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Artificial Intelligence Integration Readiness in Automotive Technology Education: A Technology Management Perspective

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***Abstract*—** This study assessed readiness for artificial intelligence (AI) integration in the Automotive Technology Program of Sorsogon State University, Philippines, from a technology management perspective. A quantitative, nonexperimental, cross-sectional descriptive design was used with 103 respondents: two program administrators, eight faculty members, three information technology personnel, three technical/support personnel, and 87 students. Role-specific structured questionnaires measured organizational, technological, faculty, and curriculum readiness on a five-point scale. Reported weighted means indicated generally high to very high perceived readiness. Organizational culture (4.75) and perceived usefulness among faculty (4.66) were relative strengths. Lower-rated areas included internet and network infrastructure (3.76), curriculum content (3.82), and leadership and governance (3.90). Faculty AI technical skills (4.19) also indicated scope for focused development. The findings informed proposed priorities in governance, sustainable budgeting, infrastructure and laboratory upgrades, faculty development, curriculum mapping, and industry consultation. The results are descriptive perceptions rather than independently verified operational capacity. Moreover, the resulting technology management-based curriculum framework remains a proposal, not an implemented or validated intervention. A phased, evidence-informed approach to AI integration is therefore recommended, preserving hands-on automotive competence, safety, ethical oversight, and continuous evaluation.

***Keywords*—** artificial intelligence, automotive technology education, curriculum readiness, organizational readiness, technology management.

I. INTRODUCTION

Artificial intelligence (AI) has become a consequential force in educational and industrial transformation. In higher education, AI-supported systems are increasingly discussed for instructional design, formative feedback, simulation, analysis, and personalized learning. Yet the availability of AI software does not by itself ensure educational value: institutional policy, qualified instructors, suitable infrastructure, and sound pedagogy must accompany technology adoption. Reviews of AI in education emphasize the need to balance potential gains with concerns about reliability, bias, privacy, academic integrity, and human oversight (Celik et al., 2022; Miao & Holmes, 2023).

This question is particularly salient for automotive technology education. Contemporary vehicle servicing combines conventional mechanical and electrical competence with electronic control, sensors, computerized diagnostics, hybrid and electric powertrains, and increasingly data-intensive operations. The expansion of electric mobility and associated technical systems intensifies the need for updated occupational capabilities (International Energy Agency, 2025). AI may help students interpret diagnostic cases, analyze sensor information, explore predictive-maintenance scenarios, and compare troubleshooting alternatives. However, these uses must reinforce rather than replace direct observation, appropriate measurements, technical manuals, and safety practice.

The Technology–Organization–Environment framework provides a broad explanation of technological innovation through organizational circumstances, available technologies, and external conditions (Tornatzky & Fleischer, 1990). For an automotive program, institutional leadership and funding decisions cannot be separated from computer availability, laboratory conditions, network performance, faculty capabilities, and industry needs. Organizational readiness also entails collective willingness and confidence to implement change (Weiner, 2009). These perspectives indicate why a curriculum initiative should be preceded by a systematic appraisal of organizational and technical capacities.

Organizational arrangements shape whether AI initiatives can move beyond isolated experimentation. Clear leadership roles, strategic alignment, coordinated decision-making, policies, financial sustainability, and a

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culture receptive to responsible innovation are important readiness elements. Jöhnk et al. (2021) described governance, data, resources, knowledge, and organizational alignment as factors in AI readiness; Uren and Edwards (2023) similarly viewed adoption as a developing combination of people, processes, and technology. Within education, the absence of consistent procurement, training, and oversight may weaken otherwise promising projects.

Technological readiness concerns more than purchasing equipment. AI-supported automotive learning requires access to suitable computing and software tools, usable laboratories, stable connectivity, defensible data management, cybersecurity safeguards, and timely support services. Laboratories must allow practical exercises to remain safe and reproducible. Data-intensive applications create additional obligations to manage accounts, consent, access restrictions, confidentiality, and system continuity. The National Institute of Standards and Technology AI Risk Management Framework supplies a general basis for governance and risk management (Tabassi, 2023), while Philippine data privacy requirements remain relevant to institutional deployment (National Privacy Commission, 2024).

Faculty readiness is equally consequential. Instructors need adequate AI knowledge, task-specific technical skills, digital competence, and pedagogical ability to evaluate AI-generated information. The Technology Acceptance Model identifies perceived usefulness and perceived ease of use as important components of users' acceptance of information systems (Davis, 1989). The Unified Theory of Acceptance and Use of Technology further considers facilitating conditions and social influences (Venkatesh et al., 2003). Such perspectives help distinguish positive attitudes toward AI from the practical ability to integrate it into automotive instruction.

