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Machine Learning and Industrial Strategy of Resilient and Predictive Maintenance: Proposal of A Conceptual Research Model in Morocco

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ABSTRACT: The rise of machine learning in predictive maintenance is redefining industrial strategies, and improving operational performance and business resilience in the face of disruptions. However, although this technology has demonstrated its potential in various sectors, the literature remains lacking regarding its precise impact in emerging economies, particularly in Morocco. This study proposes an innovative conceptual model, structuring the analysis of the links between the integration of machine learning, organizational factors, and industrial resilience. By mobilizing theoretical frameworks such as the theory of dynamic capabilities and that of complex adaptive systems, we highlight the mediating role of digital maturity, data diversity, and organizational flexibility in the optimization of predictive maintenance strategies. The proposed methodological approach is based on a mixed approach, combining a quantitative analysis using structural equation modeling (SEM), to empirically test the structural relationships, and a qualitative study using semi-structured interviews, aimed at contextualizing the dynamics underlying the adoption of machine learning. This methodological triangulation ensures robust validation of hypotheses and identifies the organizational and technological factors that determine the effectiveness of these tools. The expected results will contribute to a better understanding of the strategic levers that allow companies to fully exploit machine learning in predictive maintenance while proposing avenues for improvement for research and industrial practice. This study is thus part of an evolutionary perspective, paving the way for future empirical investigations on the optimal adoption of artificial intelligence technologies in Industry 4.0.

KEYWORDS. Machine learning, Research proposal, Resilience, Industry, Morocco

I. INTRODUCTION

The rise of artificial intelligence is strengthening industrial resilience by enabling adaptive decision-making and proactive maintenance. Through machine learning and IoT, Industry 4.0 enhances firms' ability to anticipate disruptions, optimize operations, and sustain performance in volatile environments. This transformation reinforces not only predictive and proactive maintenance strategies but also the broader capacity of organizations to absorb, recover from, and thrive amid industrial challenges, positioning data-driven decision-making and real-time adaptability at the core of resilient manufacturing systems.

In this dynamic, the Moroccan industrial ecosystem is gradually integrating into this technological paradigm **[1]**. The automation and interconnection of production chains offer unprecedented prospects for improving competitiveness **[2, 3].** More specifically, cost-reduction adoption strategies are becoming imperative in an environment marked by increased economic pressures **[4].** According to Porter **[5],** cost control is one of the most effective strategic levers for ensuring a sustainable competitive advantage, through automation, predictive maintenance, and supply chain optimization **[6].** By embracing automation and predictive maintenance, the Moroccan industrial ecosystem enhances **its resilience**, enabling firms to withstand economic pressures while sustaining long-term competitiveness.

Predictive maintenance, in particular, is an essential lever for this transition. Unlike reactive or preventive approaches, it relies on continuous analysis of data from smart sensors to anticipate breakdowns and optimize equipment availability **[7, 8].** This approach leverages AI and machine learning to improve the resilience of industrial infrastructure **[9],** reduce production interruptions **[10],** and enhance the reliability of manufacturing operations **[11, 12].** In this sense, predictive maintenance is not only a cost-reduction tool but is also an essential building block of industrial digital transformation. Machine learning, for its part, plays a central role in this reconfiguration of industrial strategies. By analyzing massive volumes of data, these algorithms can identify inefficiencies that are invisible on a human scale **[13, 14].** Their dynamic learning capacity makes it possible to adjust maintenance operations in real-time and optimize resource management **[15].** In the field of predictive maintenance, these technologies significantly reduce the costs associated with unplanned downtime and repairs, thereby improving overall operational performance **[16].** By minimizing disruptions and ensuring operational continuity, predictive maintenance strengthens industrial resilience, enabling companies to adapt to uncertainties and sustain long-term performance.

