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AI-MANUFACTURING READINESS INSTRUMENT (AI-MRI): DEVELOPMENT AND PILOT VALIDATION IN CHINESE MANUFACTURING FIRMS

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Abstract:

Artificial intelligence (AI) adoption in manufacturing depends not only on technical availability but also on whether firms have the organizational, financial, environmental, and managerial conditions needed to use AI effectively. Many existing AI readiness and digital maturity frameworks remain generic, largely conceptual, or insufficiently validated for manufacturing settings. This paper develops and pilot-validates the AI-Manufacturing Readiness Instrument (AI-MRI), a self-assessment instrument for manufacturing firms. Drawing on AI readiness, technology-organization-environment logic, organizational readiness, and manufacturing readiness literature, the study followed a systematic review of 34 peer-reviewed studies, item development, expert validation, and pilot testing. The resulting instrument includes five dimensions, 17 subdimensions, and 51 items: technological readiness, organizational readiness, financial readiness, external environment perception, and AI application awareness and perceived impact. A pilot survey of 152 organizational informants from Chinese manufacturing firms was used to examine reliability, item quality, construct structure, and preliminary known-groups validity. The five dimensions showed strong internal consistency, with Cronbach's alpha values between 0.850 and 0.907. Exploratory factor analysis supported a five-factor structure, with KMO = 0.816 and cumulative explained variance of 80.091%. Because confirmatory factor analysis was conducted on the same pilot sample, it is reported as a preliminary model check rather than independent confirmation; the model showed acceptable fit and convergent validity. Group comparisons showed meaningful differences in financial readiness and external environment perception across AI implementation levels. The AI-MRI offers a

manufacturing-specific and multidimensional readiness instrument that may serve as a preliminary diagnostic tool for firms planning AI transformation. Given the pilot design, the findings should be further tested with larger independent samples, criterion-related validity evidence, and cross-national validation.

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Keyword:

AI Readiness; Manufacturing; Digital Transformation; Scale Development; Pilot Validation; Chinese Manufacturing Firms



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Introduction

Artificial intelligence has become increasingly relevant to manufacturing strategy and operations. As firms move toward Industry 4.0 and intelligent operations, AI is being used for predictive maintenance, quality control, supply-chain coordination, production scheduling, demand forecasting, and data-driven decision-making. However, access to AI technology alone does not guarantee successful adoption. Many firms still face fragmented data systems, weak data governance, limited cross-functional cooperation, shortages of AI expertise, uncertain returns on investment, and an incomplete understanding of which operational activities are suitable for AI applications (Asaad et al., 2024; Bokrantz et al., 2024; Bustinza et al., 2024; W. Yu et al., 2020).

These barriers make AI readiness assessment a practical research problem. Before making major investments in AI, firms need to understand whether their technological base, managerial procedures, financial capacity, external environment, and managerial awareness are sufficient to support adoption. A readiness instrument should therefore do more than classify enterprises as mature or immature; it should help decision makers identify specific capability gaps and set priorities for improvement (Chatterjee et al., 2021; Dey et al., 2024; Dubey et al., 2020).

Although digital maturity and AI readiness instruments have become increasingly available, three limitations remain important for manufacturing research. First, many existing tools were designed for broad digital transformation contexts and do not fully address manufacturing-specific conditions, such as shop-floor data quality, integration with legacy production systems, production continuity, equipment constraints, and coordination among production, IT,

engineering, and management. Second, several frameworks remain mainly conceptual or practice-oriented, with limited empirical evidence on reliability, factor structure, and validity in manufacturing samples. Third, existing models often give more attention to technological resources or general organizational maturity than to managers' awareness of concrete AI applications and their perceived operational impact. These limitations suggest the need for a manufacturing-oriented AI readiness instrument that is both multidimensional and empirically examined (Holmström, 2022; Jöhnk et al., 2021; Mittal et al., 2018; Thordsen & Bick, 2023). China offers a rich empirical basis for studying AI readiness in manufacturing. It is one of the largest manufacturing economies in the world, and within China there is great variety, including some of the most advanced kinds of "smart" factories as well as many smaller producers struggling with basic resource limitations. Although national policies encouraging "intelligent manufacturing" have created considerable enthusiasm about AI among manufacturers generally, companies still differ widely in terms of their own data foundations, organizational capabilities, financial resources, and readiness to turn AI into practical benefit on the shop floor (Kinkel et al., 2023; Liang et al., 2022; Y. Wang & Su, 2021).

Against this background, this study develops and pilot-validates the AI-Manufacturing Readiness Instrument (AI-MRI), a manufacturing-specific self-assessment tool. The paper addresses three questions: which dimensions should be included in a manufacturing-oriented AI readiness instrument; whether the instrument shows sufficient internal consistency and preliminary construct validity in a pilot sample; and what initial readiness patterns can be observed among Chinese manufacturing firms. The study contributes to digital transformation and intelligent business research by translating systematic literature review evidence into an operational instrument and by providing early psychometric evidence for its use in manufacturing settings.

AI readiness assessment is useful only if it informs organizational action. Manufacturing firms often begin AI adoption through technology procurement, vendor selection, or isolated pilot projects. Yet many implementation problems arise before technology selection. A firm may purchase advanced analytics software while lacking interoperable production data, internal data governance rules, AI-literate managers, or cross-functional routines for turning model outputs into operational decisions. A readiness instrument helps make these gaps visible before firms commit scarce resources (Schumacher et al., 2016; Thordsen et al., 2020).

The present study treats AI readiness as a pre-implementation diagnostic construct rather than a post-implementation maturity indicator. Maturity models usually classify companies into stages of progress, whereas readiness tools examine whether enabling conditions for adoption are already in place. In manufacturing, these conditions involve technology, organization, finance, institutional context, and managerial cognition. A firm may have insufficient technical foundations, while another may have adequate infrastructure but weak managerial direction. In both cases, AI adoption readiness remains incomplete (Chen et al., 2022; De Carolis et al., 2025).

The pilot-validation design follows the same cautious logic. The paper does not claim that the AI-MRI is a final or universally valid measurement scale. It examines whether the proposed dimensions and item pool show enough psychometric promise to justify further validation. At this early stage, the key issues are whether the conceptual structure is plausible, whether the items behave coherently, and whether the instrument can distinguish meaningful organizational conditions. Stronger claims require independent samples, measurement invariance testing, and criterion-related validity evidence.