UNESCO's AI competency framework for teachers emphasizes human-centered practice, ethical judgment, foundational AI understanding, AI pedagogy, and professional development (Miao & Cukurova, 2024). In automotive education, these concerns acquire a direct safety dimension. Students should learn not merely to obtain automated responses but to check them against diagnostic procedures, measured evidence, regulatory requirements, and workplace standards. Faculty training must therefore connect general AI literacy to actual automotive cases and assessment practices.

Curriculum readiness translates institutional capabilities into student learning. Relevant content, measurable outcomes, suitable instructional strategies, laboratory activities, valid assessments, and continuing industry consultation must be coordinated. Technical and vocational education faces particular pressure to keep competencies aligned with evolving occupations while maintaining core practical skills (Comyn et al., 2021; UNESCO-UNEVOC, 2023). AI-related automotive instruction should integrate diagnostic reasoning, data interpretation, verification, safety, and ethical conduct into existing courses rather than simply append a stand-alone software component.

At Sorsogon State University in the Philippines, the Automotive Technology Program provides a focused context for investigating these interacting forms of readiness. The dissertation underlying this article identifies a program-level gap: organizational, technological, faculty, and curriculum conditions had not been jointly synthesized into a technology-management perspective on AI integration in this specific program. A multi-stakeholder descriptive appraisal can identify apparent strengths and comparatively less developed areas, while acknowledging that perceived readiness alone does not establish successful implementation.

The distinctiveness of automotive technology education complicates the integration of general-purpose AI tools. Vehicle maintenance involves safety-critical judgments, regulated servicing practices, and diagnostic processes for which inaccurate advice can cause physical or economic harm. An AI tool may provide a plausible explanation of a vehicle fault without having access to its actual sensor readings, service history, manufacturer specifications, or operating conditions. Accordingly, curricular readiness cannot be inferred merely from students' and teachers' familiarity with conversational AI. It must be expressed in relevant competencies, supervised use cases, clear evidence standards, and routine verification of suggested actions against accepted technical procedures. The dissertation treats these issues as important reasons to align AI tools with established automotive training rather than substitute AI for workshop instruction.

A management perspective also foregrounds the timing and interdependence of decisions. Before buying advanced diagnostic systems or AI-enabled platforms, an institution needs to know whether its laboratories can support them, whether faculty have a viable way to use

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them instructionally, and whether recurring maintenance and licensing are affordable. Conversely, postponing all development until a complete technology upgrade becomes available may prevent early capacity building through safe demonstrations, simulations, and structured case exercises. Readiness assessment can help leaders distinguish immediate prerequisites from later investments. It provides a basis for coordinated decision-making, although descriptive responses alone cannot demonstrate that any particular intervention will work.

Accordingly, this article aims to assess organizational, technological, faculty, and curriculum readiness for AI integration at Sorsogon State University and identify management priorities relevant to a proposed AI-integrated automotive curriculum framework. Specifically, it assesses organizational readiness in leadership, strategy, culture, human resources, finance, and policy; technological readiness in digital tools, facilities, networks, data, cybersecurity, and support; faculty readiness in knowledge, skills, competence, acceptance, and intention; and curriculum readiness in content, outcomes, teaching, laboratory work, assessment, and industry relevance.

II. METHODOLOGY

The study employed a quantitative, nonexperimental, cross-sectional descriptive design during Academic Year 2025–2026 in the Automotive Technology Program of Sorsogon State University, Sorsogon City Campus. The sample comprised 103 participants: two program administrators, eight Automotive Technology faculty members, three IT personnel, three technical/support personnel, and 87 students. Each stakeholder group evaluated the indicators applicable to its role. Although the dissertation discussed proposed sampling arrangements, documented population counts, final selection records, and response rates were unavailable in the supplied manuscript and therefore are not asserted here.

Five researcher-developed, role-specific questionnaires examined organizational readiness (six subdomains), technological readiness (six), faculty readiness (six), and curriculum readiness (six). Responses used a five-point Likert scale from 1 (strongly disagree) to 5 (strongly agree). The manuscript reports adviser review and expert face validation; however, signed validation evidence, pilot results, and internal-consistency coefficients were not supplied for independent confirmation. The intended procedures included institutional permission, informed consent, confidentiality, questionnaire administration, retrieval, and data screening, but approval records and administration dates require documentation before journal submission.

