Impact of Artificial Intelligence on Wood Science Education and the Malaysian Wood Industry: A Scoping Review

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Artificial intelligence (AI) is increasingly influencing technical education and manufacturing, but the implications for wood science education as well as its impact on the Malaysian wood products industry remain insufficiently mapped. This scoping review synthesized evidence from 31 peer-reviewed articles, government documents, and industry reports using the PRISMA approach, to examine three linked issues: the application of AI and Industry 4.0 technologies in wood-related production; the resulting changes in workforce competencies; and the implications for wood science and technology education in Malaysia. The review which assumed a policy-oriented theme indicated a persistent mismatch between the digital capabilities expected in technology-enabled wood manufacturing and the competencies represented in current education and training provision. At the same time, the evidence does not support an assumption that AI adoption is uniformly beneficial: implementation is constrained by SME resources, data quality, cybersecurity, workforce readiness, and the intrinsic variability of wood as a biological material. The review therefore recommends evidence-informed curriculum renewal, stronger industry-academia collaboration, targeted reskilling, and policy coordination, while emphasizing that these recommendations should be validated through stakeholder engagement and future empirical research.

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INTRODUCTION

Since human civilization began, especially over the last two centuries, manufacturing has progressed from mechanization and mass production to automation, computerization, and increasingly connected and intelligent production systems (Park *et al*. 2026). The advent of Artificial Intelligence (AI) is now an important component of this transition, although its level of adoption and effectiveness vary substantially across industries and firm sizes. Although investments into AI development have been enormous especially in the United States of America and China, other countries are also increasingly

investing into this technology (Park *et al.* 2026). From an institutional and commercial investment perspective, investment estimates into AI application are varied by definition and the market segment considered. Hence, such figures should therefore be interpreted as reported market estimates rather than as directly comparable measures of industrial adoption. Evidence on AI adoption in the various economic sectors, including the education sector, likewise uses different definitions, samples, and indicators, and is difficult to generalize and most figures reported are estimates (Kitek-Kuzman *et al.* 2024). Accordingly, the present review does not treat a single percentage as a universal adoption rate; instead, it uses reported sector or study-specific estimates to illustrate the direction and heterogeneity of change within the realms of AI adoption across the various economic sectors.

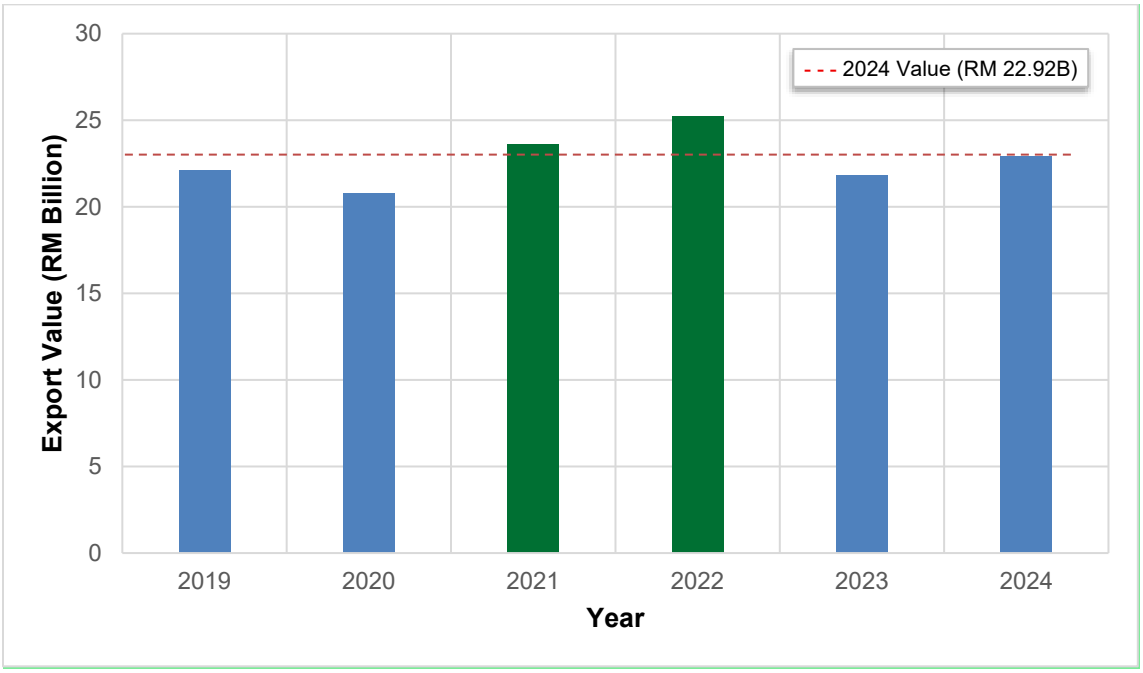


Fig. 1. Malaysia timber & wood products – Total export value, 2019–2024 (RM Billion). Sources: MTC Trade Statistics (2024); MTIB (2021a, 2022, 2023a, 2024a)

The Malaysian wood products and furniture industry has evolved from predominantly primary processing industry toward a more export-oriented and value-added manufacturing industry within the last three decades (Fig. 1). Official industry statistics indicate RM 22.92 billion in timber and wood-product export value in 2024, while subsequent industry reporting provides updated estimates for later years (MTC 2024; MTIB 2024a; MTC 2026a). Because the statistical data sources cover different reporting periods and definitions, the values are presented as source-specific observations rather than as a single continuous time series, which is in line with the previous reports by Ratnasingam *et al.* (2017, 2022).

With technological pressure growing and the increasing global competition, especially from manufacturing powerhouses such as China and Vietnam, the government launched the National Industry 4.0 Plan (MITI 2018), with the aim of facilitating greater adoption of computerization and automation, which inevitably would lead to smart factories, powered by AI. Previous studies on the adoption of Industry 4.0 (IR4.0) by Ratnasingam *et al.* (2021) have shown that the wood products industry lag behind other

industries, such as automobile, electrical and electronics (E&E), chemicals, and metalworking in terms of IR4.0 technologies adoption. Automation and AI are no longer abstract projections, instead they are commercially deployed realities, even within the agriculture sector (Młody *et al.* 2023). The types of IR4.0 technologies employed within the wood products industry have been extensively studied (Ratnasingam *et al.* 2022), and due to the predominance of SMEs in the wood products industry and their limited capital expenditure, the most common IR4.0 technologies employed are the computer-aided design and manufacturing tools, in-line quality control tools and business process optimization tools (Othman *et al.* 2025; Yi *et al.* 2021). Inevitably, the adoption of these technologies is often geared towards productivity gains and boosting price competitiveness, rather than higher value creation (Wu *et al.* 2023). Regional wood products manufacturers in China and Vietnam have adopted IR4.0 technologies much more aggressively throughout the value and supply chain, resulting in overwhelming competitiveness and productivity gain, which inevitably leads to greater market share in both traditional and non-traditional markets (Mo *et al.* 2024; Ramachandran 2023). The stagnating productivity and value-creation within the Malaysian wood products industry has been well documented (Ratnasingam 2015; Ratnasingam *et al.* 2022), yet efforts to reverse these trends are constrained by the reluctance to invest in technology among wood products manufacturing, consequential from the perennial issues related to uncertainty in production factors (Mensah *et a.* 2025).

The premise of this review article is to examine the implications of technology and AI on wood science and forestry education and consider how changes in educational competencies may affect the professional workforce of the Malaysian wood products industry. The review also identifies the constraints that may limit the translation of AI capability into productivity and value creation, which is a necessity for the industry.

REVIEW METHODOLOGY

The article follows the preferred reporting items for systematic reviews and meta-analyses extension for scoping reviews (PRISMA-ScR) approach (PRISMA 2020), which adheres to a scoping-review logic informed by established guidance for mapping heterogeneous information sources (Tricco *et al.* 2018; Bengoechea and Bell 2022). The purpose was to extract and synthesize the available evidence, rather than to estimate a single pooled effect size. To strengthen the review, a policy-oriented thematic lens was applied when reviewing previous studies, which comprise peer-reviewed research articles, government statistics, and policy documents, and industry or professional reports relevant to AI, digital manufacturing, wood science education, workforce development, and the Malaysian wood products industry.

A comprehensive search strategy was developed and executed over two major academic databases, *i.e.* Web of Sciences and SCOPUS, as well as the available government database, from the period 2010 to 2026. Further, the government database was accessed for publicly available reports, policy documents, and statistical reports to gather relevant information sources, to ensure practitioners studies were not overlooked.