Literature Review and Instrument Development

AI Readiness in Manufacturing

Readiness for AI means having satisfied some basic prerequisites before adopting AI technology itself. This does not mean simply having access to algorithms or automated machines to install on the shop floor. There must also exist certain levels of maturity regarding the quality and availability of operating information, the linkage between production and managerial IT systems, the possibility of bringing together technical and commercial departments internally, the presence of adequate financial and personnel reserves, and finally the external circumstances that determine what incentives there will be to take up new innovations in the first place (Holmström, 2022; Jöhnk et al., 2021).

Manufacturing firms also differ from service providers or platform-based firms. In manufacturing, AI adoption is tied to production processes, legacy equipment, industrial control systems, supplier networks, quality requirements, and production continuity. A manufacturing-specific readiness instrument must therefore evaluate readiness in relation to operational conditions, rather than treating it as a generic organizational quality (Bokrantz et al., 2024; Chen et al., 2022; Kinkel et al., 2022).

According to current digital transformation research, technology adoption depends on two factors: available resources and organizations' absorptive capacity. Concerning AI in manufacturing, certain amounts of data resources and IT infrastructure need to exist beforehand but turn out to be insufficient alone; AI requires standardized, accessible, and reliable data streams. Yet most likely, manufacturers' data still remain scattered across production lines, ERP systems, QMSs (quality management systems), machines' sensors, suppliers' databases, and many other places. Technical readiness thus refers here to data quality as well as systems connectivity (Chatterjee et al., 2021; Kinkel et al., 2022; Zahoor et al., 2024).

Organizational readiness also matters because AI adoption changes work routines, decision authority, and patterns of cooperation. Engineers, operators, production managers, data specialists, and senior executives need to coordinate across functional boundaries. If AI remains only an IT issue, it is unlikely to influence production decisions. Leadership support, change management capability, and cross-functional communication are therefore necessary

conditions for organizational readiness (Chatterjee et al., 2021; Peretz-Andersson et al., 2024; Tortorella et al., 2024; Zahoor et al., 2024).

Financial readiness is especially important for small and medium-sized manufacturers. AI adoption may involve hardware upgrades, cloud or software subscriptions, database construction, staff training, consulting services, process redesign, and uncertain payback periods. Even when firms recognize the potential value of AI, they may delay adoption because the investment risk appears too high. Including financial readiness therefore makes the instrument more realistic for heterogeneous manufacturing firms (Peretz-Andersson et al., 2024; Pillai et al., 2022; Sharabati et al., 2024).

External Environment Perception refers to the fact that manufacturing AI adoption occurs under certain external circumstances over which the company itself has little control. There may be policy inducements, support from industrial clusters or technology vendors, regulations about data use, competitive forces, standards set by industry associations, and many other factors affecting whether companies believe they have sufficient reason or ability to carry out such transformations in their organizations. In emerging-economy settings especially, policy cues and ecosystem readiness seem likely to matter considerably in deciding whether firms wish to prepare themselves for adopting AI in their operations (Bustinza et al., 2024; Dey et al., 2024; Dubey et al., 2021; Liang et al., 2022).

AI application awareness and perceived impact form another part of readiness. A firm may have relevant data and computing resources, but managers still need to understand where AI can be applied. Knowledge of use cases such as predictive maintenance, defect detection, demand forecasting, production scheduling, and energy optimization helps managers connect AI technologies with operational problems. Their perceptions of AI's likely effects also influence whether they consider investment in AI strategically worthwhile (Leoni et al., 2022; Valaskova et al., 2024; W. Yu et al., 2020).

Development of the AI-MRI Dimensions

AI-MRI arose out of a systematic literature review carried out among 34 peer-reviewed studies dealing with issues such as AI adoption, AI readiness, maturity assessment, and intelligent manufacturing. Through this process, certain common aspects of 'readiness' were identified, which were translated into measurable dimensions. Experts were finally asked to comment on the formulation, relevance, and understandability of what had been suggested (Bokrantz et al., 2024; Page et al., 2021).

There are finally five dimensions in the pilot instrument. Technological readiness concerns the data, infrastructure, system integration, and cybersecurity bases needed for AI adoption; organizational readiness involves considerations about leadership support, talent and skills, organizational culture, flexibility of change, cross-functional collaboration, etc.; financial readiness concerns points such as funding capacity, return expectation, and willingness to take

risks; external environment perception relates to matters such as policy support, competitive pressure, ecosystem readiness of the industry concerned, regulatory clarity, and so on; finally, there is one more dimension called "AI application awareness and perceived impact," which addresses aspects including knowledge of possible applications within the organization itself, anticipation of what kind of strategic benefit AI might bring, and prediction concerning the likely effect on operations (Binsaeed et al., 2023; Bokrantz et al., 2024; Chatterjee et al., 2021; Liang et al., 2022; Peretz-Andersson et al., 2024; Valaskova et al., 2024).

This is how the development procedure was carried out: It followed the logic of content-domain definition. From this point of view, first, the literature was reviewed to find out what kinds of readiness factors had appeared many times when scholars studied artificial intelligence adoption, Industry 4.0, smart manufacturing, digital maturity, and organizational capability. Then, second, some concepts that looked very similar were combined to form subdimensions. After that, third, these subdimensions were arranged among themselves according to their meanings so as to finally form five broad divisions reflecting separate yet interconnected areas of readiness. Finally, fourth, questions were formulated to refer to actual circumstances within enterprises instead of representing people's opinions about something (Churchill, 1979; DeVellis, 2017; Hinkin, 1998).

It was hoped that this procedure would produce a reasonable compromise between theory and practice. With too few dimensions, something important about technology adoption could slip through its net. But if there were too many separate indicators, company managers might find it hard to make sense of their results. Thus, the five-dimension structure gives enough room to accommodate technology, organization, finance, environment, and cognition, yet still offers sufficient detail to help managers carry out their diagnostic work.

There is another difference here from most generic maturity models. These place companies themselves into certain maturity levels or stages but cannot specify what kinds of problems need attention when they fall short. In fact, according to the AI-MRI, there is no such thing as "maturity" applicable to entire enterprises. It describes conditions through "readiness profiles." Thus, it shows whether there are gaps in some respects even though others may look good. One can imagine many combinations: having quite advantageous circumstances externally thanks to policy support yet lacking internal capabilities because too few people possess the necessary qualifications and teamwork among departments does not function well. An image of this sort helps managers plan actions better than just being told their level on average (Mittal et al., 2018; Schumacher et al., 2016; Thordsen & Bick, 2023).