However, despite the growth of research on machine learning and its industrial applications, the literature remains incomplete regarding its precise role in predictive maintenance strategies and its effects on industrial resilience, particularly in the Moroccan context. This observation raises a major question: **to what extent does the integration of machine learning into predictive maintenance strategies influence the resilience of the Moroccan industry, and what strategic mediating mechanisms explain this impact?** This study introduces a conceptual research model designed to examine how machine learning shapes predictive maintenance strategies and enhances industrial resilience. Rather than presenting immediate empirical findings, this work establishes a solid theoretical foundation by identifying key technological and organizational determinants influencing the effective deployment of these technologies. Grounded in an extensive literature review, this model draws from dynamic capability theory and complex adaptive systems theory, providing a structured approach to conceptualizing the interplay between machine learning algorithms, organizational processes, and industrial performance. By integrating these theoretical perspectives, the study formulates testable hypotheses, offering a roadmap for future empirical validation. To bridge the gap between theory and practice, we outline a methodological framework detailing the essential steps for empirical investigation, including research design, data collection strategies, and appropriate analytical techniques. This structured approach ensures that future studies can rigorously test and refine the proposed model, contributing both to academic discourse and industrial applications. This study constitutes a first step toward a more in-depth exploration of the conditions for the success of machine learning in predictive maintenance, providing a structuring framework for both researchers and industrial practitioners.

II. LIMITATIONS OF EXISTING RESEARCH AND JUSTIFICATION FOR A NEW CONCEPTUAL MODEL

Research on predictive maintenance and machine learning in Industry 4.0 has widely documented technological advances to improve the efficiency of industrial processes. Most of the existing work has focused on the performance of algorithms, examining their ability to anticipate failures and reduce maintenance costs **[17].** However, a more detailed analysis of this literature highlights significant blind spots, particularly regarding how these technologies fit into the strategic and organizational realities of industrial companies, particularly in emerging economies. The first major gap lies in the dominant approach of these studies, which tends to isolate the technology from its application context. While industrial engineering research has demonstrated that integrating machine learning into predictive maintenance strategies can improve equipment availability and optimize resource management **[18,19]**, it has often neglected the organizational and human factors that influence the effective adoption of these tools. However, several studies in technology management and organizational sciences highlight that the performance of a technological system depends as much on the quality of the algorithm as on how it is integrated into decision-making processes and accepted by industrial stakeholders **[20,21].** In other words, technological innovation alone does not necessarily lead to improved performance unless it is accompanied by a proper structural and strategic transformation.

A second limitation of the literature lies in the lack of models that consider industrial resilience in the analysis of predictive maintenance strategies. Current approaches focus primarily on cost reduction and short-term operational optimization, without truly considering the dynamic capacities of companies to absorb exogenous shocks (economic crises, supply disruptions, market instability) **[16, 22, 23].** However, according to dynamic capabilities theory **[24],** an organization's resilience does not rely solely on the optimization of its internal processes, but also on its ability to adapt and learn in the face of uncertainty. Applying this framework to machine learning in predictive maintenance would broaden the discussion by analyzing how these technologies can strengthen not only industrial efficiency but also the ability of companies to adjust to economic and technological disruptions **[6].**

Finally, most existing empirical studies are based on Western industrial contexts, where access to digital infrastructure and specialized skills is relatively homogeneous. Little research has explored the specific challenges of emerging countries, where industrial structures are more fragmented, access to advanced technologies is more unequal, and human resource training is often insufficient to ensure optimal adoption of these innovations **[25].** In Morocco, these structural constraints require an adaptation of traditional technology adoption models, considering local ecosystems, institutional logic, and specific economic models.

These various gaps justify the proposal of a new conceptual model, integrating a multi-dimensional approach to the role of machine learning in predictive maintenance. Unlike purely technocentric models, this framework aims to articulate the interactions between technologies, organizational processes, strategic behaviors, and macroeconomic issues. It is not simply a matter of measuring the performance of algorithms, but of analyzing the conditions necessary for their effective adoption in an emerging industrial context, highlighting the levers and structural obstacles that shape their implementation. Such an approach would not only fill an academic gap but also provide operational avenues for companies seeking to strengthen their competitiveness and resilience in the face of the challenges of Industry 4.0.

