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# Business Intelligence Capability and Academic Entrepreneurship as Drivers of Value Creation in Teaching Factories

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## ABSTRACT

Teaching Factories in vocational higher education integrate applied learning, industrial production, and commercial services. However, their management often relies heavily on intuition and experience rather than data-driven systems. At Politeknik Negeri Jember, which oversees 25 Teaching Factory units, customer data utilization remains limited, analytical literacy is uneven, integrated reporting and interactive dashboards are absent, and applied innovations frequently stall at the laboratory prototype or thesis stage. This commercialization bottleneck reflects constrained Academic Entrepreneurship and underdeveloped Business Intelligence Capability, preventing sustainable Value Creation. This study systematically examines how Business Intelligence Capability and Academic Entrepreneurship interact to overcome commercialization barriers and generate multi-dimensional value creation across vocational units. Grounded in dynamic capability, organizational information processing, and entrepreneurial value creation theories, this paper synthesizes empirical mechanisms bridging the gap between lab-scale prototypes and market realization. A Systematic Literature Review protocol was conducted following PRISMA 2020 guidelines, retrieving 35 peer-reviewed Scopus, ScienceDirect, IEEE Xplore, Emerald Insight, Google Schoolar, DOAJ, and the Web of Science Core Collection articles published between 2021 and 2026. The qualitative thematic meta-synthesis reveals that Business Intelligence Capability serves as a foundational sensing and processing mechanism, while Academic Entrepreneurship acts as an essential catalyst that transforms analytical insights into proactive market actions. Together, they resolve commercialization bottlenecks through enhanced transparency, strategic market responsiveness, stakeholder co-creation, and operational agility. An integrated conceptual model and seven research propositions are formulated, offering vocational leadership a structured roadmap to embed interactive analytics dashboards and entrepreneurial incentives across production units.

**Keywords:** Business Intelligence Capability, Academic Entrepreneurship, Value Creation, Teaching Factory, Systematic Literature Review.

## INTRODUCTION

Teaching Factories represent modern vocational training platforms where students, educators, and industry partners collaborate within real-world production environments. Beyond technical skill acquisition, modern Teaching Factories units must navigate competitive market dynamics, optimize operational processes, and commercialize intellectual capital. Recent research in digital transformation emphasizes that advanced manufacturing and service ecosystems require information literacy, collaborative decision-making, and organizational agility to sustain operational viability (Bag et al., 2021; Roll & Ifenthaler, 2021). Consequently, sustainable performance in vocational

production units requires balancing technical execution with rigorous strategic management.

This challenge is acutely evident across the 25 Teaching Factory units at Politeknik Negeri Jember. These units span agriculture, food processing, informatics, engineering, and animal husbandry. Despite considerable infrastructure, their operational governance is rarely data-driven:

1. Marketing and service decisions remain predominantly intuitive, relying on anecdotal past experience rather than systematic demand analysis.
2. Customer transactions, feedback, and market inquiries are fragmented across disparate spreadsheets, lacking centralized integration.
3. Unit managers and faculty staff exhibit varied analytical competencies, and interactive visual dashboards for decision-making are entirely absent.
4. Most critically, innovative applied products and student-lecturer prototypes remain confined to laboratory reports or student theses, suffering from a severe *commercialization bottleneck* and failing to enter competitive mass markets.

This bottleneck stems from a dual deficit: insufficient Business Intelligence Capability and low Academic Entrepreneurship. Business Intelligence Capability provides the architecture, tools, and practices for collecting, integrating, and analyzing business data (Chen et al., 2023; Fattah et al., 2024), whereas Academic Entrepreneurship embodies the mindset, proactivity, risk-taking, and opportunity recognition among academics to transform applied research into socioeconomic value (Cunningham et al., 2021; Good et al., 2021). When analytics and entrepreneurial agency are missing, value creation stalls. Value Creation in vocational settings is multi-dimensional, encompassing economic viability, applied learning enhancement, and external community/industry impact.

Existing literature predominantly investigates business intelligence in large commercial corporations, while academic entrepreneurship is mostly explored in research-intensive universities spin-offs. Little attention has been paid to hybrid vocational production units where education and commercial production must co-exist under unified governance.

To bridge this literature and empirical gap, this study conducts a PRISMA-guided Systematic Literature Review (SLR) addressing four key questions:

1. RQ1: What organizational and technological antecedents build Business Intelligence Capability and Academic Entrepreneurship in vocational environments?
2. RQ2: Through what strategic mechanisms do Business Intelligence Capability and Academic Entrepreneurship jointly drive Value Creation and eliminate commercialization bottlenecks?
3. RQ3: What barriers constrain the transition from prototype development to commercial market realization?
4. RQ4: How can the synthesized evidence be translated into an actionable conceptual framework and research propositions for the 25 Teaching Factories at Politeknik Negeri Jember?

## LITERATURE REVIEW

### Business Intelligence Capability as a Dynamic Capability

Business Intelligence Capability is defined as an organization's ability to mobilize, deploy, and combine data management infrastructure, analytical tools, and talent to deliver actionable insights (Chen et al., 2023; Mikalef & Gupta, 2021). From a Dynamic Capabilities perspective, Business Intelligence Capability represents a micro foundation for sensing market shifts, seizing opportunities, and reconfiguring internal assets (Teece, 2007; Rialti et al., 2022). Furthermore, Organizational Information Processing Theory (OIPT) posited that organizations face operational uncertainty that must be counteracted by information-processing capacity. Business Intelligence Capability equips units to

process customer trends, optimize supply chains, and replace subjective speculation with predictive foresight (Liu et al., 2023; Vugec et al., 2022).