This review covered empirical, conceptual, and case-based peer-reviewed research articles, as well as government reports such as policy documents, statistical reports, and professional organization reports, published in English. The inclusion criteria applied to articles and reports were considered relevant when they addressed at least one of the

following domains or keywords: (i) AI, machine learning, or Industry 4.0 applications in wood, forestry, furniture, or related manufacturing; (ii) wood science, forestry, or technical education and digital competencies; (iii) workforce, skills, automation, or industry-academia linkages; (iv) Malaysian education policy, graduate employment; or (v) Malaysian economic performance and outlook, unemployment, or industry conditions that affect technology adoption. The time restriction (2010-2026) was imposed to ensure contemporary trends were captured and demonstrated its current relevance to the country. Articles and reports were excluded when it was deemed as not relevant to AI and IR4.0 application on wood science and technology education in Malaysia, or the reports were considered editorial, commentaries, or duplicates.

The sources were then classified as empirical research, conceptual research, systematic or review literature, official statistics, policy documents, or industry reports, while reports containing evidence-claims based on projections are explicitly identified as projections. Efforts were made to clarify that the data-sets derived from publications reported in this review were empirically verified against official government sources, to represent future-dated figures in order to ensure epistemological validity of the review paper (Arksey and O'Malley 2005; Tricco *et al.* 2018).

Although the review followed the four-stage PRISMA process, the review did not execute a complete database-by-database search log, or screening count. Instead, the general conceptual search domains, eligibility criteria, evidence categories, and synthesis procedure, with an orientation towards policy domains is presented as the flow numbers (Appendix 1). Efforts to eliminate fabrication of retrieval statistics were taken by considering only papers with a policy-orientation to Malaysia. When warranted however, the authors used the original search records, to rigorously verify the data-sets presented, apart from eliminating duplicates as reported by Tricco *et al.* (2018).

Data extraction from the sources were standardized to systematically capture the relevant data from each source. The review considered the technology or educational issue examined, geographic context, type of evidence, reported outcome or competency, and relevance to the Malaysian wood products industry. The data synthesis employed a narrative-approach combined with a policy thematic analysis. Given the heterogeneity of the sources used, meta-analysis was inappropriate for the data-set collected. Hence, quantitative values were retained as source-specific estimates and were not statistically pooled. Where figures combine evidence from different sources, the review states that the values were illustrative, or source-specific and does not imply a weighted meta-analysis (Tricco *et al.* 2018). Policy-themes from the sources were identified inductively, by constant comparison across the sources, to ensure consistency in interpretation. Finally, recommendations were derived by linking recurring evidence themes, associated to technology readiness, skills mismatch, wood-specific data constraints, industry-academia interaction, and policy support, in relation to the educational and workforce context.

The review is, however, constrained by differences in definitions, reporting periods, sample sizes, and data quality across academic and institutional sources. The use of the Web of Science and SCOPUS databases may also have omitted other regional articles and studies. In addition, the review does not contain primary survey or interview data from educators, accreditation bodies, or SME owners. The inadequate published data on the characteristics of the wood products industry, especially those related to human capital and education, has been challenging (Ratnasingam *et al.* 2023; Othman *et al.* 2025). It must be highlighted that data derived from the Ministry of Higher Education (MOHE) and Malaysian Timber Industry Board (MTIB) are official empirically verified annual datasets

which are published for the respective cycle, and are not projections. On the other hand, when citing data from aggregate sources such as Statista, and the World Economic Forum (WEF) which provide estimated data-sets from various sources, it is explicitly stated that these figures are estimates rather than retrospective historical data. On this account, the curriculum and policy recommendations made in this review, are therefore presented as evidence-informed proposals, rather than stakeholder-validated mandates.

The Malaysian Wood Products Industry: Status and Structural Characteristics

The Malaysian wood products industry encompasses a vertically integrated set of industries, from log harvesting and sawmilling through panel products, moldings, and builders' joinery and carpentry to finished wooden furniture, meant for both domestic and export markets. Ratnasingam *et al.* (2023) showed that almost 80% of the production capacity is exported, while 20% of the production is consumed locally within the domestic market valued at RM 8.9 billion per annum. Against the strengthening of the local currency, the ringgit (RM) against the USD, coupled with the global geopolitical tension leading to higher petroleum product prices, the export market has softened significantly, leading to a sluggish export market. In the midst of the trade tension between China and the USA, trade routes have been altered to facilitate transshipment through ASEAN countries, with the final destination being the US market (Ratnasingam *et al.* 2022). As it stands, the wood products sector accounted for approximately 1.4% of Malaysia's GDP in 2024, a figure targeted to grow to 2.0% under the National Timber Industry Strategic Policy (MTIB 2025). Figure 2 reflects the resilient export volume pattern of wood products, though in recovery terms the uncertainty remains persistent (MTC 2026b).

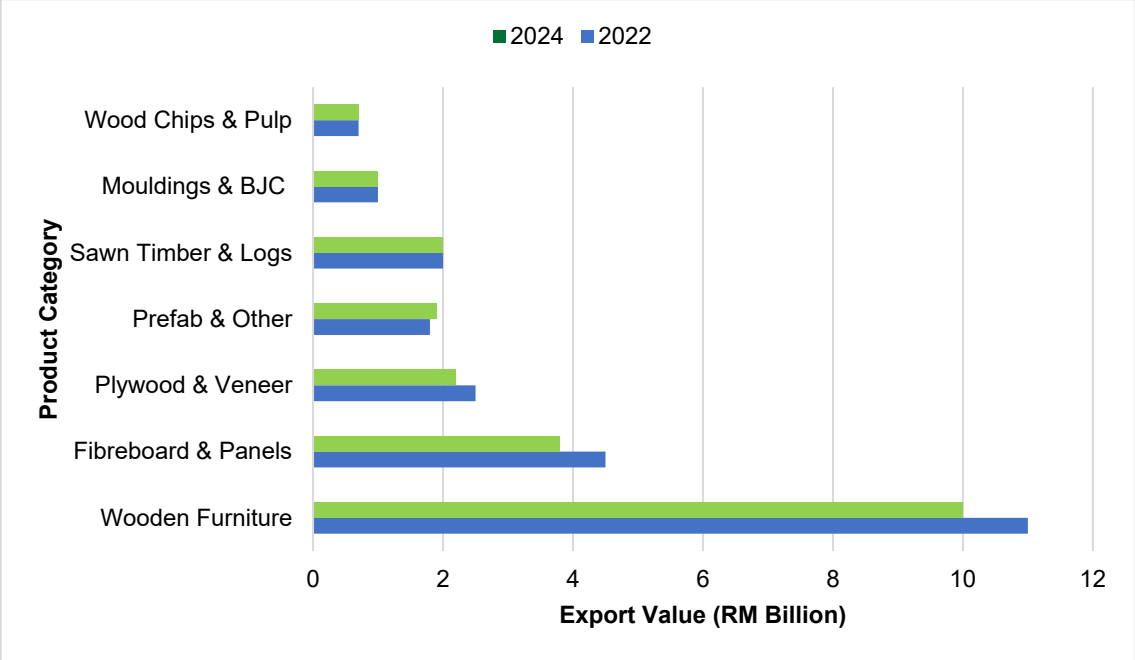


Fig. 2. Malaysia wood products export – Category breakdown, 2022 *vs.* 2024 (RM Billion). Source: MTIB (2024b)

Coupled with the challenging market sentiment, the traditional markets for Malaysian wood products such as the United States, Japan, European Union, India, and

China have emerged with signs of vulnerability, as these markets begin to become increasingly stringent on sustainability and legality of wood products, which requires increased investment in digital traceability, and supply chain transparency requirements that Malaysia's predominantly SMEs struggle to satisfy (Omowole *et al.* 2024; Mensah *et al.* 2025).

Value Chain Configuration and the Technology Imperative

Studies on the value chain within the Malaysian wood products industry have revealed that the return on investment (ROI) on technology adoption is the highest, as opposed to incremental inputs of production factors (Ratnasingam *et al.* 2019; Mo *et al.* 2024). MTIB (2025) revealed the value chain analysis of wood products in the country, as shown in Fig 3. The near 20-fold value differential between primary wood resources extraction and finished products underscores the strategic logic of downstream processing investment, yet the industry's movement along the value chain has been consistently slower than government targets anticipated.