III. FORMULATION OF HYPOTHESES

Integrating machine learning into predictive maintenance strategies and its impact on industrial resilience requires a deep understanding of the contextual, organizational, and technological factors that shape its impact. To this end, we drew on several complementary theoretical frameworks, which together provide a broader and more nuanced view of the underlying processes. These theories, far from being limited to technical models, highlight dynamic, contextual, and strategic aspects essential for understanding how these technologies are used in complex industrial environments. Dynamic capabilities theory **[26]** is particularly relevant in this context, as it emphasizes that a company's resilience depends not only on its current resources but also on its ability to react and adapt to changes in its environment. In the context of predictive maintenance, this means that adopting machine learning does not necessarily lead to immediate performance gains. These gains are mediated by the organizational capacity to reconfigure existing processes, integrate the knowledge produced by the algorithms, and use this information to adjust industrial strategies. Thus, it can be deduced that the performance of machine learning algorithms in predictive maintenance is not measured solely by their technical accuracy, but also by their integration into companies' organizational and strategic processes. This reasoning leads us to formulate the first hypothesis:

H1: The performance of machine learning algorithms in predictive maintenance is mediated by companies' organizational resilience to reconfigure their processes based on recommendations from predictive models.

From a complementary perspective, the theory of complex adaptive systems **[27]** emphasizes the dynamic and nonlinear interactions between a system's components. This perspective is crucial because it helps us understand why data diversity and granularity play a central role in the effectiveness of machine learning algorithms. The more interconnected production systems are and the more diverse and detailed their data, the more predictive models can capture complex behavioral patterns, improving their ability to accurately anticipate failures. This idea leads us to a second hypothesis, which directly links data quality to the effectiveness of machine learning tools in predictive maintenance:

H2: The accuracy of machine learning models in predictive maintenance is positively influenced by the diversity and granularity of data collected from industrial equipment.

Another key dimension is that of technological change, and more specifically, the co-evolution between technology and the economic and social environment in which it is introduced, as **[28]** emphasizes. This theory invites us to reflect on technology adoption, not only from the perspective of its technical potential but also in terms of adapting to external conditions, such as the level of digital maturity of companies. In contexts such as Morocco, where digital infrastructure can be uneven and data science skills are limited in certain industries, it is reasonable to assume that the impact of machine learning on predictive maintenance varies depending on the level of the digital readiness of companies. This reflection thus raises a third hypothesis:

H3: The impact of machine learning on predictive maintenance is modulated by the level of digital maturity of industrial companies, thus influencing their ability to effectively leverage these technologies.

Finally, industrial risk management theory **[29]** offers a crucial perspective on business resilience in the face of disruptions. This theory argues that industrial resilience goes beyond simple cost optimization: it includes an organization's ability to anticipate, absorb, and quickly recover from disruptions. In the context of predictive maintenance, this implies that companies capable of integrating machine learning systems into their maintenance strategies not only optimize costs, but also strengthen their ability to cope with crises, whether economic, technological, or structural. This leads us to formulate a final hypothesis:

H4: Integrating machine learning into predictive maintenance strategies improves industrial resilience by reducing vulnerability to production interruptions and external shocks.

These hypotheses form the basis of an empirical investigation that aims to systematically explore how these various dimensions—organizational, technological, and contextual—interact to shape the efficiency and industrial resilience of companies. This approach sheds light not only on the success mechanisms but also on the obstacles that must be overcome to maximize the impact of machine learning in complex and diverse industrial contexts, such as that of Morocco.

Figure 1 highlights a graphical summary of hypotheses relationships.