Table 1 summarizes the suggested structure of AI-MRI, and the measurement items it contains.

Table 1 Structure of the AI-MRI Dimensions and Measurement Focus

Dimension	Subdimensions	Representative measurement focus
Technological Readiness	Data quality and governance; system integration; infrastructure maturity; cybersecurity assurance	Whether production data, digital infrastructure, and system connections can support AI implementation.
Organizational Readiness	Talent and skills; leadership support; culture and change management; cross-functional collaboration	Whether the firm has human, managerial, and coordination capabilities for AI adoption.
Financial Readiness	Investment capacity; expected return; risk tolerance	Whether the firm can finance AI projects and tolerate uncertain payback periods.
External Environment Perception	Policy support; competitive pressure; ecosystem support; regulatory clarity	Whether external industrial, policy, and regulatory conditions support AI transformation.
AI Application Awareness and Perceived Impact	Use-case awareness; strategic value perception; operational impact perception	Whether managers understand where AI can be applied and how it may affect firm performance.

Theoretical Positioning of the AI-MRI

Therefore, the AI-MRI sits where several lines of inquiry meet. One concerns AI readiness and the technology-organization-environment logic, which explains why adoption readiness cannot simply boil down to technological infrastructure. Another comes from organizational readiness and capability studies, which show that readiness also comprises embedded practices and procedures, forms of coordination, resource commitment, absorptive capacity, and management attention. A further line of work concerns the digitalization of manufacturing, where AI uptake has to work together with existing modes of production, legacy equipment, shop-floor data, operational continuity, and conditions in the firm's industrial ecosystem. In this sense, the five AI-MRI dimensions are not only a practical checklist, but are linked to technological readiness, organizational readiness, financial readiness, external environment perception, and managerial cognition about AI application and perceived impact (Chatterjee et al., 2021; Chen et al., 2022; Jöhnk et al., 2021).

There is no point including measures of AI-application awareness and perceived AI impact if this aspect does not belong to the cognition component of digital change. After all, managers need a certain degree of knowledge about possible uses of AI in order to initiate the right kind

of project, choose a competent vendor, devote enough resources to it, expect certain results from its implementation, and so on. Otherwise, there will indeed be considerable distance between what people say about AI applications and what happens on shop floors. Hence, an index that pays no attention to these considerations may produce inflated estimates of readiness because it takes stock of existing installations without considering whether anyone has figured out what they could mean for production processes (Bokrantz et al., 2024; Leoni et al., 2022; Valaskova et al., 2024).

Method

Research Design

This study employed an instrument-development and pilot-validation design. The development process followed four main stages: systematic review of the literature on AI adoption and manufacturing readiness, item development, expert validation and refinement, and pilot testing with manufacturing firms. The purpose of the pilot phase was to examine whether the AI-MRI achieved adequate reliability and preliminary evidence of construct validity to warrant further large-scale validation (Boateng et al., 2018; DeVellis, 2017; Hinkin, 1998).

It was intended to be a firm-level self-assessment measure: respondents had to assess the state of affairs in their own organizations instead of merely expressing their personal views on AI. Such an arrangement stems from the consideration that AI-readiness concerns the very existence of certain kinds of organizational capability in terms of technology, structure, resources, ecosystem cognition, and managerial awareness (Churchill, 1979; DeVellis, 2017). There is also such a thing as a pilot validation design. This applies when an instrument has just been developed and there is no cumulative evidence about its properties across different samples. Here the main methodological issue concerns whether the item pool and dimension structure make enough sense, internally, to warrant pursuing their further examination. Hence, in a pilot study one looks at internal consistency, item discrimination, exploratory factor structure, some indexes of early-stage model fit, known-groups patterns, etc. None of these exhausts the validity enterprise, obviously; it merely creates an initial empirical basis for revising the measure before undertaking large-scale attempts at validation proper later on (Johanson & Brooks, 2010; Kirsch et al., 2026).

Construct validity is dealt with here in terms of accumulated evidence regarding several issues. First, there is content validity, which derives from literature-supported item construction followed by improvements suggested by experts. Second, concern about internal structure is satisfied by means of both an exploratory factor analysis (EFA) and a preliminary confirmatory factor analysis (CFA). Third, known-groups evidence comes from examining differences among some dimensions according to where firms stand along the ladder of AI implementation stages. It is preferable to adopt this kind of procedure instead of merely checking reliability indexes, because the latter cannot prove that an instrument actually measures what it was designed to measure (Fornell & Larcker, 1981; Hair et al., 2019; Lawshe, 1975; Lynn, 1986).

Participants and Data Collection

The pilot took place among organizational informants working in manufacturing companies located in mainland China. Eligible respondents were expected to have sufficient knowledge of their firms' technologies, operations, digitalization activities, or AI-related planning. They therefore included managers, production or operations personnel, engineers, IT staff, R&D staff, and other employees familiar with their organization's digital transformation practices. Purposive sampling was combined with elements of convenience sampling and snowball sampling. After data screening, the valid pilot sample contained 152 responses (Hatamlah et al., 2023; Y. Wang & Su, 2021).

It was suitable for the purposes of the first pilot study but cannot be regarded as representative of Chinese manufacturers generally. There is no probability element in its sampling procedure, nor is there sufficient subgroup size to support wider generalization. Limitations of this kind are acknowledged in the Discussion section and explain why further work eventually needs to move on to much larger samples (Etikan, 2016).

This is also true of China's manufacturing environment in general. There is considerable diversity among enterprises regarding their size, type of ownership, level of technology, degree of digitalisation, etc.; they are all encouraged by government policies to develop smart manufacturing. Such great differences make good cases for testing instruments, since more possibilities exist for changes concerning different kinds of readiness. Nevertheless, no pilot sample can mirror all types of manufacturers existing nationwide because of such huge differences as mentioned above (Liang et al., 2022; Peretz-Andersson et al., 2024).

