Pré-Inscription EDSYS

Mousa ALYARI

25 sept. 25

Directeur de thèse : Laurent GENESTE - UTTOP (ENIT) - LGP/DSS/ICE

Co-encadrants :
Cédrick BELER – UTTOP (ENIT) - LGP/DSS/ICE

Isabelle BAZET – UTTOP (IUT de Tarbes) - CERTOP/SANTAL
Philippe MARRAST – UTTOP (IUT de Tarbes) - CERTOP/SANTAL

SECTION 02

Financement

Attestation de financement / bourse / contrat de travail

(Si co-financement: 2 attestations)

■ Document obligatoire

Fichier(s) inclus:

• Attestation_de_financement_projet_NUTTeO_Symbiosis_signe.pdf

Université
de Technologie
Tarbes
Occitanie Pyrénées

ANR-23-EXES-0009

Directeur UTTOP
Responsable scientifique et technique projet NUTTeO
Jean-Yves FOURQUET
Tél. : 05 62 44 27 01
Mél. directeur@uttop.fr

Directeur des Partenariats et de l'Innovation
Gilbert ROTGÉ
Tél. : 05 62 44 29 45
Mél. gilbert.rotge@uttop.fr

Responsable Projet NUTTeO
Nicolas FLAVIGNY
Tél. : 05 67 45 01 44
Mél. nicolas.flavigny@uttop.fr

Objet : Attestation de financement du projet « Symbiosis »

Je soussigné Jean-Yves Fourquet directeur de l'UTTOP et responsable scientifique et technique du Projet NUTTeO (Nouvelle Université de Technologie à Tarbes en Occitanie),

atteste que le projet Symbiosis porté par Cedrik Beler a reçu un financement permettant la rémunération d'un doctorant sur une durée de 36 mois, dans le cadre de l'appel à projet « Impulsion » du projet NUTTeO.

Le programme NUTTeO est financé dans le cadre du PIA4 Excellence (France 2030) avec le soutien de la Région Occitanie / Pyrénées-Méditerranée, de l'Agglomération Tarbes-Lourdes-Pyrénées, et de nos partenaires académiques et industriels.

Jean-Yves Fourquet

MINISTÈRE DE L'ENSEIGNEMENT SUPÉRIEUR ET DE LA RECHERCHE ★ UNIVERSITÉ DE TECHNOLOGIE DE TARBES

J.-Y. Fourquet

RÉPUBLIQUE FRANÇAISE
Liberté
Égalité
Fraternité

anr agence nationale de la recherche

FRANCE 2030

SECTION 03

CV Candidat (*)

Curriculum Vitae mettant en évidence les expériences recherche

■ REQUIS pour pré-acceptation (*)

Fichier(s) inclus:

• PhD CV - ALIYARI Mousa.pdf

Mousa Aliyari

Pessac, France | mousa.aliyari@etu.u-bordeaux.fr | +33 7 45 38 08 49 | linkedin.com/in/mousa-aliyari-63813130a

Summary

Industrial Engineer pursuing a Masters in Industrial Engineering at the University of Bordeaux, with expertise in digital twin technology, lean manufacturing, and supply chain optimization. Proficient in programming, simulation, and model-based systems engineering (MBSE). Passionate about advancing sustainable industrial systems through innovative research. Seeking PhD opportunities to contribute to cutting-edge research in digital twins and systems engineering, available from September 2025.

Education

Master of Industrial Engineering (Enterprise Engineering) 09/2024 – Present University of Bordeaux, France

First Semester Grade: 14.34/20 (30 ECTS), Ranked 1st in Class

Bachelor of Industrial Engineering 09/2011 – 09/2015 Babol Noshirvani University of Technology

Final Grade: 14.21/20 (180 ECTS)

Research Experience

Intern – Agri-Food Digital Twin 03/2025 – Present IMS Laboratory (University of Bordeaux) & ITERG, Bordeaux, France

- Conducted literature reviews on hybrid approaches for sustainable digital twin design in vegetable oil production.
- Modeled production systems using MBSE, integrating physical flow, data, and causality models.
- Developed and tested digital twin prototypes using AnyLogic and OpenModelica, optimizing performance with AI algorithms.
- Evaluated environmental, societal, and economic impacts of AI-driven digital twins.