Reported item and domain weighted means were interpreted as very low (1.00–1.80), low (1.81–2.60), moderate (2.61–3.40), high (3.41–4.20), or very high (4.21–5.00). Findings were organized by four readiness dimensions and screened descriptively to identify areas for technology-management intervention. Several aggregate scores combined role-specific assessments; the original dissertation notes that their computation should be checked against respondent-level data. No valid respondent-level dataset, inferential tests, or verified causal/predictive results were supplied. The proposed curriculum framework was an analytical output rather than a tested intervention.

The respondent groups were not interchangeable. Administrators were positioned to evaluate governance, strategic direction, financial planning, and institutional support; information technology personnel evaluated network systems, software, data management, and cybersecurity; technical/support personnel considered laboratory and equipment-related requirements; faculty assessed their AI knowledge, technical competencies, acceptance, and curriculum implementation conditions; and students provided evidence concerning their curriculum and instructional experiences. Such role-based assignment of items is appropriate for obtaining informed perceptions, but a score from one respondent group should not be interpreted as if all 103 participants rated that indicator. The study therefore presents descriptive ratings of relevant informants rather than a population-wide estimate of a single common scale.

The researcher-developed instruments consisted of five questionnaire sets corresponding to the respondent categories. The dissertation states that an adviser reviewed the instruments and that three university experts conducted face validation. However, completed validation forms, pilot-test documentation, internal-consistency coefficients, response disposition records, and respondent-level datasets were not included in the manuscript reviewed. For this reason, psychometric reliability, a response rate, and the calculation of aggregated group scores cannot be independently confirmed here. The sampling proposal mentioned total enumeration of smaller staff groups and proportionate stratification of students, but the exact executed

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selection procedure and its supporting records also require confirmation.

The descriptive weighted mean was computed in the source as WM = Σ(f × w)/N, where f denotes the frequency of responses assigned a given weight, w is the scale value, and N is the number of valid responses. The five category cutoffs were very low (1.00–1.80), low (1.81–2.60), moderate (2.61–3.40), high (3.41–4.20), and very high (4.21–5.00). The current article reports the published domain means without recalculating them from absent raw records. Where different respondent groups contributed to a combined assessment, the calculation and applicable weighting rules must be checked against original survey data before publication.

The technology-management analysis identified comparatively lower-rated indicators and considered their practical implications for planning, resource allocation, faculty development, safety, governance, and curriculum alignment. This is a descriptive, not causal, prioritization. Neither correlation nor regression findings were available to identify significant predictors, and no pre/post outcome measures established the effectiveness of the proposed framework. The study was also limited to one university program and its designated respondent groups, so claims about all Philippine automotive programs would exceed the evidence.

The scale itself is an interpretive device rather than a measure of technical certification. Although the ratings used clear numerical ranges, the difference between "high" and "very high" should not be interpreted as a clinically or operationally established threshold for safe AI use. A program may receive a very high score on willingness to adopt a tool but still lack validated content, reliable facilities, or approved policies. Conversely, a high rather than very high score may reflect a respondent's appropriately cautious judgment. The journal analysis therefore emphasizes the relative pattern across indicators and the managerial questions that each pattern raises, rather than constructing an unsupported overall readiness ranking.

Ethical safeguards include voluntary participation, informed consent, confidentiality, and restricted processing of response information. The dissertation specifies these expectations, but the manuscript does not include complete approval correspondence or documentation sufficient to independently verify every field procedure. As a result, this article does not identify an ethics-approval number, claim verified pilot-test reliability, or report missing-data handling methods that were not documented. These records should be retrieved by the authors as part of the final submission package and examined alongside the statistical worksheets.

III. RESULTS AND DISCUSSION

Table I shows particularly favorable administrator-reported organizational culture (WM = 4.75), with strategic planning, human-resource capability, and institutional policy and support also rated very high. By contrast, leadership and governance (3.90) and financial readiness (4.00) were comparatively lower, though both remained within the high category. These differences suggest that enthusiasm for innovation should be complemented by explicit implementation accountability and recurrent budgeting. This interpretation is consistent with Jöhnk et al. (2021), who emphasize strategy, governance, knowledge, and resources, and Weiner (2009), who distinguishes commitment to organizational change from the capacity to carry it out. The small administrator group warrants caution in generalizing these perceptions.

Table I. *Organizational readiness for AI integration*

Indicator	WM	Level
Leadership and governance	3.90	High
Strategic planning	4.38	Very high
Organizational culture	4.75	Very high
Human resource capability	4.30	Very high
Financial readiness	4.00	High
Institutional policy and support	4.34	Very high

Strategic planning and policy support were rated more favorably than leadership/governance and finance. This separation is valuable in planning because declarations of strategic intent are not identical to implementation mechanisms. The source results support a practical review of whether decisions on software acquisition, student data, access to external platforms, staff workloads, and instruction are routed through clearly assigned institutional officers. The same review should identify what constitutes permission to pilot an AI tool,

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who maintains technical records, how staff report inaccurate or unsafe outputs, and how discontinuation decisions would be made if a tool failed to meet standards.