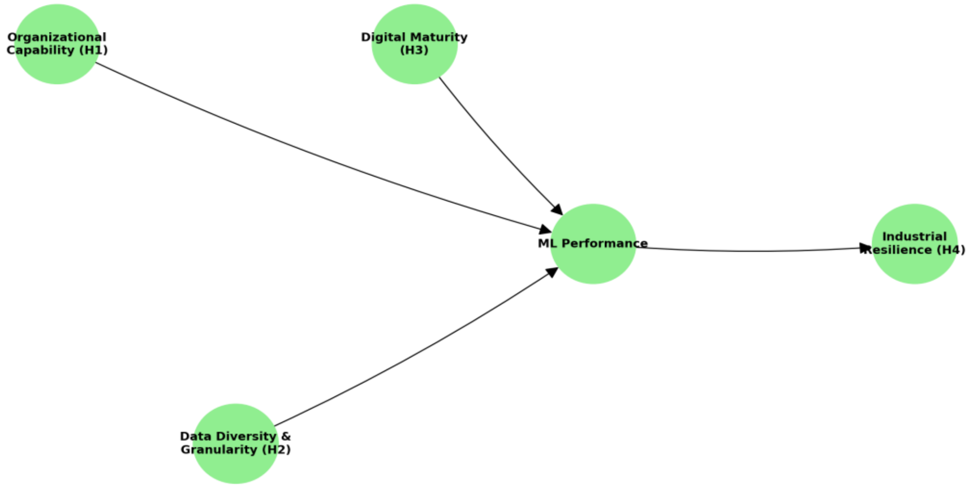

Figure 1. Summary of hypotheses relationships
Source. Authors

IV. CONCEPTUAL RESEARCH MODEL: STRUCTURING AND JUSTIFICATION

The integration of machine learning into predictive maintenance strategies represents a major technological advance, but its real impact on industrial resilience cannot be analyzed through a purely technocentric lens. Our conceptual model, shown schematically in Figure 1, offers a more systemic reading of this relationship, highlighting the structural and organizational factors that determine the effectiveness of these technologies. This theoretical framework thus makes it possible to go beyond traditional linear approaches by integrating intermediation mechanisms, which influence the transformation of the predictive capabilities of machine learning into real gains in industrial performance.

A. Presentation of the model and included variables

Table 1 presents our model and articulates three levels of variables in dynamic interaction:

Table 1. Variables modeling

Variables	Justification
Independent variable (IV)	**Integration of machine learning in predictive maintenance:** This is the degree of adoption of machine learning algorithms in industrial strategies, measured by the effective use of predictive models and their integration into decision-making processes.
Mediating variables (MV)	**Organizational adaptability:** The company's ability to restructure its internal processes to maximize the value generated by algorithmic recommendations. **Data diversity and granularity:** The richness and precision of industrial data used to train machine learning models, influencing their ability to generate actionable predictions. **Digital maturity of companies:** The level of technological readiness and data science expertise that enables the effective adoption and deployment of machine learning-based solutions.
Dependant variables (DV)	**Industrial resilience:** The ability of companies to reduce production interruptions, optimize resource management and strengthen their flexibility in the face of external shocks.

Source. Authors

B. Underlying logic of the model and interactions between variables

Integrating machine learning into predictive maintenance is a key lever for strengthening industrial resilience, but its effectiveness does not rely solely on technology adoption. It depends on several mediating factors that determine its real impact on business performance. Organizational adaptability plays a key role in enabling companies to readjust their internal processes to take full advantage of the recommendations generated by algorithms. At the same time, the diversity and granularity of data directly influence the reliability of predictive models: the richer and more precise the data, the more relevant maintenance decisions become. Finally, the digital maturity of companies determines their ability to effectively adopt, deploy, and operate these advanced solutions. When these three dimensions are aligned, companies can not only reduce production interruptions and optimize resource management but also develop greater flexibility in the face of external shocks, thus strengthening their resilience in a changing industrial environment.

Machine learning cannot be limited to simple maintenance automation; it requires the ability to reconfigure organizational processes. In companies where decision-making is centralized and rigid, predictive algorithms risk producing underutilized or even ignored recommendations. Conversely, companies with a learning culture and agile governance are more likely to leverage the information generated, thus translating the technological potential into real strategic advantages.

The performance of predictive maintenance models depends on the quantity and quality of the data that feeds them. Fragmented, biased, or homogeneous data collection drastically reduces their effectiveness, leading to erroneous decisions. This dimension is particularly critical in emerging industries, where access to reliable and diverse databases remains a challenge. Thus, data granularity is not a secondary technical variable, but a structuring factor in the success of machine learning applied to maintenance.

Adopting machine learning requires an appropriate infrastructure and data science expertise. A company with strong digital maturity will be able to fully exploit predictive models, while an ill-prepared organization risks introducing biases into its interpretation of results, or even adopting these tools superficially without significant impact. This mediation is all the more crucial in a context like Morocco's, where the degree of digitalization of industries varies considerably.

