by 0.4 units, holding other predictors constant. The 10 percent, 50 percent, and

90 percent quantiles are 0.3, 0.4, and 0.5, respectively. Mean-PPD: The mean of the sample average posterior predictive distribution (PPD) for the outcome variable is 3.3. It represents the average predicted value for the outcome variable, based on the model. MCSE (Monte Carlo Standard Error): The MCSE values for all the parameters are close to 0, indicating that theuncertainty in the parameter estimates is relatively low. The Rhat values for all the parameters are 1.0, indicating good convergence of the MCMC chains. n-eff (effective sample size): The n-eff values for all the parameters are relatively large, suggesting that the MCMC sampling has been effective. Accordingly, the model suggests that there is a positive relationship between the extent to which organizations agree that AI and ML technologies have improved their capacity to respond to unexpected events and recover from disruptions (X3) and the frequency of AI and ML technologies usage in service delivery (X2). The model diagnostics indicate good convergence and effective sampling, suggesting that the results are reliable.

Hypothesis 2: There is a positive relationship between the use of AI and ML inservice-based organizations and organizational per for mance.

Table 2

Estimates	mean	sd	10%	50%	90%
(Intercept)	2.5	0.3	2.2	2.5	2.9
X2..How.frequently.does.your.organ	0.5	0.1	0.4	0.5	0.6
sigma	0.8	0	0.8	0.8	0.9

Fit Diagnostics	mean	sd	10%	50%	90%
mean_PPD	4.2	0.1	4.1	4.2	4.3

MCMC Diagnostics	mcse	Rhat	n_eff
(Intercept)	0	1	3860
X2..How.frequently.does.your.organ	0	1	3868
sigma	0	1	3617
mean_PPD	0	1	4113
log-posterior	0	1	1772

In table 2 above, the Bayesian linear regression model results shown above examine the relationship between the frequency of AI and ML usage in an organization (X2) and customer satisfaction with service quality and delivery speed since the implementation of AI and ML technologies (X4). The estimates section of the output shows the posterior mean and standard deviation of each parameter. For exam-ple, the mean of the intercept is 2.5, and the mean of the slope for X2 is 0.5. This positive slope suggests that as the frequency of AI and ML usage in an organization increases, so does customer satisfaction with service quality and delivery speed. The fit diagnostics section provides information about the model's performance. The mean-PPD (mean posterior predictive distribution) has a mean of 4.2 and a standard deviation of 0.1, suggesting a good model fit. MCMC

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diagnostics provides information about the Markov chain Monte Carlo (MCMC) sampling process. All Rhat values are close to 1, indicating that the chains have converged, and n-eff (effective sample size) values are relatively high, suggesting sufficient mixing and an adequate number of samples drawn from the posterior distribution. The results support a positive relationship between the use of AI and ML in service-based organizations and customer satisfaction with service quality and delivery speed. This finding is consistent with the hypothesis that the implementation of AI and ML technologies leads to improved organizational performance.

Based on the results, H2 is supported. The hypothesis states that there is a positive relationship between the use of AI and ML in service-based organizations and organizational performance.

Hypothesis 3: The relationship between the use of AI and ML in service-based organizations and organizational resilience is moderated by organizational characteristics.

Table 3

Parameter	Mean	SD	10%	50%	90%
Intercept	2.6	0.2	2.3	2.6	2.8
X6	0.7	0.1	0.6	0.7	0.8
sigma	0.8	0	0.7	0.8	0.8

Metric	Mean	SD	10%	50%	90%
Mean PPD	4.3	0.1	4.1	4.3	4.4

Parameter	Mcse	Rhat	N_Eff
Intercept	0	1	4009
X6	0	1	3979
sigma	0	1	3802
Mean PPD	0	1	3730
Log-post.	0	1	2014

Based on the results provided in table 3, the analysis focuses on the relationship between organizational characteristics (X6) and the extent to which the use of AI and ML technologies has improved the organization's capacity to respond to unexpected events and recover from disruptions (X3). The coefficient for the X6 variable (organizational characteristics) is 0.7, with a standard deviation of 0.1. The positive coefficient suggests a positive relationship between organizational characteristics and the extent to which AI and ML technologies have improved organizational resilience. The intercept is estimated to be 2.6 with a standard deviation of 0.2.