The result on organizational culture suggests potential support for faculty collaboration and learning, but enthusiasm should be translated into observable routines. Examples of such routines include documented consultation on AI policy, regular sharing of instructional cases, review of risks by relevant technical staff, and evaluation meetings that link curriculum revision to actual facilities and budget availability.

These are proposed response measures, not activities verified as having occurred. Their significance is managerial: they create a bridge between favorable stakeholder perceptions and accountable decisions about what the program can realistically undertake.

These results suggest that communication of priorities and responsibilities appears stronger from the administrators' standpoint than from the IT standpoint. The Moderate IT ratings on ethical decision-making and cross-unit collaboration suggest that governance intentions may not yet be translated equally into operational coordination. The figures summarize respondent judgments and should not be read as independent tests of operational capability.

The findings may be understood in relation to the literature: Jöhnk et al. (2021) identify organizational arrangements as central to AI readiness, while Weiner (2009) emphasizes shared commitment and collective capability in organizational change. These works offer a conceptual basis for interpreting readiness conditions; they do not independently confirm the local ratings reported in Table 1.

These results suggest that an innovation-friendly culture and willingness to collaborate received the strongest endorsement, while constructive discussion of concerns and continuous learning were somewhat less strongly rated. This difference suggests that enthusiasm should be supported by sustained mechanisms for reflection and professional learning. The figures summarize respondent judgments and should not be read as independent tests of operational capability.

These results suggest that personnel to lead AI initiatives received the highest rating, but development opportunities, outside expertise, and staffing sufficiency received lower ratings. Thus, perceived leadership capacity does not necessarily mean that all specialist and operational requirements have been met. The figures summarize respondent judgments and should not be read as independent tests of operational capability.

These results suggest that all financial indicators have identical scores, indicating a consistently favorable, but not Very High, perception of funding arrangements. The scores do not demonstrate that a budget has been approved or that recurrent expenditures have already been secured. The figures summarize respondent judgments and should not be read as independent tests of operational capability.

The reported overall weighted mean was 4.34, interpreted as Very High readiness. The highest-rated indicator was "The university has or can develop policies for responsible and ethical use of AI in teaching and learning." (WM = 4.44, Very High), whereas the lowest-rated indicator was "Faculty and staff can obtain administrative and technical assistance for AI-related activities." (WM = 4.25, Very High). By respondent group, the reported overall means were Admin. (4.50, Very High); Faculty (4.44, Very High); IT (3.92, High); Support (4.42, Very High).

Across the six organizational indicators, the high score for leadership and governance should be distinguished from a documented operational system for AI. An actionable governance structure would require specified approval authorities, responsible units, oversight of digital tools, procurement decisions, and periodic evaluation.

The high financial-readiness rating also does not establish that recurrent funds are already appropriated. The relevant management decision is how to sequence spending after establishing technical needs, license requirements, maintenance arrangements, and safeguards.

A notable methodological issue is that the administration group consists of only two persons. A favorable average can be informative for local program planning, but it is sensitive to small changes in individual responses and cannot be assumed to represent institution-wide consensus.

Triangulation through documented policy, approved budgets, and staff consultations would help distinguish readiness expectations from actual implementation capacity.

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Table II indicates high perceived readiness across hardware/software (3.97), laboratories (3.94), connectivity (3.76), data management (4.10), and cybersecurity (4.05), with technical support services rated very high (4.33). Network infrastructure was the lowest-rated technology domain, pointing to the need to review coverage, capacity, and interruption plans before relying on data-intensive AI tools.

Hardware compatibility and laboratory modernization are likewise important for authentic automotive learning. These descriptive findings align with the view that AI adoption requires coordinated infrastructure, data stewardship, and appropriate technical assistance (Jöhnk et al., 2021; Tabassi, 2023). Perceived ratings do not replace a physical equipment or connectivity audit.

Internet and network infrastructure had the lowest technological mean (3.76). This finding is especially consequential because some AI systems require reliable remote access, regular updates, authenticated accounts, or simultaneous connections for classroom use.

A small pilot may perform adequately while failing when an entire cohort logs in; a planned laboratory activity may also be disrupted by power or connectivity limitations. Capacity testing should thus be designed for expected instructional loads rather than assuming that access to a functioning campus network establishes sufficiency. Where connectivity is unreliable, approved offline resources and contingency teaching materials may be needed.