Academic Projects

Digital Twin for Sustainable Aviation Fuel (SAF) Supply Chain 01/2025 – 02/2025 University of Bordeaux, France

- Designed and simulated a digital twin for SAF supply chain using AnyLogic.
- Conducted a systematic literature review, synthesizing insights from over 30 peer-reviewed articles.
- Developed a decision-support tool for real-time supply chain optimization.

Model-Based Systems Engineering for Digital Twin Systems 11/2024 – 12/2024 University of Antwerp & University of Bordeaux

- Developed a digital twin prototype for harbor infrastructure using OpenModelica.
- Applied MBSE techniques to simulate critical operations across three phases.
- Collaborated with a multidisciplinary team to deliver a comprehensive report and presentation.

Professional Experience

Production Manager 05/2021 – 09/2022 Delfan Offroad, Tonekabon

- Optimized production processes using lean manufacturing, increasing production and sales by 300%.
- Implemented seasonal aggregate planning and employee performance systems.

Project Controller 04/2019 – 04/2021 Sazeh Gostar Tahvieh Araz, Assaluyeh

- Managed ventilation system maintenance projects for an oil & gas refinery.
- Prepared weekly, monthly, and total project progress reports for stakeholders.

Industrial Engineer (Data Analyst) 09/2017 – 01/2019 YalitCo, Babol

- Enhanced software systems and inventory management using Kaizen principles.
- Developed a sizing calibration system for clothing inventory.

Skills

- **Programming**: Java, C++, Python, R, SQL
- **Software**: AnyLogic, OpenModelica, SCADA LAquis, AutoCAD, Microsoft Office, Microsoft Project, Pronest, itemis Create
- **Engineering**: Model-Based Systems Engineering (MBSE), Lean Manufacturing, Six Sigma, Kaizen, Supply Chain Management, Data Analysis, Project Management, ISO 9001:2008
- **Languages**: English (C1), French (A2)

Certifications

- Internal Audit (ISO 9001:2008), Babol Noshirvani University of Technology & ICIM, 2013
- IELTS English Language Certificate, Overall Band Score: 6.5, 2024

SECTION 04

Projet de Thèse (*)

Sujet développé par les directeurs de thèse:

- Composition direction
- Contexte et problématique
- Objectifs et plan de travail
- Qualité du suivi et environnement

■ REQUIS pour pré-acceptation (*)

Fichier(s) inclus:

• Sujet_Thèse_SYMBIOSIS_UTTOP.pdf

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Université de Technologie Tarbes Occitanie Pyrénées

Sujet de thèse

Vers une méthodologie de co-construction de communs numériques et sociotechniques dans les organisations sociales

Des frustrations individuelles aux communs collectifs – Application au campus de l'UTTOP

Contexte et ambition

Portée par un financement de la Région Occitanie et le programme NUTTéO de l'UTTOP (projet SYMBIOSIS), cette thèse explorera comment concevoir, expérimenter et pérenniser des communs numériques et sociotechniques – c'est-à-dire des ressources partagées (plateformes, outils, données, pratiques) gérées collectivement par une communauté selon des règles qu'elle définit (SI internes, espaces de travail collaboratifs, bases de connaissances partagées…).

Notre terrain d'expérimentation est l'UTTOP (Université de Tarbes Occitanie Pyrénées), 4ème université technologique française créée en 2024. L'enjeu est d'ancrer la recherche dans l'expérience réelle des usagers : étudiants, personnels, enseignants, partenaires autant que dans les réalités opérationnelles du système d'information de l'Université et des services. Partant de l'identification et de la caractérisation des irritants du quotidien, le projet vise à transformer ces obstacles en opportunités collectives grâce à une démarche de co-construction centrée sur l'expérience utilisateur et d'amélioration continue.