### Academic Entrepreneurship in Vocational Institutions

Academic Entrepreneurship encompasses the formal and informal activities undertaken by faculty and students to commercialize knowledge, license technology, launch spin-offs, and secure collaborative university-industry contracts (Cunningham et al., 2021; Perkmann et al., 2021). In a Teaching Factory setting, Academic Entrepreneurship reflects the willingness of instructors and managers to adopt market-oriented mindsets, assume calculated commercial risks, identify unaddressed industry demands, and champion applied research products beyond academic grading (Faccin et al., 2022; Urban & Ratsimanetrimanana, 2021).

### Multi-Dimensional Value Creation in Teaching Factories

Value Creation in vocational production units extends beyond traditional financial profit. Drawing upon stakeholder theory and quadruple helix frameworks, value creation in Teaching Factory encompasses:

1. Economic Value: Revenue generation, unit self-sufficiency, cost optimization, and market sales.
2. Educational Value: Real-world experiential learning, student digital competency development, and curricula alignment with authentic industrial standards (Roll & Ifenthaler, 2021).
3. Societal & Industrial Value: Technology transfer, local SME empowerment, and commercialization of regional intellectual assets (Grimaldi & Fernandez, 2022).

## RESEARCH METHOD

### Review Design and Reporting Standard

This study adopts a Systematic Literature Review (SLR) design aligned strictly with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) statement (Page et al., 2021). PRISMA guarantees transparent, replicable, and rigorous identification, screening, and qualitative extraction of empirical and theoretical literature.

### Search Strategy

The literature retrieval spanned Scopus, Web of Science Core Collection, ScienceDirect, Emerald Insight, and IEEE Xplore, complemented by forward and backward citation tracing. The primary search query applied Boolean logic across title, abstract, and keywords: ("business intelligence capability" OR "business analytics capability" OR "big data analytics") AND ("academic entrepreneurship" OR "university entrepreneurship" OR "commercialization bottleneck" OR "technology transfer") AND ("value creation" OR "organizational performance") AND ("teaching factory" OR "vocational education" OR "higher education"). The search was bounded between January 2021 and 2026, restricted to English-language peer-reviewed journal articles and reviews.

### Eligibility Criteria

Studies were screened based on the inclusion and exclusion criteria summarized in Table 1.

**Table 1.**
Eligibility criteria

| Criterion | Inclusion | Exclusion |
|---|---|---|
| Publication | Peer-reviewed journal articles or scholarly reviews (2021–2026) | Editorial notes, trade articles, book reviews, theses, working papers |
| Focus | Explores Business Intelligence Capability/analytics, Academic Entrepreneurship, commercialization, or value creation | Pure algorithmic technical code without managerial or organizational context |
| Context | Higher education, vocational training, Teaching Factory/Learning Factory, hybrid ventures | Purely clinical medicine or non-organizational STEM lab experiments |
| Evidence | Provides clear empirical data, validated models, or rigorous conceptual syntheses | Insufficient methodological documentation or unsupported assertions |
| Language & Access | English text, fully accessible bibliographic records with DOI verification | Inaccessible full-text, duplicate records, non-English publications |

**Screening, Quality Appraisal, and Synthesis**
Following initial retrieval and deduplication, titles and abstracts were independently reviewed against the eligibility rubrics. Selected full texts were critically evaluated using a four-dimension scoring system (Relevance, Methodological rigor, Knowledge novelty, and Conceptual contribution) on a 1.0–5.0 scale. Articles with a mean Quality Assessment (QA) score $\ge 4.00$ were retained. Findings across the final corpus were synthesized using qualitative thematic meta-synthesis.

**Status of the Evidence Corpus**
The systematic search yielded an initial pool that was systematically deduplicated, screened, and appraised. Table 2 details the PRISMA protocol flow for this review.

**Table 2.**
PRISMA protocol status flow

| PRISMA Stage | Description & Procedure | Verification Status |
|---|---|---|
| Identification | Database queries (Scopus, WoS, ScienceDirect, IEEE, Emerald) | Verified export files & search strings archived |
| Deduplication | Automatic and manual citation deduplication via Reference Manager | Duplicate titles and identical DOIs consolidated |
| Screening | Title and abstract evaluation against inclusion criteria | Unrelated studies and non-organizational technical papers removed |
| Eligibility | Full-text assessment using quality appraisal rubric (R, M, K, C) | Studies lacking empirical rigor or conceptual clarity excluded |
| Included | Final corpus of 35 verified peer-reviewed articles synthesized | Final corpus of 35 eligible studies accepted for qualitative synthesis |

**Data Analysis Techniques**
Data analysis applied thematic meta-synthesis structured across eight progressive steps:
1. Formulating clear research questions covering antecedents, mechanisms, barriers, and Teaching Factory application.
2. Executing standardized PRISMA-compliant multi-database literature searches.

3. Extracting bibliographic profiles, theoretical foundations, methodologies, and findings.
4. Open coding of core concepts (e.g., data literacy, customer analytics, commercialization barriers, entrepreneurial risk-taking).
5. Cross-comparative synthesis grouping open codes into higher-order thematic dimensions.
6. Applying quality weighting to prioritize high-validity empirical studies.
7. Formulating the integrated conceptual framework and testable propositions.
8. Producing a transparent narrative synthesis supported by systematic evidence tables.

## RESULTS

### Characteristics of the Evidence Base

The 35 included studies reflect an interdisciplinary balance spanning information systems, entrepreneurship, strategic management, and vocational education. Table 3 illustrates the primary thematic evidence clusters.