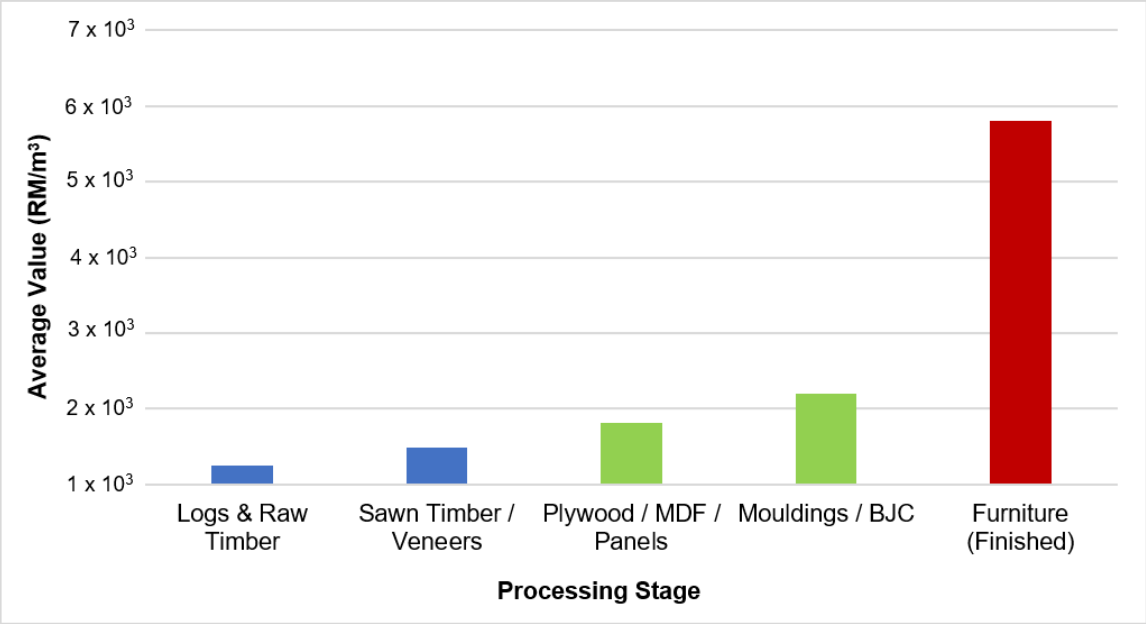


Fig. 3. Wood products value chain – Average price by processing stage (RM/m³, log scale). Sources: MTIB (2022, 2023b); MTC (2024)

Although the Malaysian wood products industry has undergone tremendous transformation over the years, the over reliance on the Original Equipment Manufacturing (OEM) manufacturing model, which strives on contract-manufacturing activities, has been the driver of the rapid industrial expansion. However, this strategy which is viable at low-cost factor inputs, has progressively lost competitiveness to other regional lower-cost suppliers (Yi *et al.* 2021). Despite the push to shift towards Original Design Manufacturing (ODM) and Original Brand Manufacturing (OBM) model, as envisaged in policy frameworks, the progress has been structurally impeded by limited in-house R&D, insufficient design talent, and a technical workforce not equipped for the computational design and AI-enabled process optimization tools that ODM and OBM manufacture now require (Gkrimpizi *et al.* 2023).

The Wood Sector Workforce: Composition, Wages, and Technology Readiness

Employment in wood, paper, and furniture manufacturing in Malaysia peaked at 298,131 persons in 2019 before the Covid-19 pandemic disruption, border closures limiting foreign worker supply, and accelerating automation investment, which resulted in a sharp contraction of workforce to 186,068 by 2022 (DOSM 2024). This number has climbed higher to 198,040 by 2024 (Fig. 4) partially sustained by growth in downstream high-skill design and engineering roles, even as low-skill positions continued to be displaced by automated equipment (DOSM 2025).

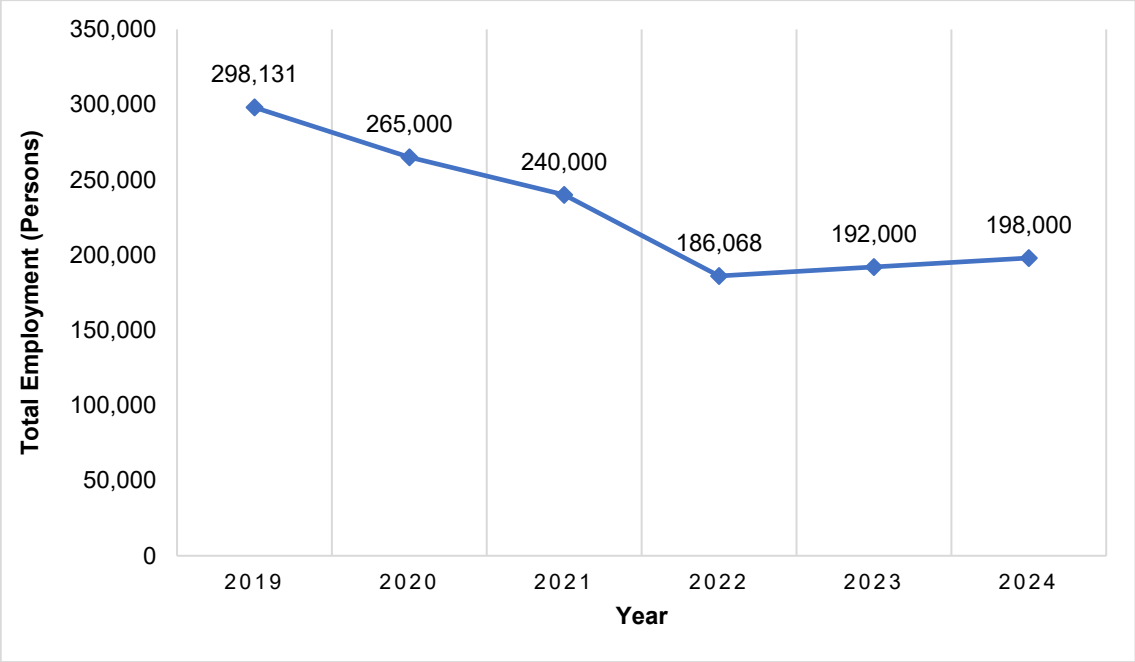


Fig. 4. Employment in wood, paper & furniture manufacturing, 2019–2024.
Sources: DOSM Salaries & Wages Survey (2022); NIMP 2030 (2023); DOSM (2024)

The wood products industry has long been regarded a low-wage economy (Ratnasingam *et al.* 2022), which is well exemplified by the sector's wage structure revealing a persistent competitiveness disadvantage relative to the national manufacturing average (Ratnasingam *et al.* 2017). According to the Department of Statistics Survey on Salaries and Wages (DOSM 2024), semi-skilled machine operators in the wood products industry earn a mean monthly wage of RM 2,404, compared with RM 2,650 nationally for the equivalent category, while professional and engineering roles attract mean wages of RM 5,480 against a national average of RM 6,100 for the same occupational group These differentials, though modest in percentage terms, translate into a persistent recruitment disadvantage relative to the electronics, automotive, and petrochemical sectors competing for the same technically qualified graduates (Omar *et al.* 2025). Interestingly, the share of skilled workers as a percentage of total workforce in the wood products industry is among the lowest, at 18%, compared to all other manufacturing sectors in the country which stood at 31%, and well below the NIMP 2030 target of 35% (DOSM Labor Survey 2022).

Technology readiness reports within the wood products industry present a sobering baseline (Legg *et al.* 2021). According to MTIB (2021b) and MWMSA (2024), 69% of surveyed wood products manufacturers relied predominantly on manual or semi-automatic machinery, while only 31% had incorporated any automated equipment such as computer

numerical control (CNC) workstations, optimizers, and edge banders. The implementation of IR4.0 elements, including IoT connectivity or AI-enabled process control were reported by a mere 11% of the respondents in the Industry4WRD readiness assessment (RA) survey (MIDA 2023). These findings run parallel to the results of previous studies (Ratnasingam *et al.* 2021).

The Impact of IR4.0 and AI Technologies on the Malaysian Wood Industry

Industry 4.0 is often considered a broad domain which encompasses: data management, manufacturing competitiveness, production processes and efficiency (Młody *et al.* 2023). In fact, IR4.0 includes a variety of key enabling technologies i.e., cyber physical systems, Internet of Things (IoT), artificial intelligence (AI), big data analytics and digital twins which are major contributors to automated and digital manufacturing environments (Červený *et al.* 2022).

Previous research indicates that Industry 4.0 technologies can improve manufacturing efficiency and decision-making, but the magnitude of the effect varies by technology, firm size, process configuration, and implementation maturity. Hence, reported improvements should therefore be interpreted as study-specific findings, rather than as universal outcomes (Wang *et al.* 2017; Jamwal *et al.* 2021). Further, it has also been implied that IR4.0 technologies may also create new requirements for data governance, cybersecurity, integration, and workforce training (Młody *et al.* 2023).

The literature identifies several potential benefits of Industry 4.0 technologies, including improved production flexibility, process monitoring, quality control, and information flow (Wang *et al.* 2017). However, these benefits are accompanied by implementation requirements related to data infrastructure, integration, cybersecurity, worker training, and capital investment (Molinaro and Orzes 2022). It is apparent that the evidence therefore supports a conditional rather than unambiguously positive interpretation of technology adoption.