Ce projet interdisciplinaire croise sciences de l'information, STS (Sciences and Technologies Studies) et design technologique. Cette approche transversale est essentielle pour appréhender les communs dans leur dimension technique ET sociale. Le projet pourra s'appuyer sur les travaux fondateurs d'Ostrom (1990) sur la gouvernance des communs, enrichis par Hess & Ostrom (2007) pour les communs de la connaissance, et les approches éthiques du numérique (Stiegler, 2015; Rouvroy & Berns, 2013).

L'ambition à terme est de créer une méthodologie reproductible de co-construction de communs numériques pour d'autres contextes organisationnels.

Principes méthodologiques

La méthodologie de co-construction sera développée selon une logique itérative inspirée de méthode d'amélioration continue telle que le cycle PDCA (PLAN DO CHECK ACT). Nous avons identifié 3 actions qui seront réalisées au cours de la thèse (voir Figure 1) :

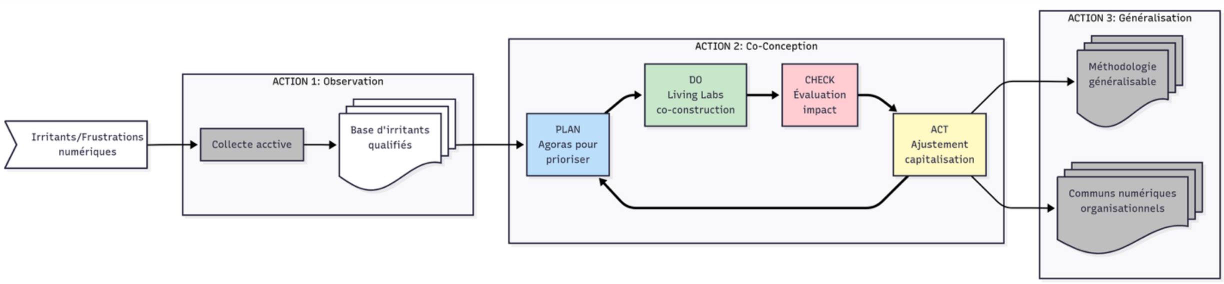

Figure 1 - Principe méthodologique de co-construction par les frustrations

Action 1 – Observation et collecte continue

Initier une dynamique participative en recueillant frustrations et irritants (anomalies, incohérences, freins d'usage). Les actions suivantes seront conduites :

- Déployer des méthodes d'enquêtes qualitatives et quantitatives dans un cadre éthique strict (RGPD, consentement éclairé, comité d'éthique)
- Cartographier, modéliser et partager les irritants et les frustrations identifiés
- Mobiliser la communauté UTTOP, et se coordonner avec les services et comités de pilotage en lien avec le projet (DSI, direction, DDRS)

Action 2 – Co-construction, expérimentation et capitalisation

Transformer les irritants identifiés en action 1 comme prioritaire par l'Agora en cas d'usage concrets, co-construits et testés, et capitaliser ces expériences dans une logique de Living-Lab avec une méthodologie inspirée de la méthodologie PDCA. Les actions suivantes sont envisagées :

- Organiser des agoras (temps d'échange ouverts) pour lister et catégoriser les irritants et les frustrations, explorer les causes systémiques et choisir les solutions à prototyper
- Constituer des groupes de travail pluridisciplinaires (Living-Labs) pour développer et tester les solutions
- Documenter, tracer, modéliser la connaissance engagée et mobilisée
- Évaluer et capitaliser à chaque itération pour alimenter l'action de modélisation (retour d'expérience)

Action 3 – Consolidation et généralisation

Formaliser des communs et une méthodologie généralisable à partir des résultats concrets au travers des actions :

- Étendre l'expérimentation selon les résultats
- Définir des grilles d'évaluation (RSE, QVT, fonctionnalités, expérience utilisateur, qualité des processus, performances, représentativité et/ou acceptabilité sociale)
- Formaliser la méthodologie et diffuser les résultats

Résultats attendus

Cette recherche prévoit la production de résultats articulant développement d'outils, expérimentation en contexte réel et formalisation méthodologique, contribuant à l'avancée des connaissances et à leur transposabilité.