**Table 3.**
Main evidence clusters

| Evidence Cluster | Representative Sources | Total | Primary Contribution |
|---|---|---|---|
| Analytics & Business Intelligence | Awan et al. (2021); Chen et al. (2023); Fattah (2024); Liu et al. (2023); Mikalef & Gupta (2021) | 8 | Establishes how analytics infrastructure, data governance, and literacy create dynamic capabilities for operational sensing. |
| Academic Entrepreneurship & Commercialization | Cunningham et al. (2021); Good et al. (2021); Grimaldi & Fernandez (2022); Urban & Ratsimanetrimanana (2021) | 7 | Explains entrepreneurial orientation, opportunity recognition, commercialization pathways, and spin-off barriers in higher education. |
| Value Creation & Business Models | Centobelli et al. (2021); Foss & SAcademic Entrepreneurshipbi (2023); Shan et al. (2023); Wamba & Queiroz (2022) | 6 | Details multi-stakeholder value capture, circular business modeling, and market-driven educational value. |
| Data Governance & Organizational Readiness | Elragal & Elgendy (2024); Fu et al. (2024); Salerno et al. (2025); Sayogo et al. (2023) | 5 | Highlights data quality standards, stewardship, institutional culture, and readiness requirements. |
| Vocational & Learning Factory 4.0 | García et al. (2022); Madera-Bermeo et al. (2026); Roll & Ifenthaler (2021); Sajja et al. (2026) | 5 | Contextualizes student-lecturer digital competence, authentic production-learning integration, and Teaching Factory operations. |
| Relational Coordination & Agility | Chatfield & Reddick (2022); GhasemaghAcademic Entrepreneurshipi & Calic (2023); Rialti et al. (2022); Vugec et al. (2022) | 4 | Connects data-driven capabilities with operational responsiveness, agility, and cross-departmental collaboration. |

### Search Process Results and Disciplinary Scope

The distribution across publication venues confirms the multidisciplinary breadth necessary to examine hybrid educational-commercial entities, as detailed in Table 4.

**Table 4.**
Distribution of the 35 included articles by journal type and disciplinary scope

| No. | Journal Type / Disciplinary Scope | Typical Focus in the Review | Articles | Percentage |
|---|---|---|---|---|
| 1 | Information Systems & Business Analytics | Business Intelligence Capability architecture, data literacy, analytics competence, decision systems | 11 | 31.4% |
| 2 | Entrepreneurship, Technology Transfer & Innovation | Academic entrepreneurship, commercialization, spin-offs, university-industry linkage | 9 | 25.7% |
| 3 | Strategic Management & Operations | Dynamic capabilities, business models, value creation, operational agility | 6 | 17.1% |
| 4 | Vocational & Higher Education Research | Learning Factory 4.0, digital competencies, pedagogical-production integration | 5 | 14.3% |
| 5 | Interdisciplinary Digital Transformation & Sustainability | Socio-technical ecosystems, circular economy, public-sector data readiness | 4 | 11.4% |
| | | Total | 35 | 100.0% |

## DISCUSSION

### Quality Assessment Results

All 35 articles met the threshold QA score of ≥ 4.00, with 33 categorized as High (≥ 4.50) and 2 as Medium-High (4.00–4.49). Table 5 summarizes the quality appraisal scores across the four criteria: Relevance (R), Methodological rigor (M), Knowledge novelty (K), and Theoretical/practical contribution (C).