Artificial intelligence (AI) and machine learning (ML) can support predictive quality control, maintenance, design, supply-chain analysis, and human-robot collaboration. Their effectiveness, however, depends on the availability and quality of training data, suitable process integration, and human oversight (Červený *et al.* 2022).

IoT technologies improve production quality and reduce downtime by digitalization in manufacturing. In developed nations, many manufacturing organizations are automated already. Automobile and metal industries are automated and digitalized on the shop floor, which is basic requirement for IR4.0 practices (Haddouche and Ilinca 2022). IoT is one of key enabling technologies for IR4.0 which contributes towards improvements of quality, plant visibility and efficient inventory management, simply by integrating internet technology (IT) with operational technology (OT) (Jamwal *et al.* 2021).

Several research reports have shown that cloud technologies is an integral part of IR4.0 technologies adoption in smart manufacturing environments, especially in those working with manufacturing execution system (MES) in manufacturing facilities (Młody *et al.* 2023). The information from MES is used to create factory digital twins, which collaborative manufacturing through improved processing and scheduling of operations (Wu *et al.* 2023). Augmented reality has a wide range of applications in IR4.0, but the manufacturing domain is more focused on product life cycle, prototyping, assembly, maintenance, and also marketing activities, through the provision of real time information (Jamwal *et al.* 2021).

Blockchain technology in IR4.0 offers new tools to address sustainability issues, security, efficiency and resiliency of systems as well as transparent and decentralized transaction systems (Červený *et al.* 2022). Aspects of sustainability, transparency and legality are of increasing concern for wood products marketed globally, and hence, with the assistance of blockchain technology, such product characteristics could be managed through the enhanced manufacturing network sustainability (Anon. 2024).

Reconfigurable manufacturing systems (RMS) and flexible manufacturing systems (FMS) are growing in importance as newer production systems suitable for IR4.0 technologies in a dynamic market place, as opposed to the traditional mass production and customized production systems (Wu *et al.* 2023). Other IR4.0 technologies, such as the robotics-enabled manufacturing helps to reduce downtime and maximize efficiency due to unscheduled downtime. Robotic technology helps to minimize the reconfigurable effort which results in minimizing errors as well as improvement quality and production (Haddouche and Ilinca 2022).

Smart factories necessitate additional cybersecurity and governance requirements because connected machines, sensors, software, and communication networks create additional attack surfaces. Cybersecurity should therefore be treated as a core component of AI and Industry 4.0 readiness rather than as a secondary technical issue (Mimoso *et al.* 2025).

Nevertheless, the application of Industry 4.0 and AI technologies to the wood industry is hampered by limitations due primarily to the material's natural characteristics. Several challenges of applying machine learning to wood's anisotropic nature, moisture-dependent variability, and the severe lack of standardized, open-source image datasets for training computer vision models on natural timber defects, which require highly specialized approaches remains unresolved, and cannot be tackled using off-the-shelf industrial AI solutions (Molinaro and Orzes 2022; Sayem *et al.* 2022; Rana and Rathore 2023; Kitek-Kuzman *et al* 2024).

It must be recognized that AI applications in wood products manufacturing cannot be transferred directly from standardized manufacturing environments without taking into consideration wood's biological and material variability. Wood is anisotropic and heterogeneous, and its density, grain orientation, anatomical structure, surface characteristics, and mechanical properties vary by species, growth conditions, processing history, and location within the material. Moisture content can further alter appearance, dimensions, strength, machining behavior, and also sensor responses (Molinaro and Orzes 2022). These characteristics complicate the development of stable machine-learning models because the relationship between an observed feature and the target outcome can vary across species, batches, moisture conditions, and processing environments (Hwang 2026; Kucuk and Buehlmann 2026a).

Computer-vision applications face a related data-problem. Natural timber defects such as knots, checks, splits, wane, resin pockets, discoloration, and fungal damage can occur at different scales and orientations, and their visual expression changes with lighting, surface preparation, species, and moisture. The lack of sufficiently large, standardized, openly accessible datasets with consistent defect labels can therefore limit model training, comparison, and external validation. In practice, wood-sector AI systems may require domain-specific image acquisition, annotation, data augmentation, transfer learning, and continuous validation rather than direct deployment of off-the-shelf computer-vision models (Rana and Rathore 2023).

These constraints also create risks of model drift and reduced generalizability in AI applications. For instance, a model trained on one wood specie, mill, camera configuration, or moisture range may not perform equally well under another production condition. Human oversight therefore remains important for high-consequence decisions, such as grading, structural classification, quality release, and process control (Rana and Rathore 2023). The technical value of AI in wood products should consequently be assessed not only by accuracy or productivity gain, but also by robustness, explainability, data provenance, transferability, and the cost of maintaining the system over time (Kitek-Kuzman *et al.* 2024).

Despite the potential benefits of Industry 4.0 and AI technologies, adoption within the Malaysian wood products industry remains uneven. Ratnasingam *et al.* (2019) documented differences in automation readiness among Malaysian furniture manufacturers as well as different wood products, while Yi *et al*. (2021) highlighted financial, organizational, and knowledge-related barriers among SMEs. The evidence therefore suggests that technology adoption is associated with firm characteristics and resource availability rather than being uniformly higher across all wood-product subsectors.

Wood Science and Technology Education in Malaysia: Status and Emerging Challenges

Wood Science and Forestry related-education in Malaysia is delivered through eight higher education institutions, including Universiti Putra Malaysia (UPM), Universiti Malaysia Sabah (UMS), Universiti Malaysia Kelantan (UMK), Universiti Teknologi MARA (UiTM), Universiti Tun Hussein Onn Malaysia (UTHM), Universiti Sains Malaysia (USM), and Universiti Malaysia Sarawak (UNIMAS). Levels of adoption of various IR4.0 features fall in a range from about 6 to 80% (Table 1).

Table 1. Status of IR4.0 Technologies Application in the Malaysian Wood Products Industry

IR4.0 Technologies	Adoption Level	Operations
Automated defect detection	6 to 8%	Panel-based manufacturing, finishing operations
CNC machine centers using CAD-CAM software	70 to 80%	Machining operations
Predictive maintenance	8 to 10%	Maintenance in large companies
Robotics technology	12 to 15%	Packaging, finishing and sorting operations
AR/VR and 3D printing for product development	20 to 25%	Design simulations, prototyping, models
IoT and cloud technology for production management and scheduling	12 to 15%	MRP/ERP systems in large companies
AI for supply chain optimization	6 to 8%	Large companies with extended supply chain
Flexible manufacturing systems (FMS)	6 to 8%	Highly customized manufacturing

Sources: Ratnasingam *et al*. (2020); Yi *et al*. (2021); Rajarethnam (2023)

Total enrolment across wood science and forestry disciplines reached 4,250 in 2024 (Table 2), while wood science-specific enrolment was reported to be approximately 830

students (MOHE 2025a). Nevertheless, these programs have continuously faced low enrollment over the years, due to falling interests among young school-leavers (MOHE 2025b), and efforts to rebrand, revamped curriculum, introduction of the dual 2U2I (university and industry) program and increased industry-orientation, have all failed to reverse the declining trend in enrollment as reported by (Gisip and Hansen 2026).

Table 2. Malaysia HEI & TVET Enrolment – Agriculture, Forestry & Wood Science Disciplines

Indicator	Public HEIs	Private HEIs	Total	Source
Total enrollment (Forestry & Wood Science)	4,250	170	4,420	MOHE Statistics (2024)
Graduate output per year (Forestry & Wood Science)	1,390	0	1,390	MOHE Statistics (2024)
Wood science-specific enrolment	830	0	830	MTIB/MOHE estimate (2023b)
TVET enrolment – wood/furniture	3,100	600	3,700	MTIB/WISDEC (2024c)

Source: MOHE Statistics (2024); MTIB/WISDEC (2024c)

Technical and vocational education (TVET) providers, including vocational colleges such as MARA Competency Institutes (IKM), the Sultan Salahuddin Abdul Aziz Shah Polytechnic (PSSAAS), the Wood Industry Skills Development Centre (WISDEC), and the Furniture Industry Technology Centre (FITEC), are faced with persistent enrollment challenges. Although negative public perceptions of wood-sector careers are relevant, it may not be taken as the sole explanation for the low enrollment. The low wages in the wood products industry relative to competing manufacturing sectors, physically demanding, less attractive working environments, limited career progression visibility, and uncertainty about long-term advancement remain the other influencing factors (Ratnasingam *et al.* 2017; Ratnasingam *et al.* 2022; Kamaruzaman *et al.* 2025). The 3D syndrome, *i.e.*, dirty, dangerous, and difficult, associated with the forestry and wood industry careers is linked to a negative social stigma, that shun away youngsters from this sector in a job market predominated by the gig-workers (Wiese *et al.* 2025).