They were regarded as representatives of organizations rather than as individuals who use AI themselves. Hence, the questionnaire concerned several organizational factors, including whether there was data governance within the company itself, what kind of situation the introduction of an AI system would cause regarding system integration, whether leaders supported using AI in their departments, whether they had sufficient budgetary resources, whether government policies encouraged companies to adopt AI, and finally whether respondents knew anything about applying AI to certain cases. Although this arrangement corresponds well with treating readiness as an organizational quality, it also causes one problem: respondents might not know everything concerning these topics within their own organizations. In future research, researchers need to take care when designing surveys, trying either to collect more than one answer per company or to check what others say against objective measures of the organization's situation.

Table 2 Sample Characteristics

Sample characteristic	Summary
Valid responses	152
Country context	Mainland China

Industry context	Manufacturing firms across multiple subsectors
Sampling strategy	Purposive sampling with convenience and snowball expansion
Respondent requirement	Employment in a manufacturing firm and awareness of technology, operations, or digital transformation activities
Study stage	Pilot validation

Measures and Analysis

There were altogether 51 items in the AI-MRI pilot questionnaire. These items formed the basis of measurement for 17 subdimensions and five higher-order readiness dimensions. Each item was measured on a Likert-type response scale. Reliability was studied by calculating Cronbach's alpha. Item discrimination was investigated via calculation of corrected item-total correlations and critical ratio tests. An exploratory factor analysis was performed on the whole set of 17 subdimensions in order to study their factor structure. Preliminary investigations concerning confirmatory factor analyses were also carried out to examine some aspects of model fit, convergent validity, and discriminant validity (Likert, 1932).

Because the CFA was carried out in the same pilot sample itself, it has been considered here only as a kind of preliminary model check rather than as true independent confirmation. Known-groups validity was investigated by making group comparisons according to three variables: level of AI implementation in the company, size of company, and amount of AI-related experience reported by respondents (Fornell & Larcker, 1981; Hair et al., 2019; Portney & Watkins, 2009).

There is also some logic behind using subdimensions as the basis for factor analysis because they reflect the hierarchy built into the instrument: while the 51 items refer to specific kinds of organizational circumstances, the 17 subdimensions correspond to somewhat more general kinds of things. Factor-analyzing this latter level allows one to see if these components cluster into the assumed five readiness domains. Such procedures make particular sense when conducting pilot work with samples too small for fitting the entire item-level model.

Interpretation of Fit Indices There is no mystery here; the usual rules apply. Obtaining good fit figures from a pilot sample can indicate that a certain kind of measurement model makes sense, but this is by itself no replacement for further demonstration through independent replication. Hence, the article presents confirmatory factor analysis results merely as indicative evidence, while also calling on readers interested in validating these indicators in general terms to replicate this work with other samples altogether, using still larger samples if possible, and checking measurement invariance across firm types (Hair, 2009; Hair et al., 2019).

Expert Validation

Then came the stage of expert validation after the first generation of the item pool had been completed, in order to examine the content validity of the emerging scale (called AI-MRI). Two experts with relevant experience in manufacturing management and AI applications were invited to evaluate the 51 items. Their task was to examine these items according to three aspects: whether they correctly reflected what their respective subdimensions referred to in theory, whether they could be understood by most producers in practice, and whether they were suitable for the production situation (Lawshe, 1975; Lynn, 1986).

Each expert evaluated each item according to three criteria: its relation to the assigned subdimension (relevance), the clarity of its wording, and its suitability for manufacturing firms. Three levels were distinguished (poor fit, moderate fit, good fit). In addition, open space was provided for noting problems concerning wording, lack of some important aspects, and possible ambiguities. According to experts' comments, the wording of some items needed revision before they were given to respondents in the pilot phase.

Data Screening and Bias Considerations

Then there was screening of the pilot sample itself prior to carrying out the analysis. Three kinds of filtering were applied because the researcher wanted to examine certain aspects of organizations through this questionnaire and therefore needed good responses from participants. She removed straight-liners, respondents who had not answered all items on the form, and individuals whose answers were inconsistent with the inclusion criteria stated above when selecting cases. She performed these steps before deciding what finally constituted her sample. In this way, she hoped to obtain pilot results relating to actual organizational situations rather than being influenced by respondents who had filled out the forms carelessly.

Some degree of common method bias may arise since the data derive from one questionnaire administered once. Hence, the present paper regards every result as being only preliminary and makes no causal statement whatsoever. In terms of procedure, certain improvements were made when designing the questionnaire: conceptual domains were separated from each other; very clear items were chosen; respondents were told repeatedly that there were no correct answers. Concerning statistics, care was taken to perform tests for common method bias (see their paper). To validate these findings later on, one needs more external information per company. There should either be multiple sources within one company or objective measures of companies in general. Alternatively, one could repeat the whole measurement procedure after some time has passed (Podsakoff et al., 2003).

Results

Reliability and Item Quality

They show firstly some evidence of the internal consistency of the AI-MRI. For reliability, Cronbach's alpha was found for each of the five scales. Values lay between 0.850 and 0.907, which exceeds normal standards in pilot-scale development. At the level of individual items, everyone fulfills basic discrimination requirements; corrected item-total correlation coefficients for all 51 items exceed 0.30 and their critical ratios reach levels of significance (DeVellis, 2017; Hair et al., 2019).

This means that there seems to be enough internal coherence among items for pilot validation purposes, but one should not conclude from this about the quality of the scale itself, because such excellent levels of reliability are no proof of good measurement. Rather, they show an instrument fit for additional testing on much larger and more representative samples.

The fact that no items had to be dropped even at this early stage is encouraging, since it means that, in general, these literature-derived items made sense and measured what they were supposed to measure. Item removal is not something one wants in and of itself, because dropping items too soon could limit what will eventually be covered by the final scale. Hence, there seems good reason here to keep everything intact for further testing in later stages and not rule out anything just yet, although researchers always reserve the right to pare down later after seeing large-N results.

Table 3 Reliability and Item Quality Results

Validation area	Key result	Interpretation
Internal consistency	Cronbach's alpha = 0.850-0.907	Strong reliability across the five dimensions.
Item discrimination	All CITC values above 0.30; CR tests significant	No item required deletion at pilot stage.
Sampling adequacy	KMO = 0.816; Bartlett's test significant	Data suitable for factor analysis.
Exploratory factor analysis	Five-factor structure; cumulative variance = 80.091%	Empirical structure aligned with theoretical model.
Preliminary CFA	CMIN/df = 0.836; GFI = 0.935; AGFI = 0.909; RMSEA = 0.000	Model fit appears acceptable, but requires independent-sample confirmation.