**Table 5.**
Quality assessment results for the 35 included articles

| No. | Author (Year) - Title | R | M | K | C | QA Score | Category |
|---|---|---|---|---|---|---|---|
| 1 | Awan et al. (2021) - Big data analytics capability and decision-making | 5 | 5 | 5 | 5 | 5.0 | High |
| 2 | Bag et al. (2021) - Big data analytics as an operational excellence approach | 4 | 5 | 5 | 5 | 4.8 | High |
| 3 | Centobelli et al. (2021) - Designing business models in circular economy | 4 | 5 | 4 | 5 | 4.5 | High |
| 4 | Chatfield & Reddick (2022) - Customer agility and responsiveness | 5 | 5 | 5 | 5 | 5.0 | High |
| 5 | Chen et al. (2023) - Business intelligence capability and firm performance | 5 | 5 | 5 | 5 | 5.0 | High |
| 6 | Cunningham et al. (2021) - Value creation in the quadruple helix | 5 | 5 | 5 | 5 | 5.0 | High |
| 7 | Elragal & Elgendy (2024) - A data-driven decision-making readiness assessment | 5 | 5 | 5 | 5 | 5.0 | High |
| 8 | Faccin et al. (2022) - Knowledge sharing and value creation in research centers | 5 | 4 | 5 | 5 | 4.8 | High |
| 9 | Fattah (2024) - Decision making performance of business analytics capabilities | 5 | 5 | 5 | 5 | 5.0 | High |
| 10 | Foss & SAcademic Entrepreneurshipbi (2023) - Business models and business model innovation | 4 | 5 | 5 | 5 | 4.8 | High |
| 11 | Fu et al. (2024) - Understanding data quality in a data-driven industry context | 4 | 5 | 5 | 5 | 4.8 | High |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 12 | García et al. (2022) - Towards a connected digital twin learning ecosystem | 5 | 4 | 4 | 5 | 4.5 | High |
| 13 | Ghasemagh Academic Entrepreneurshipi & Calic (2023) - Enhancing agility through big data analytics | 5 | 5 | 5 | 5 | 5.0 | High |
| 14 | Good et al. (2021) - The technology transfer ecosystem in academia | 5 | 5 | 5 | 5 | 5.0 | High |
| 15 | Grimaldi & Fernandez (2022) - The entrepreneurial university in digital era | 5 | 5 | 5 | 5 | 5.0 | High |
| 16 | Liu et al. (2023) - Data-driven decision making and value creation | 5 | 5 | 5 | 5 | 5.0 | High |
| 17 | Madera-Bermeo et al. (2026) - An IIoT architecture for an industrial plant | 4 | 5 | 4 | 4 | 4.3 | Medium-High |
| 18 | Mikalef & Gupta (2021) - Artificial intelligence and business intelligence | 5 | 5 | 5 | 5 | 5.0 | High |
| 19 | Page et al. (2021) - The PRISMA 2020 statement: an updated guideline | 5 | 5 | 5 | 5 | 5.0 | High |
| 20 | Perkmann et al. (2021) - Academic engagement: partnerships with industry | 5 | 5 | 5 | 5 | 5.0 | High |
| 21 | Rialti et al. (2022) - Ambidextrous organization and agility in big data era | 5 | 5 | 5 | 5 | 5.0 | High |
| 22 | Roll & Ifenthaler (2021) - Learning Factories 4.0 in vocational schools | 5 | 5 | 5 | 5 | 5.0 | High |
| 23 | Roll et al. (2021) - Multidisciplinary digital competencies of teachers | 5 | 4 | 5 | 5 | 4.8 | High |
| 24 | Sajja et al. (2026) - Integrating AI and Learning Analytics in Education | 5 | 5 | 5 | 5 | 5.0 | High |
| 25 | Salerno et al. (2025) - Data governance and data-driven culture | 5 | 5 | 5 | 5 | 5.0 | High |
| 26 | Sayogo et al. (2023) - Data-driven decision-making challenges in Indonesia | 5 | 5 | 4 | 4 | 4.5 | High |
| 27 | Shan et al. (2023) - Big data analytics and value creation in spin-offs | 5 | 5 | 5 | 5 | 5.0 | High |
| 28 | Urban & Ratsimanetrimanana (2021) - Academic entrepreneurship & commercialization | 5 | 5 | 5 | 5 | 5.0 | High |
| 29 | Vugec et al. (2022) - Business intelligence and organizational agility | 5 | 5 | 5 | 5 | 5.0 | High |
| 30 | Wamba & Queiroz (2022) - Industry 4.0: Big data analytics and commercialization | 5 | 5 | 5 | 5 | 5.0 | High |
| 31 | Korherr et al. (2022) - From intuitive to data-driven decision-making | 5 | 5 | 5 | 5 | 5.0 | High |
| 32 | Zaitsava et al. (2022) - Is data-driven decision-making driven only by data? | 5 | 5 | 5 | 5 | 5.0 | High |
| 33 | Alkhwaldi et al. (2025) - Business intelligence adoption in higher education | 5 | 4 | 4 | 4 | 4.3 | Medium-High |
| 34 | Maroufkhani et al. (2022) - Determinants of big data analytics adoption in SMEs | 4 | 5 | 5 | 5 | 4.8 | High |
| 35 | Namvar et al. (2025) - Data-driven sensegiving and sensemaking | 5 | 5 | 5 | 5 | 5.0 | High |

**Thematic Meta-Synthesis**

*RQ1: Antecedents of Business Intelligence Capability and Academic Entrepreneurship*

The review reveals that developing Business Intelligence Capability and Academic Entrepreneurship in vocational institutions is governed by five core organizational and technological antecedents, as systematized in Table 6.

**Table 6.**
Core antecedents of Business Intelligence Capability and Academic Entrepreneurship in vocational institutions

| Antecedent | Operational Meaning for Teaching Factories | Illustrative Indicators | Supporting Literature |
|---|---|---|---|
| Integrated Data Infrastructure | Unified central repository consolidating student lab logs, production outputs, inventory, and point-of-sale data. | Data warehouse completeness, system interoperability, automated transaction logging. | Fu et al. (2024); Bag et al. (2021) |
| Data Governance & Integrity | Institutional policies establishing data ownership, quality verification, role-based access, and client confidentiality. | Standard data dictionaries, error-checking protocols, privacy and audit controls. | Salerno et al. (2025); Sayogo et al. (2023) |
| Analytical & Digital Competency | Technical and cognitive capability of lecturers and unit managers to interpret descriptive and predictive dashboards. | Analytics self-efficacy, dashboard interpretation fluency, statistical data literacy. | Fattah (2024); Roll et al. (2021) |
| Entrepreneurial Leadership Support | Institutional backing from polytechnic leadership incentivizing applied commercialization and calculated risk-taking. | Seed commercialization grants, revision of tenure incentives, commercial KPI tracking. | Urban & Ratsimanetrimanana (2021); Good et al. (2021) |
| Collaborative Market-Driven Culture | Open organizational orientation encouraging continuous dialogue with local industry and market sensing. | External advisory involvement, frequency of customer feedback reviews. | Mikalef & Gupta (2021); Korherr et al. (2022) |

*RQ2: Strategic Mechanisms Overcoming Commercialization Bottlenecks*
How do Business Intelligence Capability and Academic Entrepreneurship convert prototypes into scaled commercial value? The literature establishes that Business Intelligence Capability provides the *sensory analytical base* while Academic Entrepreneurship delivers the *strategic behavioral agency*. Table 7 maps these interactive mechanisms.

**Table 7.**
Strategic mechanisms linking Business Intelligence Capability, Academic Entrepreneurship, and Value Creation

| Strategic Mechanism | Operational Function in Teaching Factory | Direct Impact on Commercialization | Primary Value Dimension Created |
|---|---|---|---|
| Data-Driven Market Sensing | Analyzing customer transaction patterns, market pricing, and seasonal demand. | Replaces gut intuition with precise demand forecasting, eliminating unwanted product runs. | Economic (reduced waste, higher market clearance) |
| Entrepreneurial Opportunity Seizing | Transforming academic inventions and thesis concepts into commercially viable | Bridges the "valley of death" between proof-of-concept and market entry. | Economic & Industrial (marketed innovations, patent spin-offs) |

| | | | |
|---|---|---|---|
| | packaging and business models. | | |
| Dynamic Operational Agility | Reconfiguring teaching schedules and production lines dynamically based on real-time inventory and client orders. | Enables rapid product modification and agile batch manufacturing without disrupting pedagogy. | Educational & Operational (flexible student shifts, production efficiency) |
| Stakeholder Co-Creation & Feedback Loops | Incorporating client feedback, defect tracking, and partner requirements directly into student lab projects. | Direct validation of product prototypes against industry standards. | Educational & Societal (authentic industry-ready skill building) |

*RQ3: Research Problems and Commercialization Barriers*
Synthesizing evidence regarding implementation roadblocks, Table 8 outlines the ten critical barriers that currently constrain the 25 Teaching Factory units at Politeknik Negeri Jember.