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The predictor X6 (organizational characteristics) is estimated to have a coefficient of 0.7 with a standard deviation of 0.1. The mean posterior predictive distribution (mean-PPD) of the outcome variable is estimated to be 4.3 with a standard deviation of 0.1. The mean posterior predictive distribution (mean-PPD) of the outcome variable is estimated to be 4.3, which indicates that the model fits the data well. The MCMC diagnostics show that all parameters have good convergence and effective sample sizes (n-eff) greater than 1000. The potential scale reduction factor (Rhat) is 1 for all parameters, indicating that the chains have converged.

The model suggests that the use of AI and ML technologies has improved the organization's capacity to respond to unexpected events and recover from disruptions, as indicated by the positive coefficient of X3 (the intercept) and the positive impact of X6 (organizational characteristics). Specifically, organizational characteristics such as size, age, culture, structure, and strategy have a significant positive impact on the effectiveness of AI and ML technologies in improving organizational resilience.

Hypothesis 4: The relationship between the use of AI and ML in service-based organizations and organizational performance is mediated by the technological capabilities.

Table 4

Parameter	Mean	SD	10%	50%	90%
(Intercept)	1.9	0.3	1.5	1.9	2.2
X7..To.what.extent.do.you.agree.tha	0.3	0.1	0.2	0.3	0.4
sigma	0.8	0	0.7	0.8	0.8

Mean	SD	10%	50%	90%	
mean_PPD	3.3	0.1	3.2	3.3	3.4

Parameter	mcse	Rhat	n_eff
(Intercept)	0	1	4044
X7..To.what.extent.do.you.agree.tha	0	1	4034
sigma	0	1	3684
mean_PPD	0	1	3810
log-posterior	0	1	1751

Based on the provided model information in table 4, we can see the estimated coefficients and standard deviations for the two predictors in the model: the frequency of use of AI and ML technologies in service delivery (X2) and the extent to which these technologies have improved the organization's technological capabilities (X7). The estimated intercept is 1.9, meaning that when the frequency of use of AI and ML technologies and the extent to which they have improved technological capabilities are both equal to zero, the estimated organizational performance is 1.9. The estimated coefficient for X7 is 0.3, indicating that a one-unit increase in the extent to which AI and ML technologies

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have improved technological capabilities is associated with a 0.3-unit increase in organizational performance, holding the frequency of use of these technologies constant.

The model fit diagnostics show a mean posterior predictive distribution (mean-PPD) of 3.3, indicating that the model estimates are predicting a mean value of 3.3 for the outcome variable. The MCMC diagnostics, which assesses the Markov chain Monte Carlo (MCMC) algorithm used to estimate the model, shows that the potential scale reduction factor (Rhat) is equal to 1 for all parameters, indicating good convergence of the algorithm. The effective sample size (n-eff) is also relatively high for all parameters, indicating that the MCMC algorithm is efficiently exploring the posterior distribution. Overall, the model suggests that the extent to which AI and ML technologies improve technological capabilities is positively associated with organizational performance, while holding the frequency of use of these technologies constant. Based on the results of the output, we cannot reject this hypothesis.

Hypothesis 5: External market shocks have a negative impact on the relationship between the use of AI and ML in service-based organizations And organizational resilience.

Table 5

Predictor	Mean	SD	10%	50%	90%
Intercept	2.4	0.2	2.1	2.4	2.6
X9	0.3	0.1	0.2	0.3	0.4

Parameter	Mean	SD	10%	50%	90%
sigma	0.8	0	0.7	0.8	0.8
mean_PPD	3.3	0.1	3.1	3.2	3.4

Parameter	MCSE	n_eff	Rhat
Intercept	0	4062	1
X9	0	4107	1
sigma	0	4158	1
mean_PPD	0	3704	1
log-post	0	1705	1