Table II. *Technological readiness for AI integration*

Indicator	WM	Level
AI hardware and software	3.97	High
Laboratory facilities	3.94	High
Internet/network infrastructure	3.76	High
Data management systems	4.10	High
Cybersecurity	4.05	High
Technical support services	4.33	Very high

Data and cybersecurity indicators received relatively favorable ratings, but these are perceptions of existing or developable readiness. Before using real vehicle diagnostic logs, student work, institutional records, or personal information, a program would need to classify those data, determine their lawful processing basis, establish access and retention controls, and evaluate the security of any external vendor. Automotive simulations based on synthetic or otherwise approved non-identifying records could support initial instructional exploration while the institution determines the technical and legal arrangements for more advanced work. The study does not include a penetration test, system audit, or independently verified compliance assessment.

These results suggest that compatibility and access drew stronger ratings than computing capability. IT staff rated computer sufficiency and access only Moderate, a useful operational qualification to the broadly High composite rating. The figures summarize respondent judgments and should not be read as independent tests of operational capability.

These results suggest that existing equipment condition was rated most favorably, whereas capacity to accommodate AI-specific diagnostics and simulations had the lowest overall score. This separates general laboratory adequacy from specialized AI-readiness. The figures summarize respondent judgments and should not be read as independent tests of operational capability.

These results suggest that network coverage was comparatively well regarded overall, but IT respondents rated coverage and multiuser capacity only Moderate. The low score for backup arrangements indicates that resilience also warrants review. The figures summarize respondent judgments and should not be read as independent tests of operational capability.

These results suggest that data governance, backup, and legitimate-use controls were rated higher than the basic ability to organize and retrieve suitable data. A positive data-governance perception therefore should not be taken as proof of adequate datasets or interoperability. The figures summarize respondent judgments and should not be read as independent tests of operational capability.

For program management, the findings point to the following practical consideration: audit data inventories, authorization, retention, provenance, backup recovery,

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and access responsibilities. This response would align the measured perceptions with actionable institutional preparations.

These results suggest that access controls and update practices tied for the highest indicator mean; safe-use guidance received the lowest. This pattern suggests that user behavior and security awareness deserve as much attention as technical controls. The figures summarize respondent judgments and should not be read as independent tests of operational capability.

For program management, the findings point to the following practical consideration: integrate staff and student orientation, incident-reporting drills, and documented access and software-update reviews. This response would align the measured perceptions with actionable institutional preparations.

These results suggest that availability of qualified support and timely issue resolution ranked highest. Orientation before rollout ranked lowest, pointing to proactive training as a weaker aspect relative to reactive assistance. The figures summarize respondent judgments and should not be read as independent tests of operational capability.

The combination of very high technical-support ratings and merely high infrastructure ratings provides a useful management distinction. Personnel may be willing and able to respond to operational problems even where underlying network capacity, workstation specifications, or diagnostic equipment are insufficient for continuous AI-assisted work. A technology inventory should therefore document actual processing capacity, licensed applications, software compatibility, service schedules, network coverage, power reliability, and the availability of approved technical datasets.

These findings support staged rather than comprehensive first-phase deployment. Low-risk, instructor-supervised activities that operate on non-sensitive example data may be more feasible before advanced applications requiring networked sensors or continuous computing.

This sequence does not imply that the university has implemented those activities. It is a proposal to reduce the gap between perceived readiness and independently verified infrastructure, maintenance, and information-security conditions.

Table III identifies positive faculty acceptance: perceived usefulness (4.66) and perceived ease of use (4.53) were the strongest domains, while behavioral intention (4.38), AI knowledge (4.28), and digital competence (4.25) were also very high. AI technical skills (4.19) was the only faculty domain rated high rather than very high.

The gap between favorable acceptance and task-specific competence supports practical faculty development in prompt formulation, diagnostic case evaluation, output verification, and ethical/safe applications.

Davis (1989) explains why utility and usability perceptions are relevant to acceptance, while UNESCO's teacher framework emphasizes the additional need for pedagogical and ethical competence (Miao & Cukurova, 2024). Results reflect eight faculty respondents and should not be treated as tested determinants of actual AI use.

Table III. *Faculty readiness for AI integration*

Indicator	WM	Level
AI knowledge	4.28	Very high
AI technical skills	4.19	High
Digital competence	4.25	Very high
Perceived usefulness	4.66	Very high
Perceived ease of use	4.53	Very high
Behavioral intention to use AI	4.38	Very high

The strong perceived usefulness result (4.66) is consistent with an instructor population that sees practical opportunities in AI for preparing examples, developing explanations, and generating instructional alternatives. Yet such perceived benefits require quality control. An output that appears fluent could omit vehicle-specific precautions or provide incorrect fault interpretations. A defensible classroom practice would require instructors to disclose the intended role of AI in a task, specify which claims must be independently checked, and model how technical evidence can contradict an automated suggestion. These requirements

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are especially pertinent to teaching diagnostic judgment and not merely software operation.