V. THE PROPOSED METHODOLOGY

Empirical evaluation of the proposed conceptual model requires a methodological approach combining analytical robustness and interpretative depth. A strictly quantitative analysis would risk reducing the complexity of the phenomenon to superficial statistical relationships, without capturing the organizational and strategic dynamics that influence the effectiveness of machine learning in predictive maintenance. Conversely, a purely qualitative approach would offer a more nuanced understanding of adoption mechanisms and internal resistance but would suffer from limited generalizability. Thus, a mixed methodology emerges as the best alternative. Quantitative structural equation modeling (SEM) allows for rigorous testing of the relationships between variables and the identification of the mediating and moderating effects that structure the impact of machine learning on industrial resilience. In addition, a qualitative analysis using semi-structured interviews sheds light on the underlying factors influencing these relationships, including strategic decisions, organizational processes, and barriers to technology adoption. This integrated approach aims not only to confirm or refute hypotheses but also to deconstruct the mechanisms that determine the real effectiveness of machine learning in an industrial context. It thus provides a more detailed understanding of the strategic and organizational levers needed to transform technological advances into real assets for industrial resilience.

A. Quantitative Approach: Testing Structural Relationships Using SEM

The quantitative analysis will be based on a structural equation model (SEM), which offers several methodological advantages. Unlike traditional linear regression approaches, SEM allows: The simultaneous analysis of multiple causal relationships, rather than limiting itself to direct effects. The integration of latent variables, is essential for modeling complex organizational processes. The consideration of mediation and moderation effects, thus allows us to test whether the impact of machine learning on industrial resilience is direct or conditioned by intermediary factors.

In our conceptual model, we posit that the effectiveness of machine learning in predictive maintenance is not automatic, but depends on several intermediary variables (organizational adaptive capacity, data diversity, and digital maturity). A simple linear regression would not isolate these mediation effects, whereas SEM allows us to explicitly model these relationships and empirically verify the hypothesized causal paths. Data collection will be conducted through a structured questionnaire administered to Moroccan industrial companies that have adopted predictive maintenance solutions. Variables will be measured using scales validated in the literature, and the data will be processed using specialized SEM software (such as AMOS or SmartPLS).

B. Qualitative Approach: Contextualizing the Underlying Dynamics

While quantitative analysis allows us to test the robustness of the conceptual model, it is not sufficient to explain the variations observed between companies. Why do some organizations, with access to the same technologies, benefit more from machine learning than others? What are the obstacles that cannot be measured statistically but that strongly influence the actual performance of these tools?

To answer these questions, we will use a complementary qualitative approach, based on in-depth case studies in a sample of industrial companies. Far from being a simple illustration of quantitative results, this method allows us to identify variables invisible to statistical analyses: internal resistance and political issues related to the adoption of machine learning, strategic choices, and economic trade-offs that influence investment in industrial AI, and the concrete limitations of algorithms in the face of companies' specific operational constraints. Semi-structured interviews will be conducted with: Maintenance managers, to understand the technical challenges encountered in implementing machine learning solutions, Strategic decision-makers, to analyze the motivations and barriers to investing in predictive maintenance, and Industrial data science experts, to identify the gaps between the theoretical potential of machine learning and its actual performance in companies. These interviews will be analyzed using a thematic approach, allowing for the identification of recurring trends in the responses and the identification of explanatory factors for performance gaps.

VI. PROCESS OF THE EMPIRICAL STUDY:

The methodological proposed approach in this study **(Figure 2)** relies on a rigorous combination of quantitative and qualitative data collection and analysis techniques, allowing for an in-depth and nuanced examination of the underlying mechanisms linking the adoption of machine learning in predictive maintenance to industrial resilience. Rather than relying on a deductive and linear approach, we favor an integrated methodology, where quantitative analyses will empirically test structural relationships, while qualitative exploration will offer a more contextual and interpretative reading of the organizational dynamics influencing the adoption and effectiveness of these technologies.