Reliability There is some supporting reliability evidence regarding the practical usability of the AI-MRI. An instrument's purpose is to help companies assess their readiness. Therefore, if an organization uses such an instrument, this tool must generate internally consistent dimension scores. Otherwise, managers will lose confidence when interpreting profiles because they cannot tell whether observed discrepancies reflect true differences among dimensions or

measurement noise. In this sense, the very high alpha values found indicate that there is enough common variance within each dimension to give confidence about its ability to produce reliable information. However, future work needs to supplement Cronbach's alpha with other reliability indices, including composite reliability, test-retest reliability, and interrater reliability (when many responses come from one company).

Exploratory Factor Analysis

They were appropriate for factor analysis because the KMO index of sampling adequacy was 0.816 and Bartlett's test of sphericity was also statistically significant. Exploratory factor analysis confirmed that there is indeed support for the theoretically proposed five-factor model. Extraction of these five factors accounts for 80.091% of the total variation. Again, factor loadings follow closely what one might expect according to theory; thus, they seem reasonable. There appear to be five interpretable factors corresponding to the technology factor, organization factor, finance factor, external environment factor, and the artificial intelligence awareness factor (Hair et al., 2019; Kaiser, 1974).

The EFA results matter because they indicate that the AI-MRI dimensions arise not merely from theory but also come apart empirically in the pilot dataset. Thus, they give some reason in advance to think that there will turn out to be several factors behind AI readiness among manufacturers.

It makes sense that there are indeed five factors. One factor appears to be technological readiness, because having certain kinds of data available, adequate infrastructure, the ability to integrate systems, and sufficient cybersecurity all appear together. Another factor seems to capture organizational readiness, because having leaders who understand what AI can do, relevant skills among employees, a culture that embraces change, and mechanisms for coordinating work appear together. A third factor seems to involve financial readiness, because investment ability and risk tolerance appear together.

There was also some separation of external environment perception and AI application awareness from the three usual technology-organization-finance dimensions. This matters because it extends how one thinks about being ready for AI. Companies cannot choose whether to adopt AI by themselves; they have to react to certain incentives in policy, receive help from their ecosystem, deal with competitors' behavior, and worry about regulation. But companies also need to know something about concrete examples of AI use and possible payoffs. Thus, the factor pattern makes sense if there really is more to 'readiness' than just technology, organization, and finance; instead, there will also be some element of institutional perception and managerial thinking.

One needs some caution with respect to the very high cumulative explained variance. This means only that these five factors indeed explain much of the variation on these seventeen subdimensions for this particular pilot sample, but nothing about whether the factor structure

itself will generalize to another sample; hence, again, such results are at most suggestive of where more work is needed before they can count as final validation.

Preliminary CFA and Construct Validity

Because the CFA was conducted on the same pilot sample used for the exploratory analysis, the results should be interpreted as a preliminary model check rather than independent confirmation of the measurement structure. With this limitation in mind, the preliminary CFA findings still provided some support for the proposed five-factor measurement model. The reported model fit indices met conventional criteria: CMIN/df = 0.836, GFI = 0.935, AGFI = 0.909, and RMSEA = 0.000. Convergent validity was also supported, with AVE values ranging from 0.649 to 0.756 and composite reliability values ranging from 0.847 to 0.925 (Fornell & Larcker, 1981; Hair, 2009; Hair et al., 2019).

Discriminant validity was also satisfied to some extent, since, for each construct, the square root of its AVE turned out to be greater than its correlation with any other construct. There were very few correlations higher than 0.3 in magnitude, and this finding indicates that the AI-MRI measures five related but separate aspects of readiness.

Table 4 Convergent Validity Results

Dimension	AVE	Composite reliability
Organizational Readiness	0.681	0.895
Technological Readiness	0.756	0.925
Financial Readiness	0.728	0.889
AI Application Awareness and Perceived Impact	0.649	0.847
External Environment Perception	0.729	0.890

The convergent validity results show that there is enough shared variance among the indicators included in each readiness dimension. Again, this seems especially important when developing a multidimensional measure of readiness. Each dimension has to describe one coherent domain. In fact, organizational readiness combines four aspects: leadership support, talent, culture, and collaboration. According to their AVE and composite reliability values, therefore, they seem suitable proxies for this larger concept of organizational readiness.

There also needs to be some discriminant validity evidence. By definition, there will be relationships among these AI readiness dimensions, since together they describe a company's overall state of readiness regarding AI adoption. They cannot collapse entirely into just one generic AI readiness value, however. The low-to-moderate correlations among dimensions suggest that firms may have uneven readiness profiles. Thus, the whole point of using a measure such as the AI-MRI, as described above, is that management can then determine which

particular type of deficiency exists concerning technology, organization, financial resources, external circumstances, thinking styles, and so on.

There will likely need to be unusual reasons if such very good values occur ($RMSEA = 0.000$), and transparency requires pointing this out carefully. For small to medium N in pilots, perfect fits may occasionally arise due to particularities of models or samples, but this means only that the claimed relationships seem worth pursuing, certainly not that they have been demonstrated here.

Readiness Profile and Known-Groups Evidence

The descriptive results show a clear readiness profile. Technological Readiness obtained the highest mean score, followed by Organizational Readiness, External Environment Perception, and AI Application Awareness and Perceived Impact. Financial Readiness had the lowest mean score and was the only dimension below 3.0. This pattern suggests that the sampled firms had made some progress in technological foundations, while financial constraints remained a potential barrier to AI transformation.

Table 5 Readiness Profile of the Sampled Firms

Readiness dimension	Mean	Interpretive note
Technological Readiness	3.252	Highest dimension; indicates relatively stronger technical foundations.
Organizational Readiness	3.180	Moderate readiness; capability building remains important.
External Environment Perception	3.170	Moderate external support perception.
AI Application Awareness and Perceived Impact	3.146	Moderate awareness with relatively high dispersion.
Financial Readiness	2.985	Lowest dimension; key barrier for AI transformation.

Some known-groups comparison results based on the level of AI implementation produced preliminary validity evidence. In this study, firms were compared according to whether they had not yet adopted AI, were planning or piloting AI, or had already implemented AI in at least some organizational or operational activities. Significant differences were found for financial readiness and external environment perception among firms at different AI implementation levels, whereas no statistical differences appeared for the remaining dimensions. This pattern is reasonable because firms are more likely to move from non-adoption toward planning, piloting, or implementation when they consider themselves financially able to absorb AI-related investment risks and when they perceive policy, regulatory, and ecosystem conditions as supportive.