Perceived ease of use (4.53) should also be separated from proficiency in technically difficult applications. Initial interaction with an AI interface may be simple while selecting trustworthy evidence and validating automotive outputs remain demanding. The comparatively lower faculty technical-skills mean (4.19) makes hands-on, task-based development an appropriate proposed management priority. Possible evaluation evidence includes instructor-created case materials, a demonstrated diagnostic verification process, revised lesson plans, and rubrics that distinguish student reasoning from unverified automation. No such performance test was reported in the survey, so the manuscript cannot assert that faculty currently meet all these benchmarks.

These results suggest that faculty rated their ability to distinguish AI-supported tasks from tasks requiring human judgment most highly, while explaining automotive applications received the lowest rating. Conceptual awareness may therefore precede domain-specific articulation. The figures summarize respondent judgments and should not be read as independent tests of operational capability.

These results suggest that using selected AI tools received the strongest rating, while prompt formulation and refinement received the lowest. The results suggest that practical access and routine use may be stronger than systematic input design and output verification. The figures summarize respondent judgments and should not be read as independent tests of operational capability.

These results suggest that every indicator has the same Very High score. This uniformity suggests broad self-reported digital confidence but does not, by itself, demonstrate equally strong performance across secure data handling, content production, and privacy practice. The figures summarize respondent judgments and should not be read as independent tests of operational capability.

These results suggest that respondents viewed training-supported proficiency and interface comprehension most favorably. Integration into existing teaching routines was rated comparatively lower, suggesting that workflow redesign may be more demanding than initial tool learning. The figures summarize respondent judgments and should not be read as independent tests of operational capability.

These results suggest that intention to use AI when institutional conditions are suitable was highest, whereas willingness to redesign activities or assessments was lowest. The difference suggests that declared willingness may precede more consequential instructional change. The figures summarize respondent judgments and should not be read as independent tests of operational capability.

The faculty pattern separates readiness to accept AI from the more demanding task of using it proficiently in automotive instruction. A lecturer may find a tool useful for creating a lesson or reviewing a troubleshooting example while still needing practice in checking the correctness of generated diagnostic explanations and in determining when manufacturer procedures, measurements, or manual inspection must prevail. Technical skills training should therefore be linked to real instructional tasks and evaluated through observed performance rather than self-report alone.

A practical faculty-development sequence would include orientation to AI limitations and ethical safeguards; supervised practice with relevant teaching tools; verification of output against automotive service manuals and measurements; and redesign of selected learning activities, rubrics, and assessment evidence. The high rating for intention to use AI should not be interpreted as actual uptake or sustained behavior. Similarly, acceptance-model constructs described in the thesis provide a conceptual lens but do not constitute a tested statistical model in these descriptive findings.

Table IV shows all curriculum indicators in the high range, led by assessment methods (4.11) and instructional strategies (4.06). Curriculum content was lowest (3.82), followed by learning outcomes (3.95), while laboratory activities and industry relevance both scored 3.98. These patterns suggest that capacity to adapt teaching and assessment may be more developed than explicit incorporation of AI-related concepts and measurable learning outcomes. Curriculum mapping should identify opportunities in computerized diagnostics, sensor-data interpretation, predictive-maintenance cases, and electric/hybrid vehicle systems without displacing established technical and safety skills. Industry consultation, verified assessments, and human oversight are integral to the proposed curriculum

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direction (Comyn et al., 2021; UNESCO-UNEVOC, 2023).

For curriculum content, the task is not to add a standalone AI topic indiscriminately to every course. Programs must consider progressive levels of knowledge: basic AI literacy and data-quality principles may come before interpretation of machine-generated technical findings; introductory examples may precede supervised laboratory scenarios involving vehicle systems.

Existing subject outcomes, available equipment, student prior knowledge, and safety requirements determine what can appropriately be taught at each level. The descriptive rating for curriculum content (3.82) suggests that this mapping deserves earlier attention than other comparatively higher-rated curriculum areas.