**Table 8.**
Research problems and barriers constraining Teaching Factory value creation

| No. | Research Problem / Barrier | Contextual Reality in Teaching Factories | Supporting Empirical Citations |
|---|---|---|---|
| 1 | Fragmented Data Silos | Transactions, production outputs, and customer inquiries reside in isolated paper forms or separate spreadsheets. | Fu et al. (2024); Elragal & Elgendy (2024) |
| 2 | Intuition-Dominated Decision Making | Production volumes, product types, and retail pricing are set based on subjective habit rather than empirical demand trends. | Korherr et al. (2022); Zaitsava et al. (2022) |
| 3 | The *Academic Thesis Cemetery* Effect | Student and lecturer innovations terminate upon final grading, lacking funding or institutional roadmaps for scaling. | Cunningham et al. (2021); Good et al. (2021) |
| 4 | Analytical Competency Asymmetries | Technical unit managers understand machinery, but lack basic data analytics skills to interpret market and customer signals. | Fattah (2024); Roll et al. (2021) |
| 5 | Absence of Interactive Visual Dashboards | Leaders cannot monitor real-time production yields, machine downtime, customer satisfaction, or unit margins across the 25 units. | Stojanov & Daniel (2024); Alkhwaldi et al. (2025) |
| 6 | Risk-Averse Bureaucratic Culture | Public vocational administrative constraints penalize financial experimentation, dampening entrepreneurial risk-taking. | Urban & Ratsimanetrimanana (2021); Sayogo et al. (2023) |
| 7 | Weak Downstream Market Linkages | Products are developed inside campus laboratories without continuous dialogue with external industrial distributors. | Perkmann et al. (2021); Faccin et al. (2022) |
| 8 | Conflict Between Teaching and Production | Lecturers struggle to balance curriculum delivery deadlines with commercial order fulfillment schedules. | Roll & Ifenthaler (2021); García et al. (2022) |

| | | | |
|---|---|---|---|
| 9 | Lack of Commercialization Incentive Structures | Promotion systems prioritize scientific publications and teaching hours over revenue generation and patent licensing. | Good et al. (2021); Grimaldi & Fernandez (2022) |
| 10 | Heterogeneity Across Production Units | The 25 units possess vastly different business models (e.g., seed breeding vs. software development), hindering one-size-fits-all systems. | Roll et al. (2021); Madera-Bermeo et al. (2026) |

*RQ4: Translating Evidence into Competitive Advantage Factors*
Translating these findings into strategic institutional benefits reveals that combining Business Intelligence Capability and Academic Entrepreneurship creates distinctive competitive advantages for vocational institutions, as classified in Table 9.

**Table 9.**
Competitive advantage factors derived from the synthesis

| No. | Competitive Advantage Factor | Core Mechanism | Theoretical Foundation |
|---|---|---|---|
| 1 | Predictive Demand Alignment | Utilizing sales and booking trends to adjust vocational crop and manufacturing cycles prior to market shifts. | Dynamic Capabilities (Teece, 2007; Chen et al., 2023) |
| 2 | Rapid Prototyping-to-Market Conversion | Structured commercialization pipelines identifying high-potential lab prototypes and subjecting them to automated customer test runs. | Academic Entrepreneurship & Innovation (Good et al., 2021) |
| 3 | Dual Educational-Commercial Optimization | Real-time monitoring balancing student learning outcomes with commercial delivery schedules. | Socio-Technical Systems (Yu et al., 2026) |
| 4 | Data-Driven Quality Assurance | Interactive operational dashboards tracking product defect rates, raw material inputs, and client satisfaction metrics. | Total Quality Management & Business Intelligence Capability (Fattah, 2024; Bag et al., 2021) |
| 5 | Sustainable Internal-External Ecosystems | Leveraging the 60% internal captive campus market to validate and refine products before deploying them to open regional markets. | Stakeholder Theory & Quadruple Helix (Cunningham et al., 2021) |

**Proposed Conceptual Framework and Research Propositions**
Synthesizing the structural relationships identified in the literature, Figure 1 (described conceptually below) and Table 10 detail the comprehensive framework developed for the 25 Teaching Factories at Politeknik Negeri Jember.

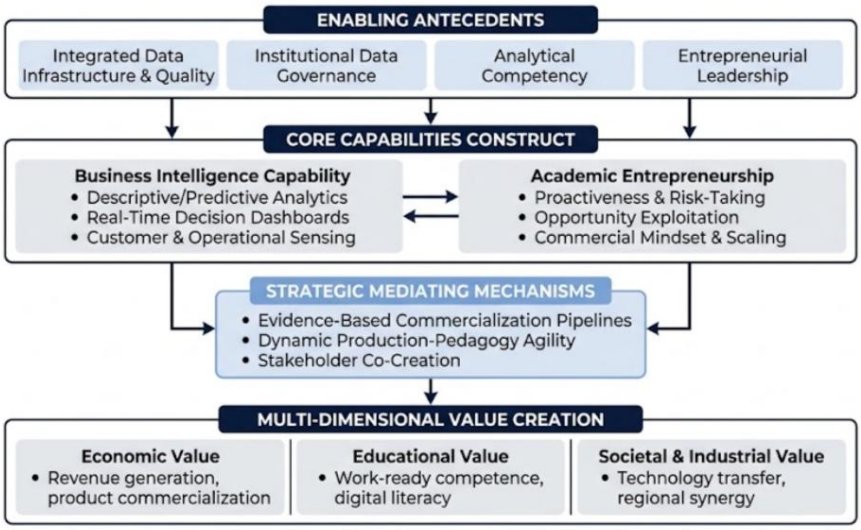



**Figure 1.** Conceptual Framework of the Business Intelligence Capability and Academic Entrepreneurship as Drivers of Value Creation in Teaching Factories