This is also true according to many descriptions one finds: some manufacturers have started investing in digital infrastructure, but they remain reluctant to expand their AI projects further, since profits cannot yet be calculated precisely and implementation costs cannot yet be estimated accurately enough either. Financial readiness might then constitute another limiting factor: although a company sees opportunities presented by AI technologies and holds sufficient amounts of structured data, it could nevertheless postpone adoption due to unsatisfactory investment costs, overly long payback times, or insufficient appetite for risk.

There is also great difference among these implementations in terms of the external environment they perceive. All this shows that how companies formulate their own artificial intelligence plans is also affected by their assessment of policies and ecosystems. Enterprises that believe there will be greater policy benefits, more transparent rules and regulations, richer sources of industry ecosystems, and so on, may be more likely to proceed from being aware of artificial intelligence to planning accordingly. In this sense, there seems to be some truth in the claim that government policy and industrial clusters play important roles under China's intelligent manufacturing program.

There is no significant difference according to company size and respondent AI experience. This does not mean much by itself; there might actually be very complicated prerequisites regarding firm size and people's own experience with AI technologies, but they cannot yet be discovered because there are too few cases here. Therefore, in further research with greater numbers of enterprises, attention should also be paid to interactions among firm size, ownership type, subsector, location, stage of AI implementation, etc., when looking at what kinds of readiness businesses need to make before introducing artificial intelligence technology.

Common Method Bias and Result Summary

There was also some concern about common method bias because of the use of self-report surveys in this study. Therefore, as part of the pilot validation process, common method bias was assessed according to the logic behind Harman's single-factor test. For unrestricted factor extraction, the largest eigenvalue obtained was 5.082. It accounts for 29.897% of the total variance and does not exceed the often-mentioned critical value of 50%. Thus, there does not appear to be one overwhelming factor among these items (Podsakoff et al., 2003).

But there is still some chance that common method bias may occur to some degree under such a cross-sectional self-report research design. Therefore, what has been reported above can only serve as a preliminary test rather than conclusive proof that no method bias occurred. Accordingly, one should understand the results here as referring to people's own sense of how ready their organization was regarding AI, rather than taking them literally as observations concerning the amount of actual AI-related ability possessed by organizations themselves.

Collectively, they seem to show that, in general, the AI-MRI works as intended. Reliability shows adequate internal consistency. An exploratory factor analysis yields the expected five-

factor solution. Preliminary confirmatory factor analyses suggest acceptable model fit, and the descriptive profile points out both strengths and weaknesses regarding readiness. Technologically speaking, it seems to indicate more readiness than there is financially. Therefore, for certain manufacturers at least, AI adoption difficulties might now involve fewer problems concerning whether needed facilities exist and many more about having confidence in what purchase decisions need to be made and being willing to take risks on what else needs to happen beyond that.

Discussion

It is therefore the authors' hope that they have created and pilot-tested the AI-MRI as a manufacturing-oriented AI readiness instrument and found some evidence supporting its reliability and construct structure in this article. Together, literature-based dimension development and pilot psychometrics constitute another small step toward addressing what seems to be one serious gap in AI readiness research today: there are still far too many frameworks that remain very general, largely conceptual, or hardly tested at all.

It is conceptual in the first place because the paper tries to distinguish AI readiness from general digital maturity in terms of five dimensions representing conditions under which such adoption occurs in manufacturing. These dimensions are technological readiness, organizational readiness, financial readiness, external environment perception, and AI application awareness and perceived impact. Hence, these multiple aspects avoid reducing AI readiness simply to being concerned about what kind of technology one has in place (Chen et al., 2022; Jöhnk et al., 2021; Schumacher et al., 2016).

This is the second respect in which the study makes a methodological contribution. It converts what was found through the systematic literature search into something that can actually be measured, and it puts the suggested structure through some pilot reliability and validity tests. In this way, the AI-MRI also moves beyond generic digital-readiness models, since it focuses on manufacturing-specific readiness conditions rather than a general level of digital maturity. The evidence cannot yet count as fully conclusive, but there is more empirical support behind these claims about 'readiness' than if the framework were merely conceptual, because several types of investigation have been carried out: item analysis, EFA and preliminary CFA model checking, and known-groups comparisons (Boateng et al., 2018; Churchill, 1979; Hinkin, 1998).

There is also some practical value in this third respect. Manufacturing leaders might use the AI-MRI instrument before deciding whether to embark on AI transformation themselves. As shown by the pilots, they might especially want to consider their own financial situation and their own views about the external world. Even if they have adequate digital resources, they may still find that they cannot proceed because they do not have enough financial resources to invest, they cannot bear the risks involved, they do not trust government policies sufficiently,

or there is no ecosystem assistance available (Kopka & Fornahl, 2024; Peretz-Andersson et al., 2024; Sharabati et al., 2024).

They also support research transfer because they transform academic evidence into something managers can use when diagnosing their own situation, benchmarking their level of readiness, and planning what kind of competence-building activities they need to carry out.

As far as theory is concerned, then, the AI-MRI links AI adoption research back to organizational capability perspectives more generally. There is considerable discussion about AI's presence in manufacturing in relation to its own technological logic, but readiness concerns what companies actually have available internally in order to take up AI in terms of their established ways of working and decision-making mechanisms. Hence readiness cannot refer only to one element but must look collectively at five kinds of things: technical infrastructure, organizational capacity, finance, external environment encouragement, and degree of application knowledge (Bustinza et al., 2024; Chatterjee et al., 2021; Tortorella et al., 2024).

It is also hoped that this will serve as an example for measurement researchers of what they might achieve by using systematic literature review findings in their own scale development processes. In fact, very few review articles move beyond simply presenting a conceptual framework, whereas many instruments seem to arise almost entirely from experts' ideas or certain types of practical templates. One intention behind developing the AI-MRI was therefore to bring together these two procedures. Its dimensions derive directly from what has been reported in refereed journals, but the actual instrument must still pass an empirical test. There is thus no gap regarding where something comes from and whether it eventually appears among the final measures chosen (Boateng et al., 2018; DeVellis, 2017; Hinkin, 1998).