Quantitatively, data collection via a structured questionnaire will be conducted among a representative sample of Moroccan industrial companies that have adopted or are in the process of adopting machine learning in their maintenance strategy. To ensure reliable and valid measurement of the conceptual variables, the questionnaire items will be developed using scales validated in the literature, adjusted to the specific context of Moroccan industries, where the challenges related to digital transformation and the adoption of advanced technologies may differ from those of Western industrial environments. Data analysis will be based on a structural equation model (SEM), allowing for the simultaneous examination of the direct, indirect, and moderating effects that structure the impact of machine learning on industrial resilience. Unlike traditional linear regression models, which are often limited to a unidimensional interpretation, SEM offers a more comprehensive view of the interactions between organizational and technological variables. Before estimating the final model, an exploratory factor analysis (EFA) will be performed to verify the underlying structure of the latent variables, followed by a confirmatory factor analysis (CFA) to test the internal consistency and validity of the measurement model. Model fit will then be assessed using standardized criteria (CFI, TLI, RMSEA, SRMR) to ensure optimal statistical robustness. This approach will not only test the hypotheses formulated, but also provide a better understanding of the organizational and technological conditions under which machine learning strengthens industrial resilience.

However, a strictly quantitative approach would not fully capture the complex dynamics influencing the implementation of machine learning in predictive maintenance, including the organizational, decision-making, and cultural factors that determine its adoption and effectiveness. To overcome this limitation, an in-depth qualitative study will be conducted, based on a series of semi-structured interviews with key stakeholders in the industrial sector: maintenance managers, technical directors, data scientists, and strategic decision-makers. The objective is to explore the perceptions, resistance, and strategic trade-offs surrounding the adoption of machine learning, highlighting the underlying barriers and drivers not captured by quantitative models. The interviews will be recorded, transcribed, and analyzed using an inductive thematic approach, utilizing specialized tools such as NVivo or MAXQDA, to identify recurring patterns and explanatory schemas. Unlike traditional content analyses, which are often limited to a descriptive categorization of responses, the thematic approach will establish connections between the collected discourses and the quantitative results, thus providing a more nuanced interpretation of the performance gaps observed between companies using the same technologies. This qualitative analysis aims not only to illustrate trends emerging from the SEM, but also to identify explanatory mechanisms that may complement, qualify, or call into question certain statistical relationships.

To ensure a rigorous and consistent interpretation of the results, we will adopt a triangulation strategy, cross-referencing quantitative and qualitative data to compare statistical trends with actual organizational dynamics observed in the field. If, for example, quantitative analyses reveal a weak relationship between the adoption of machine learning and industrial resilience, qualitative research can identify structural barriers or managerial resistance hindering the effectiveness of these technologies. Conversely, if statistically significant links emerge from the SEM, qualitative research will help us understand the concrete mechanisms by which these effects manifest themselves in practice.

This integrated methodology, combining advanced modeling techniques and in-depth field analysis, guarantees a robust and contextualized scientific evaluation, thus avoiding the biases of purely econometric or descriptive approaches. It not only allows empirical validation of the hypotheses of the conceptual model, but also offers a critical and operational reading of the factors influencing the digitalization of industrial maintenance strategies. This analytical framework thus constitutes a significant contribution to the literature on machine learning and industrial resilience, while providing strategic recommendations that can be used by companies wishing to optimize their transition to Industry 4.0.