The problem associated with skills mismatch among fresh graduates have also been the center of discussion for some time. The study by Ratnasingam *et al.* 2021 highlighted the mismatch between industry expectations and graduate skills set, which often led to manufacturing resorting to the hiring of foreign contract workers. According to the latest survey (MTIB 2025), almost 59% of the workforce in the wood products industry are foreign contract workers, paid RM 1700 per month in accordance with the government's minimum wage guideline. However, in compliance with other regulations such as minimum housing standard (Act 446), contribution to employees' provident fund (EPF), etc., the amount payable to each worker increases to nearly RM 2200, which is still cheaper than the expected salary of a local graduate at RM 2850 per month (DOSM 2024). Perhaps, a technology and AI-oriented curriculum reform can improve the forestry and wood industry career relevance, but it should also be accompanied by measures that improve job quality and career progression.

The Digital Skills Deficit

The most consequential issue identified in the available curriculum and workforce evidence is not aggregate enrollment alone, but a potential competency mismatch. The review's earlier estimate that only 15% of wood science-related programs incorporate dedicated AI or digital manufacturing content should be treated as a source-specific curriculum audit rather than a nationally standardized measure. Talent Corp's 2024 national impact study identified 60 emerging roles across ten economic sectors, of which 43 (72%) were AI- and digital-related; and these findings are not wood-industry-specific and therefore should be used only to contextualize broader Malaysian skills trends (TalentCorp 2024). Nevertheless, the shortfall in AI and technology related content in forestry and wood science related programs must be addressed, so as to ensure that graduates are equipped with sufficient skills set that would facilitate their venture into other fields, should they opt to divert from the forestry and wood product sectors.

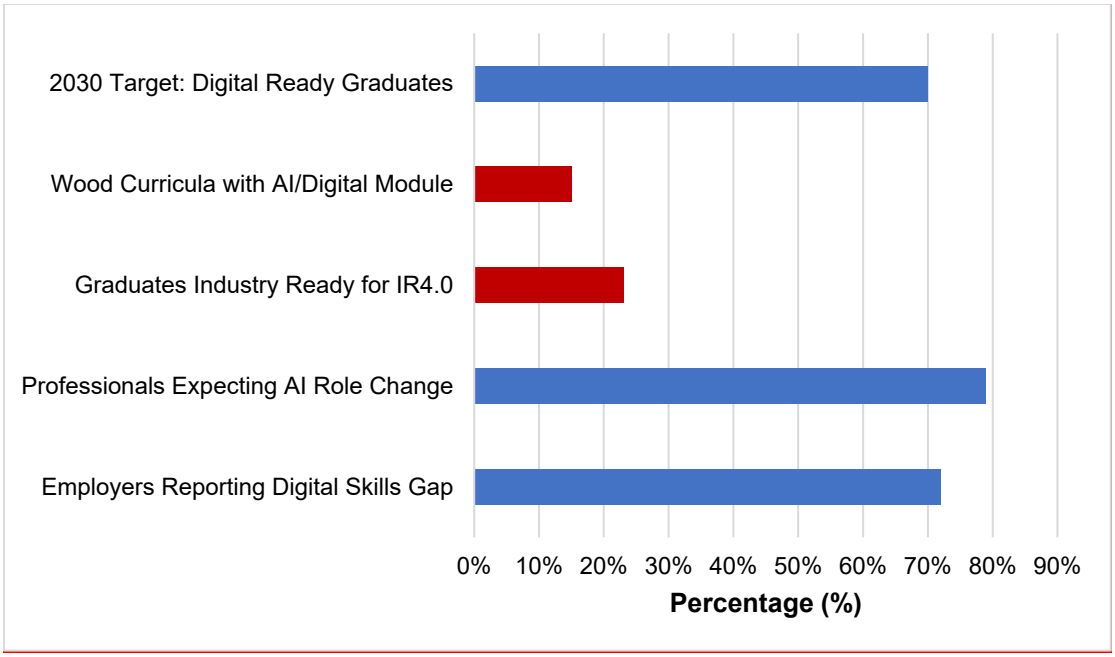


Fig. 5. Digital readiness and AI-integration indicators reported by the cited source documents. Note: the values are source-specific and are not a pooled national estimate. Sources: TalentCorp (2024); MTIB (2023b); HRD (2023).

ASEAN Regional Comparison

A comparison of wood science education across ASEAN can provide contextual insight, but the reported percentages should not be interpreted as directly comparable performance scores because programs differ in scope, definitions of AI content, student populations, institutional missions, and measurement methods. Malaysia's reported position can therefore be used to identify areas for learning rather than to establish a simple league table. Singapore provides a useful example of stronger digital integration within a smaller, more research-intensive system, whereas Vietnam and Thailand illustrate the potential value of linking technical education more closely with advanced manufacturing and industrial skills (MIDA 2026). For Malaysia, the transferable lesson is not to replicate another country's curriculum wholesale, but to strengthen applied digital competencies, industry exposure, and modular upskilling within the existing forestry, wood science and TVET ecosystem.

One point to highlight is the prevailing stringent environmental and labor regulation in Singapore, necessitates greater technology and AI application within the wood products industry, while the Malaysian wood products industry continues to strive on the prevailing low-wage economy, with compliance to environmental, social and governance (ESG) matrixes being partially fulfilled (Ratnasingam *et al.* 2023). The fact that ESG compliance leads to a transformative manufacturing ecosystem that contributes towards overall competitiveness is apparently much more appreciated in Singapore compared to Malaysia, and thus, explains the industrial performance disparity (Chow and Fung 2025).

AI Application in the Wood Products Industry: Global Landscape and Malaysia's Position

The application of AI in wood and furniture manufacturing over-arch several production and design activities, but the maturity of these applications varies considerably by process and firm (Rana and Rathore 2023). Computer vision has been investigated for defect detection and grading; machine learning can support process monitoring and predictive maintenance; generative and parametric design can assist product development; and digital twins can support simulation and scheduling (Kitek-Kuzman *et al.* 2024). These applications should be distinguished from established commercial adoption, because evidence from pilot studies, large manufacturers, and broader manufacturing sectors is not necessarily transferable to Malaysian wood SMEs (Kucuk and Buehlmanna 2026a; Hwang 2026).

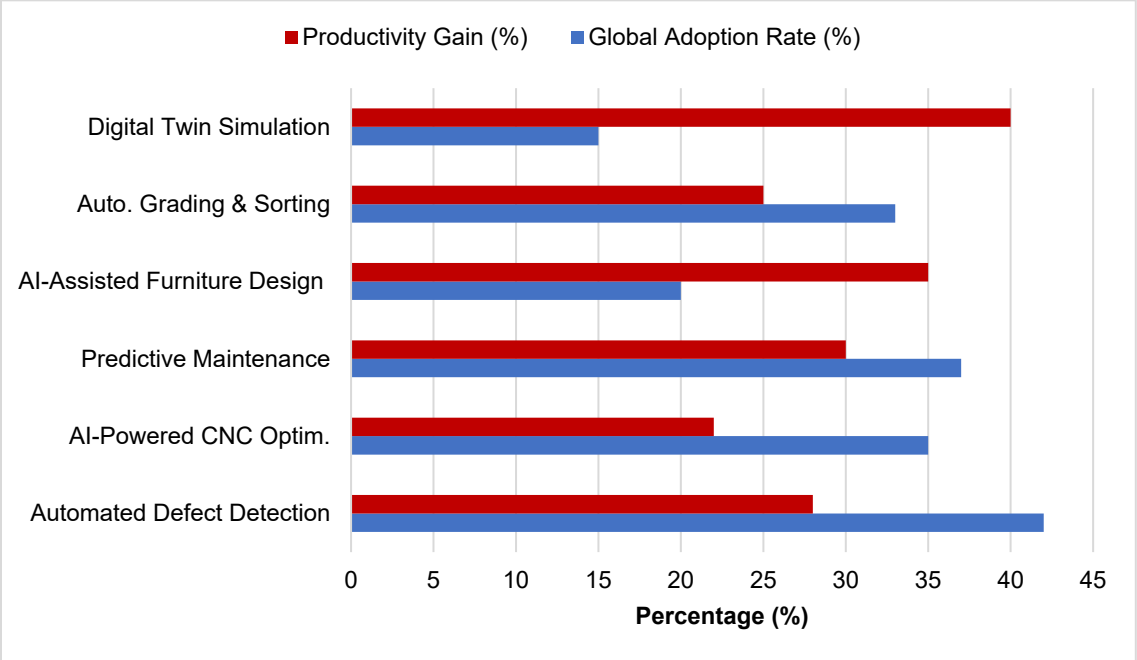


Fig. 6. Examples of AI applications in wood manufacturing and study-specific reported indicators. Note: values originate from different sources and are not statistically pooled, weighted, or normalized; they should be interpreted as illustrative evidence rather than a composite adoption index.