As practice, then, there are three stages of decision making that the tool could facilitate. At the beginning of exploration, a manufacturing company might want to know from the AI-MRI if it even makes sense to proceed on the basis of existing data governance and infrastructure. At the planning stage, one wants to know what organizational and financial hurdles remain. And once a company implements AI in production, it wants to find out why pilots cannot go further. Here again, what matters is not some readiness rating but a domain-specific diagnosis.

It is also important for policymakers and ecosystem actors themselves. If companies consider these issues and find them unsatisfactory, then although there is some willingness within the company to adopt AI, actual adoption will be deferred. Therefore, if "readiness building" is required, measures should involve more than simply training firms or providing grants for certain kinds of equipment. Something else also needs attention: helping industries organize themselves better, improving the way people manage their own data, running pilot programs, providing sound advice about what trust means in such matters, and so forth (Dey et al., 2024; Dubey et al., 2021; Liang et al., 2022).

Managerial Use of the AI-MRI

And, indeed, there will probably be three stages involved if AI-MRI is applied practically as a diagnostic aid. First, managers may want to administer the instrument to obtain their own "readiness profiles" along each of the five dimensions. Second, they could examine their dimension scores closely to identify where their lowest readiness levels appear. Finally, companies might translate these low-scoring domains into concrete actions, such as improving their data governance efforts, building stronger cross-functional teams, setting clearer investment limits, seeking more government assistance, and working harder to gain acceptance of AI technology among managers themselves.

It can also help talk through issues raised when technical people discuss problems with non-technical managers. Decisions about adopting AI usually concern IT departments, production units, finance teams, senior executives, and outside suppliers of technology. These groups will likely have their own definitions of what being ready means. With a organized instrument available, there can then be more discussion about readiness itself. There will also probably be less chance of AI becoming just another sort of technological acquisition.

For manufacturing SMEs, the diagnostic function might matter particularly much. They probably will not have dedicated AI teams themselves and therefore depend largely on vendors or outside advisors. Hence, before starting AI initiatives, they might want to see if they can build enough competence internally to take advantage of whatever is offered externally. Then there is less chance that something very clever technologically turns out to be unsuitable in practice because the firm cannot cope organizationally with what it bought (Mittal et al., 2018; Peretz-Andersson et al., 2024).

Limitations and Future Research

There are also some limitations worth mentioning here. For one thing, although the sample size of the pilot study was sufficient for preliminary exploration according to the results of power analysis, nonprobability sampling was adopted, there were only 152 valid responses, and thus no strong external validity could be claimed. In addition, both EFA and CFA were based on the pilot sample, making it necessary to carry out CFA again in later research by means of another independently collected sample. Besides, since the data came from a questionnaire survey carried out once among individuals themselves, problems such as common-method variance occurred easily, and hence no causal conclusions could be drawn accordingly (Etikan, 2016; Johanson & Brooks, 2010).

Future research needs to replicate its results by means of a larger and more representative sample regarding manufacturing subsectors, regions, and company size. Measurement invariance ought to be tested among some subgroups; researchers need to investigate criterion-related validity through objective measures of AI adoption or performance; they also need to carry out longitudinal investigations in order to determine whether there is any relationship

between initial levels of AI-readiness and future degrees of AI deployment and transformation. Finally, cross-national research will show whether such an instrument may remain useful outside the case of Chinese manufacturers (Kirsch et al., 2026; Portney & Watkins, 2009).

There is also another limitation concerning the level of analysis. AI-MRI intends to measure company readiness. However, in this pilot study, individuals act as organizational informants. More research is needed to obtain responses from several people within each enterprise; then it will become possible to examine differences by management echelon and functional department within companies. One can find out if there really is such a thing as organizational readiness or whether different types of managers (senior executives versus engineers, IT workers, or production personnel) give divergent answers on this issue.

There will probably also have to be some adaptation for different manufacturing subsectors. Electronics manufacturing, automotive components, textiles, machinery, and process industries may have quite distinct profiles when it comes to the technology base available, regulation, kinds of data, etc., so further validation needs to investigate whether this five-dimension structure holds up regardless of what kind of manufacturer one looks at or whether some degree of sector specificity is called for.

Another issue there is the issue of investigating the predictive value of AI-MRI scores. An inventory measuring readiness will become much more helpful if it explains or predicts something important, such as starting an AI project, implementing one successfully, improving operations, increasing digitization maturity, and so on. Demonstrating this kind of criterion-related validity would change the AI-MRI from a first-stage diagnostic device into a more powerful aid for decision-making.

Conclusion

This paper reports on the development of such an instrument, called the "AI-Manufacturing Readiness Instrument" (hereafter AI-MRI). It consists of five scales, each measuring one dimension of manufacturing companies' degree of AI readiness. Pilot results showed first indications of reliability and validity regarding factor structure, convergent validity, discriminant validity, and known-groups validity. With respect to theory, the AI-MRI contributes to digital transformation and intelligent business research by being a manufacturing-specific instrument with which to diagnose the extent of AI readiness. Practitioners may use it as a means of determining where they stand regarding their own AI readiness in order to decide whether to allocate more resources to bridging readiness gaps before starting on an AI journey. However, much remains to be done in terms of collecting further large samples and having others replicate these findings. Only thus will it become possible to use the AI-MRI as a well-established measurement scale.

It's worth lies in bringing research findings to instruments that could facilitate management practice and policy making. By themselves, then, the AI-MRI will not resolve problems of AI

adoption. However, they may help indicate what is ready and what needs attention, as well as where efforts might best intervene first. Hence their potential usefulness is likely not just to researchers studying digital transitions but also to companies and other ecosystem participants trying to become better informed about how they adopt artificial intelligence.