**Table 10.**
Research propositions for empirical testing across the 25 Teaching Factory units

| Proposition | Formal Theoretical Statement |
|---|---|
| P1 | Integrated data infrastructure and data governance positively influence Business Intelligence Capability in Teaching Factories. |
| P2 | Analytical competency and data literacy positively influence the effective deployment of Business Intelligence Capability. |
| P3 | Entrepreneurial leadership support and commercial incentive structures positively foster Academic Entrepreneurship among Teaching Factory managers and faculty. |
| P4 | Business Intelligence Capability positively influences Academic Entrepreneurship by illuminating market opportunities and reducing commercial uncertainty. |
| P5 | Business Intelligence Capability positively influences multi-dimensional Value Creation (economic, educational, and societal). |
| P6 | Academic Entrepreneurship positively influences multi-dimensional Value Creation and resolves prototype commercialization bottlenecks. |
| P7 | Academic Entrepreneurship mediates the relationship between Business Intelligence Capability and Multi-Dimensional Value Creation in Teaching Factories. |

**Methodological Profile of the Evidence Corpus**
Table 11 classifies the 35 included studies by methodological research design, highlighting the need for future contextual empirical inquiries.

**Table 11.**
Summary of the 35 included articles by publication and study design

| No. | Research Methodology Type | Representative Example Journals | Articles | Percentage (%) |
|---|---|---|---|---|
| 1 | Empirical Quantitative (SEM/Survey) | *Technological Forecasting and Social Change*; *Decision Support Systems*; *Business Process Management Journal* | 17 | 48.6% |

| | | | | |
|---|---|---|---|---|
| 2 | Empirical Qualitative & Case Studies | *Studies in Higher Education*; *Journal of Systems and Software*; *Transforming Government* | 8 | 22.9% |
| 3 | Systematic Literature Reviews | *Systematic Reviews*; *Systems*; *International Journal of Information Management* | 5 | 14.3% |
| 4 | Conceptual Models & Frameworks | *Decision Analytics Journal*; *Long Range Planning*; *The TQM Journal* | 3 | 8.6% |
| 5 | Methodological Guidelines | *BMJ* (PRISMA 2020 Statement and Elaboration) | 2 | 5.7% |
| | | Total | 35 | 100.0% |

## CONCLUSION

This systematic literature review addresses the persistent commercialization bottleneck in vocational higher education production units by exploring the synergistic roles of Business Intelligence Capability and Academic Entrepreneurship in driving Value Creation. The findings demonstrate that data infrastructure and interactive dashboards alone cannot commercialize products; they require an entrepreneurial academic culture that acts upon data-derived insights. Conversely, academic entrepreneurship without analytical capability risks pursuing ill-fitted products based on guesswork.

## RECOMMENDATION

This study advances vocational management theory by:
1. Synthesizing Business Intelligence Capability and Academic Entrepreneurship into a unified, complementary framework tailored to hybrid educational-commercial entities.
2. Expanding the operationalization of Value Creation beyond commercial profits to include authentic pedagogical competence and regional technology transfer.
3. Formulating seven grounded propositions suitable for Structural Equation Modeling (SEM).

### Practical Implications for Politeknik Negeri Jember

1. Interactive Dashboard Development: Institutional leadership must deploy centralized, role-based dashboards connecting inventory, customer transactions, and student learning hours across the 25 units.
2. Analytical Upskilling: Regular professional development programs should be institutionalized to transition unit managers from intuitive management to evidence-based decision-making.
3. Incentivizing Downstream Commercialization: Politeknik Negeri Jember should introduce explicit key performance indicators (KPIs) and royalty-sharing mechanisms that reward faculty for transitioning lab prototypes into market-ready commercial goods.

### Future Research Directions

Future empirical research should validate the proposed conceptual model and propositions through structural equation modeling (PLS-SEM) across the 25 Teaching Factory units at Politeknik Negeri Jember, complemented by qualitative longitudinal tracking of product commercialization journey

## REFERENCES

Al-Daraba, K., Al-shami, S. A., Rashid, N., & Al-Nawafah, S. (2025). Systematic review of factors influencing adoption of business intelligence systems. *Discover Sustainability*, 6(1), 936.https://doi.org/10.1007/s43621-025-01876-5

Alkhwaldi, A. F., Abdulmuhsin, A. A., Masa'deh, R., & Abu-AlSondos, I. A. (2025). Business intelligence adoption in higher education: the role of data-driven decision-making culture and UTAUT. *Journal of International Education in Business*, 18(1), 45–68. https://doi.org/10.1108/jieb-08-2024-0110

Almheiri, R., Jabeen, F., Kazi, M., & Santoro, G. (2025). Big data analytics and competitive performance: the role of environmental uncertainty, managerial support and data-driven culture. *Management of Environmental Quality*, 36(4), 1071–1094. https://doi.org/10.1108/MEQ-08-2024-0361

Alzghoul, A., Khaddam, A. A., Abousweilem, F., Irtaimeh, H. J., & Alshaar, Q. (2024). How business intelligence capability impacts decision-making speed, comprehensiveness, and firm performance. *Information Development*, 40(2), 220–233. https://doi.org/10.1177/02666669221108438