Generative AI, parametric CAD, and related digital design tools may shorten design-to-production iterations and support ODM-oriented product development.

Table 3. AI Application Areas in Wood & Forestry Manufacturing – Global Adoption & Productivity Impact

AI Application	Typical Wood-sector Use	Evidence Reported	Interpretation
Automated defect detection	Computer vision / machine learning	Widely studied for defect recognition and quality assessment (Tulbure *et al.* 2022)	Promising, but performance depends on species, moisture, lighting, defect definitions, and labelled datasets.
AI-powered CNC optimization	Machine learning / optimization algorithms	Reported to support toolpath and process optimization (MIDA 2023)	Potential for material and time savings; Malaysian firm-level outcomes require direct validation.
Predictive maintenance	IoT sensors + machine learning	Reported in manufacturing literature as a means of anticipating equipment failure (PwC 2024)	Requires sensor coverage, historical maintenance data, and integration with production systems.
Precision forestry & harvesting	Drones / satellite data + AI	Digital tools support monitoring, planning, and forest operations (FAO 2023)	More directly relevant to forestry than downstream manufacturing; transferability depends on use case.
AI-assisted furniture design	Generative AI / parametric design	Generative and parametric approaches are increasingly used in design workflows (McKinsey 2024)	Potentially relevant to ODM transition, but design quality and manufacturability still require human validation.
Automated grading and sorting	Computer vision + robotics	AI-based grading and sorting are active research and application areas in wood processing (Kucuk and Buehlmann 2026a)	Wood-specific variability makes robust validation across species and operating conditions essential.
Supply-chain AI optimization	Machine learning / demand forecasting	AI can support demand forecasting and supply-chain decision-making (McKinsey 2024)	Benefits depend on data quality, integration, and the reliability of upstream and downstream information.
Digital twin / factory simulation	IoT + AI-enabled simulation	Digital twins are identified as an emerging Industry 4.0 capability for manufacturing systems (MIDA 2023)	Potentially valuable for process optimization, but adoption requires substantial digital infrastructure.

However, reported productivity or cycle-time improvements from broader manufacturing studies should not be interpreted as measured outcomes for the Malaysian wood products industry, unless the cited study directly examines that context (Kitek-Kuzman *et al.* 2024; Mo *et al.* 2024). Similarly, digital twins remain an emerging capability for many wood manufacturers and require adequate sensor, process, and data infrastructure before their potential benefits can be realized (Kucuk and Buehlmann 2026b).

Table 3 summarizes examples reported in the literature rather than a meta-analytic estimate of global AI adoption. The review combined percentages from studies with different samples, definitions, and outcome measures. Hence, the table presents a qualitative evidence map, to avoid the cited literature being presented as a statistically comparable pooled dataset.

Against the global development of AI-enabled manufacturing, Malaysia's wood and furniture sector presents a more modest technology-adoption profile. MIDA's Industry4WRD program reported a relatively high participation across Malaysian manufacturing, but the wood-sector participation represented only a small share of the total

program (MIDA 2023). Technology-support measures indicate policy interest in accelerating SME adoption, but program participation should not be interpreted as equivalent to sustained AI deployment, as the evidence revealed a substantial readiness gap between larger firms and SMEs (Talent Corp 2024). These observations support the need for capability-building alongside capital investment, rather than assuming that grants alone will produce durable AI adoption.

Matching The Workforce with AI-Enabled Production: Skills Demand and Automation Risk

In a report by the World Economic Forum (2025b), it was identified that AI and big data as the single fastest-growing global skill domain, with demand growth of 68% projected across sectors, followed by networks and cybersecurity at 54% and technological literacy at 51%. Creative thinking and analytical reasoning, with direct relevance to furniture and wood products design and production planning, rank fourth and fifth respectively.

Table 4. Top AI & Digital Skills in Demand and Relevant to the Wood Industry

Skill Domain	WEF Rank	Demand Growth (%)	Relevance to Wood Sector
AI and Big Data	1	68%	Defect detection, yield optimization, predictive maintenance
Networks & cybersecurity	2	54%	Industrial IoT security, connected factory infrastructure
Technological literacy	3	51%	Digital twin operation, ERP/MES system use
Creative thinking	4	45%	AI-assisted furniture design, product innovation
Analytical thinking	5	42%	Production data analysis, supply chain optimization
Data engineering	6	58%	Quality data pipelines for AI training in wood grading
AI fluency / prompt engineering	7	62%	GenAI tools for design and documentation
Sustainability awareness	8	40%	FSC/PEFC compliance, carbon accounting in supply chain

Source: Talent Corp (2024)

On the other hand, the study by Talent Corp. (2024) reveals that AI fluency, data engineering and management, and sustainability-linked digital competencies as the most acute workforce gaps in Malaysia, with 72% of the 60 identified emerging roles being AI or digitally oriented (Talent Corp 2024). Table 4 shows the important AI and digital skills set required within the wood products industry in Malaysia.

For the wood products and furniture sector, automation risk should be interpreted as an occupational exposure estimate rather than a prediction that a specific percentage of jobs will disappear. Routine sorting, grading, packing, materials handling, and repetitive machine-operation tasks are more vulnerable to automation than roles requiring design, engineering judgement, problem-solving, and complex coordination. The balance between task substitution and task augmentation will depend on technology cost, process design, worker skills, and organizational choices (WEF 2025a; McKinsey 2024).

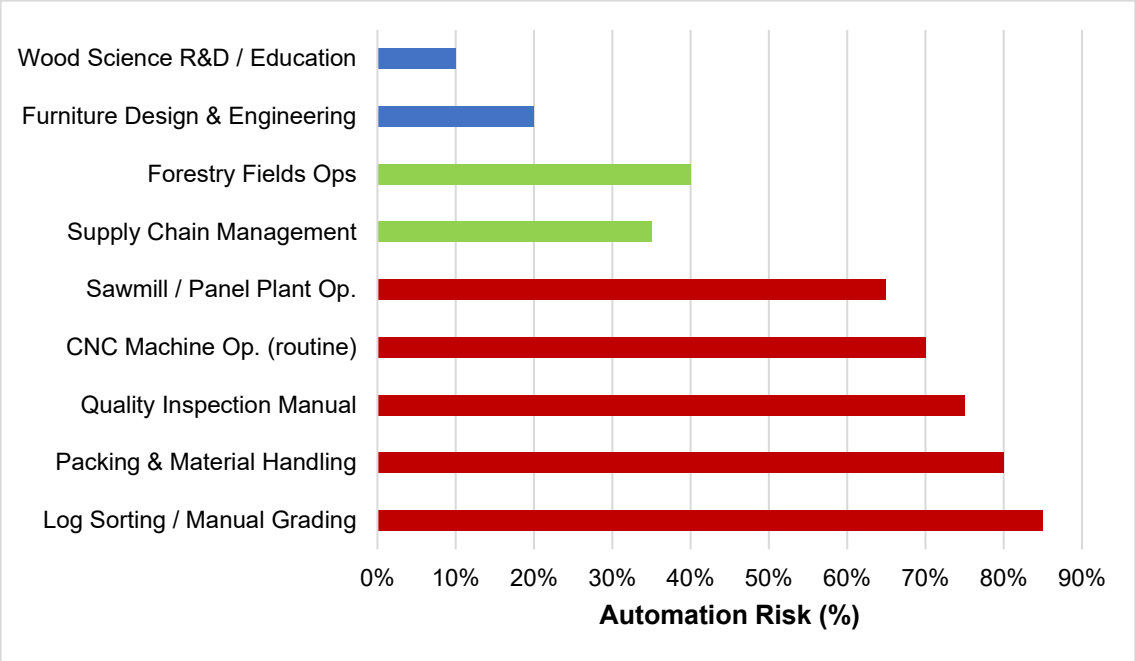


Fig. 7. Wood-sector job automation-risk profile based on estimates reported in the cited sources. Note: these are source-specific occupational exposure estimates, not a statistical prediction of job losses and not an estimate independently calculated by the authors.

Wood science research and education are likely to experience lower direct task-substitution risk, than highly routine production activities, but the skills required within these fields are changing. Recent literature identifies defect detection, machine-learning-based quality assessment, process monitoring, parameter optimization, and AI-assisted materials design as important application areas (Kucuk and Buehlmann 2026b; Hwang 2026). These developments strengthen the case for digital competencies, while also increasing the need for domain expertise capable of evaluating model assumptions and material behavior.