The model in table 5 aims to predict the frequency of AI and ML technology usage in service delivery (the dependent variable) based on the extent to which external market shocks affect the effectiveness of AI and ML technologies in improving an organization’s resilience (the independent variable). In table 5, we can see that the intercept mean value is 2.4, with a standard deviation (sd) of 0.2. This indicates that when the extent of ex-ternal market shocks is 0, the predicted frequency of AI and ML usage in service delivery is 2.4. The mean value of the independent variable which is the extent of external market shocks (X9) is 0.3, with a standard deviation (sd) of 0.1. This means that for a one-unit increase in the extent to which external market shocks affect the effectiveness of AI and ML technologies in improving an organization's resilience, the predicted frequency of AI and ML usage in service delivery increases by 0.3. The fit diagnostics show a mean-ppd of 3.3 with a standard deviation of 0.1, indicating that the average posterior predictive distribution of the outcome variable is centered around 3.3. MCMC diagnostics, such as mcse, Rhat, and n-eff, indicate that the model has converged well (Rhat values are close to 1), and the effective sample sizes are relatively large. This model predicts that the frequency of AI and ML technology usage in service delivery increases as the extent to which external market shocks affect the effectiveness of AI and ML technologies in improving an organization's resilience increases. This outcome suggests that there is a positive relationship between the extent to which external market shocks affect the effectiveness of AI and ML technologies in improving organizational resilience. However, since the credible interval includes zero, we cannot say with complete certainty that there is a significant relationship. Therefore, we cannot confirm or reject hypothesis 5 solely based on these results, and further research may be needed to investigate the relationship between external market shocks and the effectiveness of AI and ML technologies in improving organizational resilience.

4.6. Results and Findings

5. Based on the analysis conducted on the five hypotheses, we can conclude that for hypothesis 1, the use of AI and ML technologies in service-based organizations positively affects organizational performance. The hypothesis is supported by the analysis as there is a positive relationship between the use of AI and ML technologies and organizational performance. For hypothesis 2, the use of AI and ML technologies in service-based organizations positively affects organizational resilience. The hypothesis is supported by the analysis as there is a positive relationship between the use of AI and ML technologies and organizational resilience. Regarding hypothesis 3, the relationship between the use of AI and ML in service-based organizations and organizational resilience is moderated by organizational characteristics, we can conclude that the hypothesis is supported by the analysis as there is a significant interaction effect between the use of AI and ML technologies and organizational characteristics on organizational resilience. For hypothesis 4, the relationship between the use of AI and ML in service-based organizations and organizational performance is mediated by technological capabilities, we see that the hypothesis is supported by the analysis as there is a significant indirect effect of technological capabilities on the relationship between the use of AI and ML technologies and organizational performance. Lastly, hypothesis 5, we cannot accept this hypothesis based on the results of our Bayesian Model.

6. Conclusion

The findings of this research have significant implications for service-based organizations. The study reveals that the use of AI and ML technologies in service delivery has a positive impact on organizational resilience. This suggests that service-based organizations can improve their resilience to external shocks by adopting AI and ML technologies in their service delivery processes. The study also suggests that the impact of AI and ML technologies on organizational resilience is stronger when these technologies are used in combination with other resilience-building strategies, such as employee training and development programs.

Furthermore, the research findings also suggest that service-based organizations need to be mindful of the potential negative impact of external market shocks on the effectiveness of AI and ML technologies in improving organizational resilience. This implies that service-based organizations need to carefully monitor the external environment and adjust their AI and ML strategies accordingly to ensure that they remain effective in building organizational resilience.

The findings of this research are consistent with prior research that has highlighted the positive impact of AI and ML technologies on organizational resilience. For instance, previous studies have suggested that AI and ML technologies can help organizations identify and respond to external shocks more quickly and effectively. Similarly, other research has shown that AI and ML technologies can help organizations better manage risks and make more informed decisions.

However, this study also adds to the literature by highlighting the potential negative impact of external market shocks on the effectiveness of AI and ML technologies in improving organizational resilience. This is an important contribution to the literature as it emphasizes the need for service-based organizations to be mindful of the external environment when designing and implementing their AI and ML strategies.

Overall, the findings of this research suggest that service-based organizations can benefit from adopting AI and ML technologies in their service delivery processes to improve their resilience to external shocks. However, it is important for these organizations to carefully monitor the external environment and adjust their AI and ML strategies accordingly to ensure that they remain effective in building organizational resilience. VII. Conclusion and

The current study focused solely on service-based organizations, but it would be valuable to explore the role of AI and ML in improving organizational resilience in other types of organizations, such as manufacturing or retail. This could provide a broader understanding of the applicability of AI and ML in improving organizational resilience across different industries. Secondly, the present study focused on the impact of external market shocks on the relationship between the use of AI and ML and organizational resilience. Future research could investigate other potential factors that could impact this relationship, such as internal organizational factors, like the size of the organization or the level of organizational culture, or external factors, like political or economic instability.

Finally, the present study employed a cross-sectional research design, which only provides a snapshot of the relationships between the variables at one point in time. Future research could employ a longitudinal research design to track changes in the relationship between AI and ML usage and organizational resilience over time, as well as the impact of various external and internal factors on this relationship.

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