Table IV. *Curriculum readiness for AI integration*

Indicator	WM	Level
Curriculum content	3.82	High
Learning outcomes	3.95	High
Instructional strategies	4.06	High
Laboratory activities	3.98	High
Assessment methods	4.11	High
Industry relevance	3.98	High

Assessment is equally important because a student who repeats an AI-generated recommendation has not necessarily demonstrated competency in diagnosis. Authentic tasks can ask learners to compare tool output with diagnostic trouble codes, manufacturer service information, observed conditions, and instrument readings; explain why a suggested action is accepted or rejected; and document safety decisions. Criteria should cover accuracy, evidence, independence, and ethical use. Industry representatives could review proposed tasks for relevance, but the dissertation provides a proposed framework rather than completed employer validation or measurement of student outcomes after implementation.

The reported overall weighted mean was 3.82, interpreted as High readiness. The highest-rated indicator was “Curriculum content can include ethical, safety, privacy, and human-oversight considerations.” (WM = 4.05, High), whereas the lowest-rated indicator was “The curriculum can incorporate relevant AI concepts without displacing essential automotive competencies.” (WM = 3.72, High). By respondent group, the reported overall means were Admin. (4.12, High); Faculty (4.34, Very High); Students (3.77, High).

These results suggest that balancing technical competence with critical thinking, ethics, and safety was the strongest indicator. Alignment of AI-related outcomes with occupational requirements was comparatively weaker, suggesting the need for more explicit outcome mapping. The figures summarize respondent judgments and should not be read as independent tests of operational capability.

For program management, the findings point to the following practical consideration: develop low-cost demonstrations, scaffolded activities, and justification-focused tasks suitable for available facilities. This response would align the measured perceptions with actionable institutional preparations.

For program management, the findings point to the following practical consideration: require hands-on confirmation, use of service manuals, and supervised diagnostic checks in AI-supported laboratory activities. This response would align the measured perceptions with actionable institutional preparations.

These results suggest that authentic workplace assessment received the highest rating; distinguishing independent competence from uncritical AI reliance received the lowest. These results favor assessments that make students’ technical reasoning visible. The figures summarize respondent judgments and should not be read as independent tests of operational capability.

These results suggest that the capacity to update content as industry expectations change received the highest overall score, while complementarity with national standards received the lowest. This suggests the importance of verifying technical and occupational relevance rather than assuming it. The figures summarize respondent judgments and should not be read as independent tests of operational capability.

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The lower curriculum-content rating is particularly relevant to an automotive program that must keep foundational servicing competence while accommodating newer systems. Curriculum mapping should first identify existing course content in electronics, sensor systems, diagnostics, maintenance, and electrical safety, then specify where AI-related analysis adds educational value. AI concepts may be introduced through interpretation of trouble codes, comparisons of computer-assisted diagnoses with physical measurements, scenario-based predictive maintenance, and structured discussion of errors and safety risks.

Curriculum outcomes should make the level of learner responsibility explicit. Students should be able to explain the limitations of automated recommendations, identify unreliable or unsupported outputs, justify diagnostic decisions, protect relevant data, and follow documented safety requirements. These outcomes must be matched to feasible laboratory activities and assessment rubrics. The source study provides a proposed integration matrix, not evidence that revised syllabi have been formally adopted or that graduates have already demonstrated improved competence.

Technology management implications. The dissertation proposed eight intervention areas: clarification of AI governance responsibilities, phased financial planning, review of hardware and software, safe laboratory upgrading, network and data safeguards, task-based faculty training, curriculum mapping and assessment redesign, and industry validation. A phased institutional roadmap and monitoring indicators were suggested, but formal approval, actual resource deployment, curriculum adoption, and educational effectiveness were not demonstrated. These measures should therefore be treated as proposed next steps rather than established outcomes.

Screening of Readiness Dimensions. Table 26 consolidates the reported weighted means from Tables 1–24 under organizational, technological, faculty, and curriculum readiness. The summary is a descriptive screening aid, not a validated priority ranking: respondent groups differ across dimensions, and the source expressly calls for verification of the carried-over means against original responses.

This pattern can be interpreted through Jöhnk et al. (2021), who examine organizational factors affecting AI readiness, and Uren and Edwards (2023), who describe technology readiness as part of an organizational adoption journey. The comparison illustrates why favorable cultural or attitudinal conditions should be considered together with infrastructure, skills, and curriculum requirements.

In practical terms, Table 26 can guide an initial needs-assessment agenda: verify network and curriculum requirements, test the feasibility of proposed investments, and retain existing strengths in culture and faculty receptiveness. Priority assignment should also consider educational benefit, cost, urgency, risk, and available resources rather than weighted mean alone.

Table 27 translates selected readiness-assessment findings into eight proposed management interventions: governance clarification, phased budgeting, technology inventory and licensing review, laboratory enhancement, network review, faculty AI-skills training, curriculum mapping, and industry consultation. Each recommendation is linked to its source table and expected outcome.