The comprehensive review of the development of wood technology by Teischinger (2010) had argued that minimizing the natural variability in wood materials remains the biggest challenge in expanding its use as the most sustainable material known to mankind. In this context, the application of AI and the related technologies are enabling greater predictability of the wood material, minimizing its variability, while increasing its reliability for many other applications. In essence, AI will fundamentally alter the wood products industry, in which the workforce will need specific AI-related skills profile to perform effectively, in an industry that would become an effective sustainable and circular industry (Poudel *et al.* 2026).

Implications for Wood Science Curriculum Reform

The case for substantive wood science curriculum reform is supported by converging evidence of skills mismatch, technological change, and evolving occupational requirements (Ahmed and Fatma 2026; Gisip and Hansen 2026; Kucuk and Buehlmann 2026b; Olowookere *et al.* 2026). However, the evidence does not by itself establish which specific curriculum components should be made mandatory. The SME-dominated structure of the industry, variation in technology maturity, and differences between wood-processing subsectors mean that curriculum reform should combine a common digital foundation with

flexible, industry-specific modules. The absence of primary stakeholder data in this review also means that proposed reforms should be treated as evidence-informed options requiring validation with educators, accreditation bodies, students, and employers.

Core Competency Additions

A global survey of wood science and technology programs have shown that many of the traditional material science focused programs in many Anglo-Saxon countries have ceased due to low enrollment, and poor industry demand (FAO 2025; Gardner *et al.* 2005). In fact, Japan and South Korea have also experienced declining interests in traditional wood science and technology programs (Gisip and Hansen 2026; Ratnasingam *et al.* 2022).

In some Western European contexts, wood science and technology programs have adopted stronger engineering and applied-technology orientations, providing a useful reference for curriculum development (Anon 2024; FAO 2025; Larasatie *et al.* 2024). For Malaysia, four competency areas appear particularly relevant: data literacy and applied analytics; AI-integrated design; smart manufacturing systems; and sustainability data management. Data literacy should include the ability to collect, interpret, validate, and act on production data. AI-integrated design should include parametric CAD, generative design, and human-AI collaboration. Smart manufacturing should cover IoT, computer vision, manufacturing execution systems, and digital twins at an applied level. Sustainability data management should address digital traceability, carbon accounting, and certification-related information management (Gisip and Hansen 2026; Kaulen *et al.* 2023; Ratnasingam *et al.* 2022).

Industry-Academia Collaboration Structures

Curriculum reform in isolation is unlikely to produce the graduate outcomes the industry needs without stronger industry-academia collaboration (Zakari *et al.* 2022). Evidence from the Malaysian furniture sector indicates that customer requirements, market signals, and supplier technologies can influence innovation decisions alongside internal capabilities (Ratnasingam *et al.* 2018; HRDC 2025). Curriculum content should therefore be developed and periodically validated with industry practitioners, while recognizing that academic staff and industry professionals contribute different forms of expertise. The aim should be structured co-development rather than a presumption that either group alone can define future competencies.

Potential collaborative mechanisms include industry co-teaching, structured industrial training in digitally enabled facilities, joint applied research, and advisory panels involving industry representatives in curriculum review. These mechanisms can improve relevance, but their effectiveness will depend on institutional capacity, sustained participation, and appropriate incentives. They should therefore be implemented incrementally and evaluated rather than assumed to be effective solely because they are structurally plausible (FAO 2025; ElKadi *et al.* 2026; Wiese *et al.* 2025).

Policy Framework and the 2030 Outlook

The policy architecture bearing directly on the wood products industry's AI transition includes several overlapping frameworks. The NIMP 2030 provides a national direction for smart manufacturing, including a target of 3,000 smart factories, while MyDIGITAL and the other sectoral timber-industry policies, including the National Timber Industry Strategic Plan 2026-2030 (MIDA 2026) provide broader digital and value-add objectives. These targets are policy aspirations rather than achieved outcomes and

should therefore be interpreted as forward-looking benchmarks. The connection between such targets and education is indirect: policy goals create a demand signal for skills, but the actual competencies required will depend on technology choices, firm size, and the pace of adoption within individual subsectors.

The critical link between these policy targets and their realization runs directly through the education and workforce development system (Ratnasingam *et al.* 2025). A target of 3,000 smart factories implies demand for thousands of engineers, data technicians, and AI system operators who can design, commission, and manage AI-enabled production lines (Table 5). A RM 32.8 billion wood products export target implies design and quality capability substantially above the current OEM baseline. Neither is achievable if the pipeline of technically qualified wood science and engineering graduates remains calibrated to a pre-AI manufacturing paradigm.

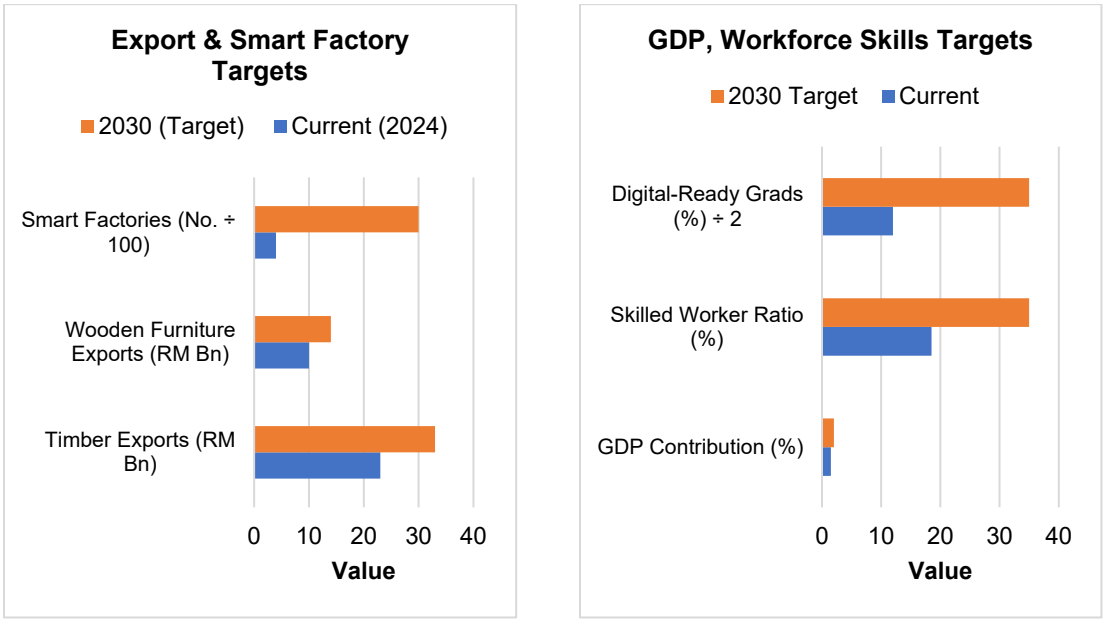


Fig. 8. Malaysia wood industry and AI economy – policy targets and current indicators.
Note: targets are forward-looking policy benchmarks and current values are source-specific; they are not evidence of achieved outcomes.

Table 5. Malaysia Government Targets – Wood Industry & AI Economy (2025–2030)

Target / Policy	Current Value	2030 Target	Policy Document	Source
Timber Exports	RM 22.92 Bn	RM 32.8 Bn	NTIP 2030 / MTIB	MTIB 2026
Wooden Furniture Exports	RM 10.2 Bn	RM 14.1 Bn	NIMP 2030 / MFC	NIMP 2030
Smart Factories (No.)	450	3,000	NIMP 2030 / MITI	MITI NIMP 2030
AI Contribution to GDP	RM 6 Bn/yr	RM 13–20 Bn/yr	MyDIGITAL Blueprint	Min. of Digital MY 2023
Wood Industry GDP Share	1.4%	2.0%	NIMP 2030	MTC 2024
Skilled Worker Ratio (Wood)	18%	35%	NIMP 2030 Talent Chapter	DOSM 2022; NIMP 2030
Digital Economy Value	RM 189 Bn	RM 257.2 Bn	MyDIGITAL / MDEC	MDEC 2024

DISCUSSION AND RECOMMENDATIONS

Revisiting the evidence on wood science and technology education reveals a recurring structural issue: technological change can progress faster than the human-capital systems required to support it (Kanowski *et al.* 2025; Wise and Parker 2025). In the Malaysian wood products sector, this gap is shaped not only by technology and capital constraints but also by workforce availability, wage competitiveness, career attractiveness, and the limited scale of some firms. The review therefore suggests that curriculum renewal should be treated as one component of a broader workforce and industry-development strategy rather than as a stand-alone remedy.