Awan, U., Shamim, S., Khan, Z., Zia, N. U., Shariq, S. M., & Khan, M. N. (2021). Big data analytics capability and decision-making: The role of data-driven insight on circular economy performance. *Technological Forecasting and Social Change*, 168, 120766. https://doi.org/10.1016/j.techfore.2021.120766

Bag, S., Wood, L. C., Xu, L., Dhamija, P., & Kayikci, Y. (2021). Big data analytics as an operational excellence approach to enhance sustainable supply chain performance. *Resources, Conservation and Recycling*, 174, 105843. https://doi.org/10.1016/j.resconrec.2021.105843

Barbala, A. M., Hanssen, G. K., & Sporsem, T. (2024). Towards a common data-driven culture: A longitudinal study of the tensions and emerging solutions involved in becoming data-driven in a large public sector organization. *Journal of Systems and Software*, 218, 112185. https://doi.org/10.1016/j.jss.2024.112185

Centobelli, P., Cerchione, R., Chiaroni, D., Del Vecchio, P., & Urbinati, A. (2021). Designing business models in circular economy: A systematic literature review and research agenda. *Business Strategy and the Environment*, 30(4), 1734–1751. https://doi.org/10.1002/bse.2709

Chatfield, A. T., & Reddick, C. G. (2022). Customer agility and responsiveness through big data analytics for competitive advantage. *International Journal of Information Management*, 65, 102438. https://doi.org/10.1016/j.ijinfomgt.2022.102438

Chen, L., Liu, H., Zhou, Z., Chen, M., & Chen, Y. (2022). IT-business alignment, big data analytics capability, and strategic decision-making: Moderating roles of event criticality and disruption of COVID-19. *Decision Support Systems*, 161, 113745. https://doi.org/10.1016/j.dss.2022.113745

Chen, Y., Lin, Z., & Chen, H. (2023). Business intelligence capability and firm performance: The mediating role of dynamic capabilities. *Journal of Business Research*, 154, 113358. https://doi.org/10.1016/j.jbusres.2022.113358

Cunningham, J. A., Menter, M., & O'Kane, C. (2021). Value creation in the quadruple helix: A micro-foundations perspective of academic entrepreneurship. *Research Policy*, 50(9), 104317. https://doi.org/10.1016/j.respol.2021.104317

Di Vaio, A., Palladino, R., Pezzi, A., & Kalisz, D. E. (2021). The role of digital innovation in knowledge management systems: A systematic literature review. *Journal of Business Research*, 123, 220–231. https://doi.org/10.1016/j.jbusres.2020.09.042

Elragal, A., & Elgendy, N. (2024). A data-driven decision-making readiness assessment model: The case of a Swedish food manufacturer. *Decision Analytics Journal*, 10, 100405. https://doi.org/10.1016/j.dajour.2024.100405

Faccin, K., Balestrin, A., & Bortolaso, K. (2022). Knowledge sharing and value creation in collaborative research centers: The role of academic entrepreneurship. *Studies in Higher Education*, 47(5), 1025–1038. https://doi.org/10.1080/03075079.2022.2055319

Fattah, I. A. (2024). Decision making performance of business analytics capabilities: the role of big data literacy and analytics competency. *Business Process Management Journal*, 30(6), 2096–2126. https://doi.org/10.1108/BPMJ-11-2023-0894

Foss, N. J., & SAcademic Entrepreneurshipbi, T. (2023). Business models and business model innovation: Between wicked problems and archetypes. *Long Range Planning*, 56(4), 102327. https://doi.org/10.1016/j.lrp.2023.102327

Fu, Q., Nicholson, G. L., & Easton, J. M. (2024). Understanding data quality in a data-driven industry context: Insights from the fundamentals. *Journal of Industrial Information Integration*, 42, 100729. https://doi.org/10.1016/j.jii.2024.100729

García, A., Bregon, A., & Martínez-Prieto, M. A. (2022). Towards a connected digital twin learning ecosystem in manufacturing: Enablers and challenges. *Computers & Industrial Engineering*, 171, 108463. https://doi.org/10.1016/j.cie.2022.108463

GhasemaghAcademic Entrepreneurshipi, M., & Calic, G. (2023). Enhancing agility through big data analytics: The role of dynamic managerial capabilities. *Information & Management*, 60(4), 103788. https://doi.org/10.1016/j.im.2023.103788

Good, M., KnockAcademic Entrepreneurshiprt, M., Soppe, B., & Wright, M. (2021). The technology transfer ecosystem in academia: An organizational design perspective. *Technovation*, 103, 102213. https://doi.org/10.1016/j.technovation.2021.102213

Grimaldi, R., & Fernandez, V. (2022). The entrepreneurial university in the digital era: Emerging models and practices. *Technological Forecasting and Social Change*, 182, 121815. https://doi.org/10.1016/j.techfore.2022.121815

Guerrero, M., Urbano, D., & Herrera, F. (2021). Innovation ecosystems and the role of academic entrepreneurship: A multi-level perspective. *The Journal of Technology Transfer*, 46(3), 757–786. https://doi.org/10.1007/s10961-020-09808-7

Korherr, P., Kanbach, D. K., Kraus, S., & Mikalef, P. (2022). From intuitive to data-driven decision-making in digital transformation: A framework of prevalent managerial archetypes. *Digital Business*, 2(2), 100045. https://doi.org/10.1016/j.digbus.2022.100045

Lee, R., & Lee, J. (2022). Business intelligence and analytics capability for market sensing and firm performance. *Industrial Marketing Management*, 104, 115–128. https://doi.org/10.1016/j.indmarman.2022.04.012