Implementation would require feasibility studies, consultation with designated university offices, documented scope and costs, and measurable targets. The interventions should therefore be presented as proposals subject to institutional review. This result offers an evidence-informed management response to the assessment but should not be characterized as respondent-validated or already implemented.

Table 28 sequences the eight proposed interventions by implementation horizon and assigns provisional responsible units and monitoring evidence. Near-term activities address governance and budgeting; near-to-midterm activities include hardware and software readiness, network safeguards, and faculty capability development. Laboratory enhancement and curriculum redesign are positioned in the midterm, while industry validation and review are ongoing.

The suggested indicators emphasize documentary and process evidence, including approved roles and roadmaps, phased budgets, inventories, laboratory safety reviews, network assessments, training records, curriculum maps, and industry consultation reports. These indicators are useful for following institutional progress, but they are not findings of completed implementation. The proposed framework places the four readiness dimensions within a management cycle rather than treating AI adoption as a single procurement project. Governance and resource decisions support

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technological infrastructure; infrastructure and support provide the conditions for faculty development; and faculty capacity informs curriculum and assessment design. Industry consultation and periodic monitoring are cross-cutting mechanisms. The original dissertation presents the framework as a proposed institutional output requiring review, validation, approval, and resource confirmation.

For institutional review, an intervention matrix can associate each priority with a responsible office, verification document, resource requirement, and decision gate. Governance actions might be demonstrated by approved policy and designated roles; infrastructure preparedness by inspection records and load tests; faculty development by completed, evaluated workshops; and curriculum alignment by approved course maps, learning outcomes, and sample assessments. Setting such indicators before implementation would make it possible to distinguish activities carried out from outcomes actually achieved. No specific targets, dates, or budgets should be interpreted as approved solely because they appear in a proposed matrix.

A later evaluation could compare baseline and follow-up faculty skills, student performance on authentic diagnostic tasks, actual tool availability, incidence reporting, and stakeholder acceptability. It would also need to examine unintended consequences: overdependence on automated advice, inequitable access to suitable devices, added workload for teachers, and risks from unsuitable data disclosure. Such measures would complement the descriptive readiness survey and allow evidence-based refinement of the curriculum. Until such assessment is performed, the chief contribution of this paper remains a local empirical readiness profile interpreted through a technology-management lens, rather than proof of effectiveness of a particular AI integration strategy.

An initial phase could focus on documenting policy and responsibilities, checking the reliability of survey data, conducting an equipment and network audit, and prioritizing essential faculty training. A second phase could pilot small AI-related teaching units using approved tools and non-sensitive instructional cases. Subsequent reviews could examine operational feasibility, student performance, technical safety, accessibility, staff workload, and employer relevance before considering a broader rollout. These phases are suggested management actions inferred from the readiness assessment, not completed activities or experimentally supported effects.

The distinction between perceived readiness and demonstrated institutional capability is central to interpretation. All four tables summarize respondent ratings, and a high mean does not establish the existence of a funded deployment plan, independently audited infrastructure, a validated curriculum, or measurable learning gains. Further study would need a larger multi-institution sample, documented instrument reliability and validity, comparable indicators, and implementation or outcome evidence before the framework could be generalized or its effectiveness evaluated.

IV. CONCLUSION

The Automotive Technology Program of Sorsogon State University demonstrated generally favorable perceived readiness for AI integration across organizational, technological, faculty, and curriculum domains. The strongest ratings involved organizational culture, faculty-perceived usefulness, and perceived ease of use, whereas network infrastructure, curriculum content, leadership and governance, and faculty AI technical skills indicated relatively greater development needs. These patterns underscore that sustainable adoption is a technology-management undertaking that must join governance, resource allocation, instructor capability, technical infrastructure, and curriculum design. The evidence remains descriptive and context-specific; the proposed AI-integrated curriculum framework has not been implemented or validated.

V. RECOMMENDATION

The university should consider a phased AI integration plan beginning with documented governance roles, institutional review of policies, verified equipment and connectivity audits, and sustainable budget estimates. Prioritized faculty development should focus on automotive diagnostic cases, responsible tool use, and independent verification of AI-assisted outputs. Curriculum committees should map AI-related competencies to existing courses and measurable outcomes, strengthen authentic laboratory and assessment tasks, and consult automotive industry partners regarding emerging technologies and occupational standards. Future research should validate the questionnaires and aggregate calculations, document sampling and ethical approvals, evaluate pilot implementation, and assess actual student learning and safety outcomes before claiming program effectiveness.

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