Against the evidence assembled in this review, the following recommendations are proposed as evidence-informed options for discussion with education providers, industry representatives, government agencies, and accreditation bodies. They are deliberately framed as adaptable measures rather than mandatory prescriptions because the present review did not include primary stakeholder validation.

Recommendation 1: Establish a Common AI and Digital-manufacturing Competency Framework

MOHE, MTIB, HEIs, and relevant industry representatives should consider developing a common competency framework for AI and digital manufacturing in Wood Science and Forestry programs (Jegatheswaran *et al.* 2018). A phased approach could prioritize core competencies in data literacy, AI-assisted design, smart manufacturing, cybersecurity, and sustainability data management, while allowing institutions to adapt modules to their program strengths and industry context. Any proposed competency benchmarks should be evaluated through curriculum mapping and consultation with accreditation bodies and employers before formal adoption (Goropečnik *et al.* 2025).

Recommendation 2: Expand Structured Industry Exposure to Digitally Enabled Facilities

Current industrial training arrangements could be strengthened by encouraging placements in facilities using automation, digital production systems, or AI-enabled applications where suitable opportunities exist. HEIs could maintain industry-placement registers and use structured feedback from host companies to identify emerging competency requirements (Devenport *et al.* 2020; Komdeur and Ingenbleek 2021). This approach would increase practical exposure without assuming that every student, or every wood-processing firm requires the same technology profile.

Recommendation 3: Develop Targeted AI and Digital Reskilling Pathways

WISDEC, HRD Corp, and industry associations could develop targeted reskilling pathways covering areas such as materials informatics, computer-vision operation, AI-assisted CNC programming, predictive maintenance, cybersecurity, and basic production-data analytics. Training priorities should be determined through periodic industry needs assessments, rather than through a fixed list of competencies. Monitoring participation, completion, and workplace application would also help establish whether training translates into measurable capability.

Recommendation 4: Strengthen the Connection between Technology Investment and Workforce Development

Technology-support program could consider incorporating workforce-development indicators alongside technology investment outcomes. Rather than making grant eligibility automatically conditional on a specific training commitment, programs could provide incentives for firms that demonstrate a credible plan for worker training, system integration, and post-implementation capability development. This would recognize that technology acquisition alone does not guarantee effective adoption, and that SME needs vary substantially across the wood products sector (Ab Latib *et al.* 2022; Alainati *et al.* 20206; Ahmed and Fatma 2026).

GENERALIZABILITY AND LIMITATIONS

The findings in this review are most directly applicable to the Malaysian wood products and wood-related education context. Some implications may be relevant to other countries with SME-dominated wood industries, labor constraints, and increasing pressure for digitalization, but direct generalization should be avoided. ASEAN comparisons are particularly sensitive due to differences in program definitions, institutional missions, industrial structure, and data availability. In addition, the review relies heavily on secondary evidence and does not include primary stakeholder validation. The recommendations should therefore be regarded as a framework for policy and curriculum discussion, rather than as empirically tested interventions.

CONCLUSIONS

1. The intersection of AI and wood science education is an emerging operational and strategic issue for the Malaysian wood products industry. The reviewed evidence indicates a sector that remains economically significant but is characterized by uneven technology readiness, a large SME base, workforce constraints, and increasing pressure to improve productivity, design capability, traceability, and sustainability. The evidence also highlights that AI adoption should not be interpreted as an automatic source of productivity gains, because implementation depends on data, infrastructure, skills, cybersecurity, and the material complexity of wood.
2. The Malaysian wood industry has demonstrated resilience across three decades of transformation, navigating shifts in raw material availability, foreign worker policy volatility, and changing export market requirements.
3. The AI transition differs from those predecessors in one critical respect: the technology demands a different kind of knowledge at every level of the production organization, from design and engineering through production management to shop floor operation. That knowledge is principally produced and transmitted through the transformative education system.
4. The available evidence points to a need for stronger digital competencies in wood science and technology education, but the precise scale and content of reform cannot be determined from the present review alone. Source-specific indicators such as the reported share of programs containing AI content, or the proportion of emerging roles

classified as AI- and digital-related provide useful signals, but they are not equivalent measures and should not be combined into a single national readiness score. Curriculum reform should therefore be accompanied by systematic stakeholder consultation and outcome monitoring.

5. Malaysia's policy targets provide an important direction for industrial and workforce development, but their achievement will depend on the interaction of technology investment, firm capability, education, training, and market demand. The principal implication of this review is the fact that AI modules alone will not solve the industry's competitiveness challenges, but that wood science education, TVET, reskilling, and industry development policies need to evolve together. Future empirical research should test these propositions using data from educators, students, accreditation bodies, technology providers, and wood-products SMEs.

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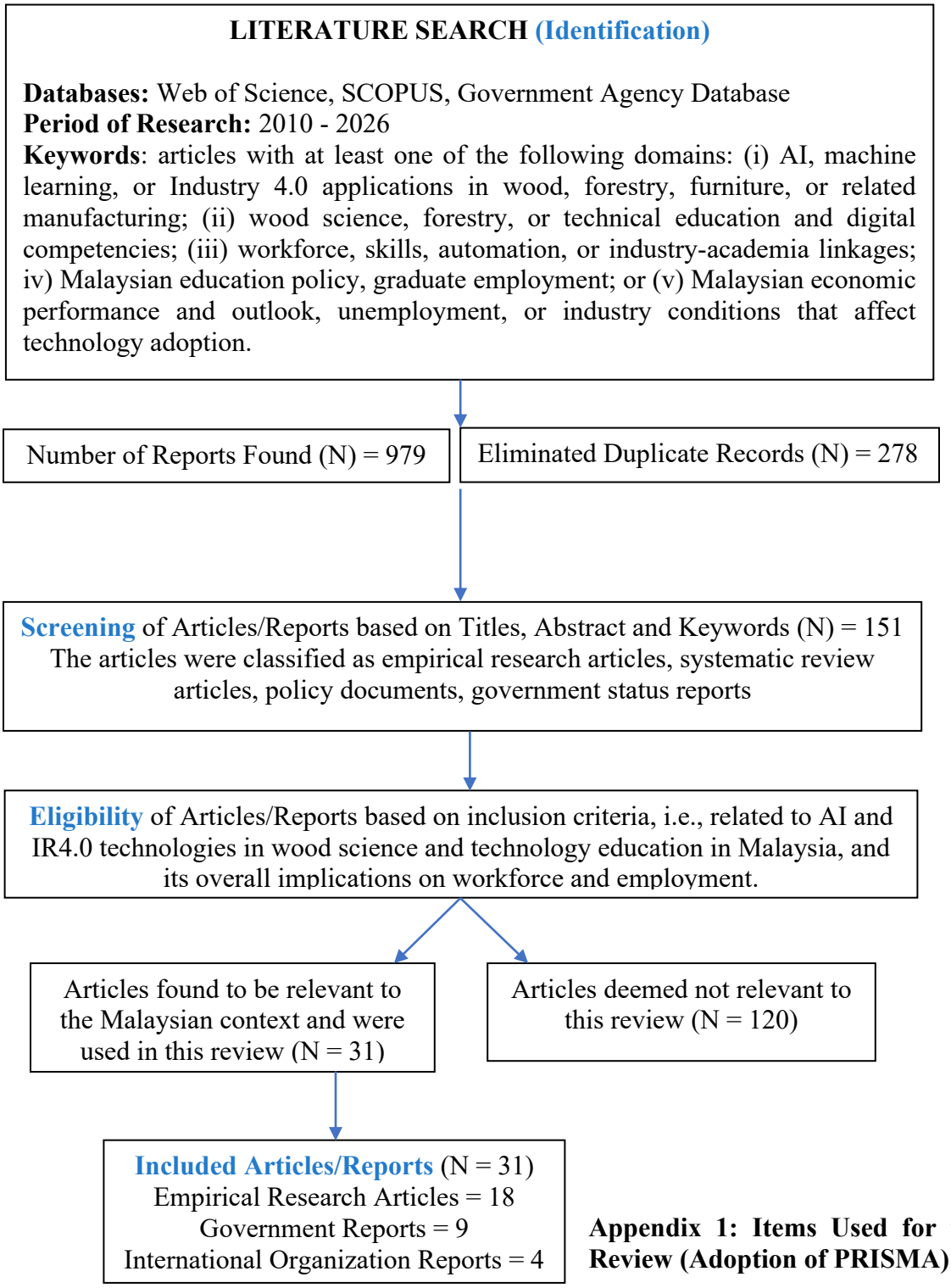
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APPENDIX



Appendix 1: Items Used for the Review (Adoption of PRISMA)