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Appendix A. Full AI-MRI Item Pool

Table A1 Full AI-MRI Item Pool

Dimension	Subdimension	Item code	Item statement
Technological Readiness (TR)	Data Quality & Governance	TR1	Our company has structured, standardized production data that can support AI model training.
Technological Readiness (TR)	Data Quality & Governance	TR2	We have clear data governance policies and procedures in place.
Technological Readiness (TR)	Data Quality & Governance	TR3	Our data collection systems provide real-time, accurate production data.
Technological Readiness (TR)	System Integration Capability	TR4	Our existing IT systems (e.g., ERP, MES) can be effectively integrated with AI solutions.
Technological Readiness (TR)	System Integration Capability	TR5	We have the technical capability to connect different data sources across departments.
Technological Readiness (TR)	System Integration Capability	TR6	Our legacy systems are compatible with emerging AI-based tools and platforms.
Technological Readiness (TR)	Infrastructure Maturity	TR7	We have sufficient computing power (e.g., cloud, GPU) to support AI applications.
Technological Readiness (TR)	Infrastructure Maturity	TR8	Our IoT sensors and network infrastructure can support real-time data collection.
Technological Readiness (TR)	Infrastructure Maturity	TR9	We have invested in scalable data storage infrastructures for AI deployment.
Technological Readiness (TR)	Cybersecurity Assurance	TR10	We have implemented adequate cybersecurity measures to protect AI-related data.
Technological Readiness (TR)	Cybersecurity Assurance	TR11	Our data handling processes comply with relevant privacy and security regulations.
Technological Readiness (TR)	Cybersecurity Assurance	TR12	We have protocols in place to address cybersecurity risks associated with AI systems.
Organizational Readiness (OR)	Talent & Skills	OR1	Our company has (or can recruit) professionals with data science or AI-related skills.

Organizational Readiness (OR)	Talent & Skills	OR2	Our employees have received training related to AI or digital transformation tools.
Organizational Readiness (OR)	Talent & Skills	OR3	We have multidisciplinary teams capable of supporting AI project implementation.
Organizational Readiness (OR)	Leadership & Strategic Alignment	OR4	Our senior management actively supports AI adoption as a strategic priority.
Organizational Readiness (OR)	Leadership & Strategic Alignment	OR5	There is a clear digital transformation strategy aligned with overall business goals.
Organizational Readiness (OR)	Leadership & Strategic Alignment	OR6	Management allocates sufficient resources for AI-related initiatives.
Organizational Readiness (OR)	Organizational Culture & Change Management	OR7	Our organizational culture is open to adopting new technologies and ways of working.
Organizational Readiness (OR)	Organizational Culture & Change Management	OR8	Employees are generally willing to embrace changes brought about by AI implementation.
Organizational Readiness (OR)	Organizational Culture & Change Management	OR9	We have effective change management processes to support digital transformation.
Organizational Readiness (OR)	Cross-departmental Collaboration	OR10	Different departments in our company collaborate effectively on technology-related projects.
Organizational Readiness (OR)	Cross-departmental Collaboration	OR11	There is effective communication between IT/technical teams and business operation units.
Organizational Readiness (OR)	Cross-departmental Collaboration	OR12	We share AI-related knowledge and resources across organizational boundaries.
Financial Readiness (FR)	Investment Capacity & Willingness	FR1	Our company is willing to allocate a dedicated budget for AI technology adoption.
Financial Readiness (FR)	Investment Capacity & Willingness	FR2	Management considers AI investment critical for maintaining future competitiveness.
Financial Readiness (FR)	Investment Capacity & Willingness	FR3	We have the financial capacity to absorb the high initial costs of AI implementation.
Financial Readiness (FR)	ROI Evaluation Capability	FR4	We are able to evaluate the expected return on

			investment (ROI) of AI projects.
Financial Readiness (FR)	ROI Evaluation Capability	FR5	We have clear metrics and criteria for assessing the business value of AI initiatives.
Financial Readiness (FR)	ROI Evaluation Capability	FR6	We use structured approaches (e.g., cost-benefit analysis) to evaluate AI investments.
Financial Readiness (FR)	Sustainable Investment Capability	FR7	Our company can sustain ongoing investment for the maintenance and upgrading of AI systems.
Financial Readiness (FR)	Sustainable Investment Capability	FR8	We plan for long-term AI-related expenditures beyond the initial implementation phase.
Financial Readiness (FR)	Sustainable Investment Capability	FR9	We have a financial strategy to support the iterative development of AI solutions.
External Environment Perception (EE)	Policy & Regulatory Support	EE1	The government in our region provides policies or incentives that support digital transformation in manufacturing.
External Environment Perception (EE)	Policy & Regulatory Support	EE2	Government-funded programs are available to help manufacturing companies adopt AI technologies.
External Environment Perception (EE)	Policy & Regulatory Support	EE3	The regulatory environment for AI adoption in our industry is clear and supportive.
External Environment Perception (EE)	Industry Collaboration Ecosystem	EE4	We have access to AI technology support from industry associations or research institutions.
External Environment Perception (EE)	Industry Collaboration Ecosystem	EE5	Our company actively participates in collaborative networks related to digital innovation.
External Environment Perception (EE)	Industry Collaboration Ecosystem	EE6	We benefit from partnerships with technology providers or academic institutions for AI implementation.
External Environment Perception (EE)	Regulatory Clarity	EE7	There are clear industry standards and guidelines governing AI use in our sector.
External Environment Perception (EE)	Regulatory Clarity	EE8	We understand the legal requirements related to AI, data privacy, and algorithmic transparency.

External Environment Perception (EE)	Regulatory Clarity	EE9	Compliance with AI-related regulations is manageable and does not significantly hinder adoption.
AI Application Awareness & Perceived Impact (AAPI)	AI Application Awareness	AI1	I understand how predictive maintenance can be applied in our manufacturing operations.
AI Application Awareness & Perceived Impact (AAPI)	AI Application Awareness	AI2	I am aware of the potential of AI in automated quality control and defect detection.
AI Application Awareness & Perceived Impact (AAPI)	AI Application Awareness	AI3	I understand how AI can optimize inventory management and supply chain logistics.
AI Application Awareness & Perceived Impact (AAPI)	Perceived Operational Impact	AI4	AI adoption can significantly improve our company's operational efficiency.
AI Application Awareness & Perceived Impact (AAPI)	Perceived Operational Impact	AI5	AI technologies can help reduce production costs and minimize waste in our operations.
AI Application Awareness & Perceived Impact (AAPI)	Perceived Operational Impact	AI6	AI can enhance our ability to make faster, data-driven decisions.
AI Application Awareness & Perceived Impact (AAPI)	Perceived Strategic Impact	AI7	AI adoption can strengthen our company's competitive advantage in the market.
AI Application Awareness & Perceived Impact (AAPI)	Perceived Strategic Impact	AI8	AI can help our company develop new business models and innovative products/services.
AI Application Awareness & Perceived Impact (AAPI)	Perceived Strategic Impact	AI9	AI implementation can enhance our company's ability to adapt to market changes and disruptions.