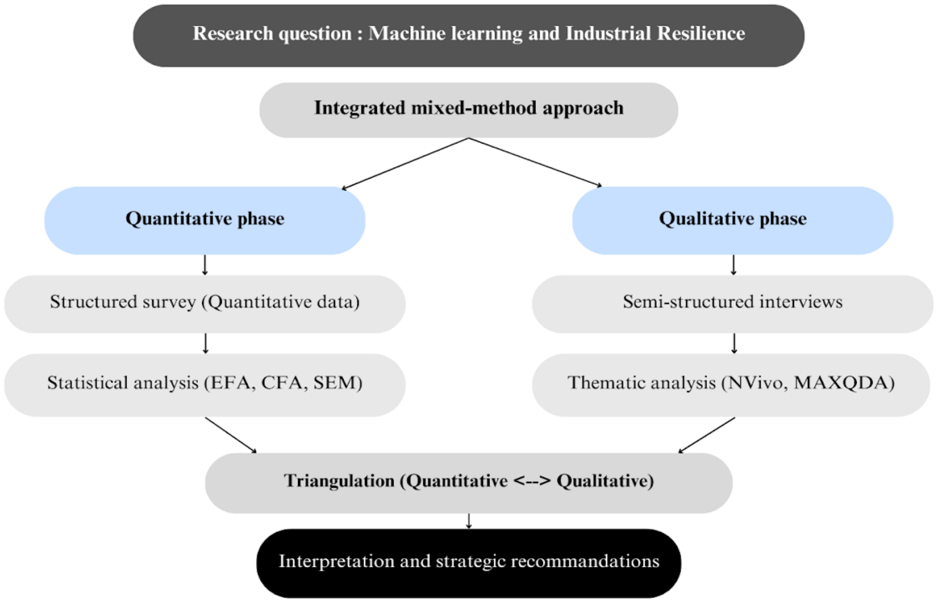

Figure 2. Process of the Empirical Study Synthesis
Source. Authors

VI. VALIDITY AND RELIABILITY OF MEASUREMENT INSTRUMENTS

One of the major challenges in the empirical evaluation of machine learning in predictive maintenance and its impact on industrial resilience lies in ensuring the validity and reliability of the measures used. The robustness of a study's conclusions depends largely on the ability of the measurement instruments to faithfully capture the theoretical concepts defined in the conceptual model. With this in mind, we adopted a rigorous approach to validating the measurement scales, combining quantitative and qualitative analyses, to ensure their relevance and applicability in the industrial context studied.

In terms of validity, we followed a multi-step methodological process to ensure that the measures used accurately reflect the underlying theoretical dimensions. First, we established content validity by using scales already validated in the academic literature, while adapting them to the specificities of the Moroccan industrial sector. This adaptation was carried out through an in-depth review of previous work, as well as exploratory interviews with industry experts and researchers specializing in digital transformation and industrial maintenance. This phase allowed us to verify the conceptual relevance of the selected items, ensuring that they adequately captured the key dimensions of the model, such as organizational adaptability, digital maturity, and the diversity of data used by machine learning algorithms. Construct validity was then assessed through exploratory factor analysis (EFA), which identified the underlying structure of the latent variables and tested whether the selected indicators loaded correctly on their respective factors. A confirmatory factor analysis (CFA) was then conducted to validate the factor structure of the measurement model, examining item loadings, scale internal consistency, and overall model fit indices. Key fit criteria, such as the Comparative Fit Index (CFI), the Tucker-Lewis Index (TLI), and the Root Mean Square Error of Approximation (RMSEA), were used to ensure that the empirical data satisfactorily aligned with the theoretical structure of the model.

Ultimately, this study does not limit itself to validating a conceptual model but offers a new interpretation of the interactions between machine learning, industrial strategies, and organizational resilience. It thus constitutes a theoretical advance by integrating dimensions often neglected in the literature on the digital transformation of industries. Furthermore, its practical implications allow companies to adapt their machine learning adoption strategies by considering not only technological challenges, but also the human, organizational, and managerial issues that determine the success of these innovations. Finally, by raising questions about the evolutionary trajectories of predictive maintenance and its conditions for long-term success, this research opens the door to new investigations into the role of machine learning as a vector of competitiveness and adaptability in Industry 4.0.

CONCLUSIONS

This research is part of an exploratory approach aimed at proposing a conceptual model to analyze the impact of machine learning in predictive maintenance on industrial resilience. By integrating the theories of dynamic capabilities and complex adaptive systems, this analytical framework highlights the organizational and technological mechanisms that determine the effectiveness of predictive algorithms. More specifically, this proposal emphasizes that digital maturity, data governance, and organizational flexibility are not simply contextual variables, but determining factors that modulate the performance of machine learning within industrial strategies.

To test this theoretical framework, a mixed methodological approach is proposed, combining a quantitative analysis using a structural equation model (SEM) and a qualitative exploration through semi-structured interviews. This dual approach will allow us to empirically test the hypothesized relationships, highlight mediation and moderation effects, and identify organizational dynamics invisible to statistical analyses alone. As a research proposal, this study paves the way for future empirical validation, which is essential to refine and generalize the findings. Prospects for further study include expanding the analysis to other industrial sectors and geographical contexts, adopting a longitudinal approach to observe the evolution of machine learning effects over time, and examining the role of public policies and institutional dynamics in the adoption of these technologies. By providing a structured framework for future studies, this research aims to provide a solid theoretical foundation and guide industrial practitioners in optimizing their predictive maintenance and digital transformation strategies.

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