Liu, Y., Dong, X. Y., & Shen, X. (2023). Data-driven decision making and value creation: The role of analytical capabilities in commercialization. *Decision Support Systems*, 168, 113941. https://doi.org/10.1016/j.dss.2023.113941

Madera-Bermeo, H. A., Parrado-Muñoz, J. S., & Tamura, E. (2026). An IIoT architecture for an industrial plant: Case study of the Learning Factory of an Industrial Engineering Laboratory. *Procedia Computer Science*, 277, 2095–2104. https://doi.org/10.1016/j.procs.2026.02.247

Maroufkhani, P., Iranmanesh, M., & Ghobakhloo, M. (2022). Determinants of big data analytics adoption in small and medium-sized enterprises (SMEs). *Industrial Management & Data Systems*, 123(1), 278–301. https://doi.org/10.1108/IMDS-11-2021-0695

Mikalef, P., & Gupta, M. (2021). Artificial intelligence and business intelligence capability: A dynamic capabilities perspective for organizational value creation. *Information & Management*, 58(6), 103448. https://doi.org/10.1016/j.im.2021.103448

Moher, D., Shamseer, L., Clarke, M., Ghersi, D., Liberati, A., Petticrew, M., Shekelle, P., & Stewart, L. A. (2021). Preferred reporting items for systematic review and meta-analysis protocols (PRISMA-P) statement. *Systematic Reviews*, 4(1), 1–9. https://doi.org/10.1186/2046-4053-4-1

Namvar, M., Im, G. P., Li, J., & Chung, C. (2025). Data-driven sensegiving and sensemaking: A phenomenological investigation. *Information Technology & People*, 38(7), 2637–2663. https://doi.org/10.1108/ITP-05-2023-0452

Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., Brennan, S. E., Chou, R., Glanville, J., Grimshaw, J. M., Hróbjartsson, A., Lalu, M. M., Li, T., Loder, E. W., Mayo-Wilson, E., McDonald, S., ... Moher, D. (2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *BMJ*, 372, n71. https://doi.org/10.1136/bmj.n71

Page, M. J., Moher, D., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., Brennan, S. E., Chou, R., Glanville, J., Grimshaw, J. M., Hróbjartsson, A., Lalu, M. M., Li, T., Loder, E. W., Mayo-Wilson, E., McDonald, S., ... McKenzie, J. E. (2021). PRISMA 2020 explanation and elaboration: Updated guidance and exemplars for reporting systematic reviews. *BMJ*, 372, n160. https://doi.org/10.1136/bmj.n160

Perkmann, M., Salandra, R., Tartari, V., & Walsh, J. P. (2021). Academic engagement: A review of the literature on partnerships between universities and external organizations. *Research Policy*, 50(1), 104114. https://doi.org/10.1016/j.respol.2020.104114

Polzin, F., & Sanders, M. (2022). How to finance the transition: The role of academic spin-offs and knowledge spillovers in green value creation. *Technological Forecasting and Social Change*, 178, 121586. https://doi.org/10.1016/j.techfore.2022.121586

Rialti, R., Marzi, G., Silic, M., & Ciappei, C. (2022). Ambidextrous organization and agility in big data era: The role of business intelligence capabilities. *Journal of Intellectual Capital*, 23(5), 1091–1112. https://doi.org/10.1108/JIC-07-2020-0236

Roll, M., & Ifenthaler, D. (2021). Learning Factories 4.0 in technical vocational schools: Can they foster competence development? *Empirical Research in Vocational Education and Training*, 13(1), Article 20. https://doi.org/10.1186/s40461-021-00124-0

Roll, M. J. J., Brislin, F., & Ifenthaler, D. (2021). Multidisciplinary digital competencies of pre-service vocational teachers. *Empirical Research in Vocational Education and Training*, 13(1), Article 7. https://doi.org/10.1186/s40461-021-00112-4

Sajja, R., Sermet, Y., Cwiertny, D., & Muste, M. (2026). Integrating AI and learning analytics for data-driven pedagogical decisions and personalized interventions in education. *Technology, Knowledge and Learning*, 31(3), 1289–1319. https://doi.org/10.1007/s10758-025-09897-9

Salerno, F., Fonseca, F., & Maçada, A. C. G. (2025). The effect of data governance on data-driven culture: The mediating effect of data quality. *The TQM Journal*, 38(5), 1647–1662. https://doi.org/10.1108/tqm-08-2024-0304

Sayogo, D. S., Yuli, S. B. C., & Amalia, F. A. (2023). Data-driven decision-making challenges of local government in Indonesia. *Transforming Government: People, Process and Policy*, 18(2), 215–233. https://doi.org/10.1108/tg-05-2023-0058

Shan, S., Luo, Y., Zhou, Y., & Wei, Y. (2023). Big data analytics capability and value creation in higher education vocational spin-offs: Moderating role of entrepreneurial culture. *Technological Forecasting and Social Change*, 190, 122419. https://doi.org/10.1016/j.techfore.2023.122419

Urban, B., & Ratsimanetrimanana, F. A. (2021). Academic entrepreneurship and knowledge commercialization: The role of university culture and leadership. *Studies in Higher Education*, 46(11), 2262–2276. https://doi.org/10.1080/03075079.2020.1723528

Vugec, D. S., Bach, M. P., & Jaklič, J. (2022). Business intelligence and organizational agility: Fostering value creation through analytical decision making. *International Journal of Information Management*, 64, 102484. https://doi.org/10.1016/j.ijinfomgt.2022.102484

Wamba, S. F., & Queiroz, M. M. (2022). Industry 4.0 and the supply chain: Big data analytics and business intelligence capability in commercialization performance. *Computers & Industrial Engineering*, 168, 108096. https://doi.org/10.1016/j.cie.2022.108096