- Déploiement d'un dispositif de collecte active des irritants/frustrations numériques
- Co-construction et évaluation de communs numériques en contexte réel
- Publications scientifiques interdisciplinaires adossées à la collecte et aux expérimentations
- Première formalisation d'une méthodologie opérationnelle et transposable
- Perspectives de généralisation à d'autres contextes

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Profil recherché

Le candidat doit avoir une formation permettant de comprendre enjeux techniques ET sociaux. Il devra également avoir :

- Intérêt pour la recherche-action et le design participatif
- Goût pour l'interdisciplinarité et la co-construction
- Motivation pour l'innovation sociale numériques

Encadrement et environnement de travail

Le doctorant ou la doctorante bénéficiera de l’accompagnement d’une équipe pluridisciplinaire (61eme et 71eme section) et d’un terrain d’expérimentation concret au sein de l’UTTOP. Il aura une posture expérimentale, incarnée dans un contexte local, et sera ouvert à une théorisation interdisciplinaire.

Direction : Laurent GENESTE (PR, CNU 61), Isabelle BAZET (MCF, CNU 71), Cédrick BÉLER (MCF, CNU 61), Philippe MARRAST (MCF, CNU 71)

Lieu : Localisée sur le campus de l’UTTOP, à Tarbes (65), cette thèse s’appuie sur un environnement de recherche stimulant et un contexte unique. L’UTTOP est le fruit du rapprochement récent entre un IUT et une école d’ingénieurs (ENIT) historiquement voisines, séparées autrefois par une simple barrière. Ce campus à taille humaine, et en devenir, offre l’opportunité de participer à une dynamique académique et territoriale à inventer. Située dans une ville moyenne agréable et abordable, entre Pyrénées, nature et océan, cette implantation favorise un cadre de vie de qualité et une ouverture concrète sur le territoire.

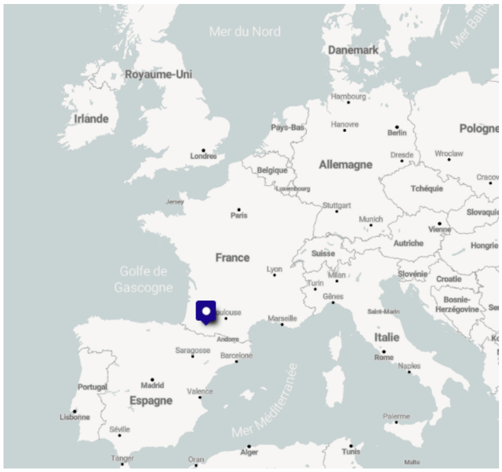

Figure 2 - Localisation de l'UTTOP

Salaire : 2200€ brut/mois

Contacts : isabelle.bazet@uttop.fr, cedrick.beler@uttop.fr, laurent.geneste@uttop.fr, philippe.marrast@uttop.fr

Candidature

Candidatures au fil de l'eau. Merci de nous contacter pour discuter de vos motivations et questions. Des entretiens seront organisés d’ici fin août et potentiellement la première semaine de septembre pour préciser l’adéquation entre votre profil et le projet.

Date du début de la thèse : 1er octobre 2025

Figure 3 - QRCode de contact

SECTION 05

Diplômes (*)

Copie de TOUS les diplômes obtenus dans le supérieur:

- Bac+5 (Master 2, Ingénieur)

- Tous autres diplômes supérieurs

(Français, Anglais ou traduction française)

■ REQUIS pour pré-acceptation (*)

Fichier(s) inclus:

• 22415465-2024-attestation-M2 Enterprise engineering.pdf

• Bachelor's Degree - Mousa Aliyari - T.pdf

• IELTS Degree.pdf

université de BORDEAUX

N° étudiant : 22415465

Attestation de réussite

Le Directeur du collège Sciences et Technologies atteste que
Monsieur Mousa ALIYARI
né le 25/06/1993 à TONEKABON (IRAN)
a été déclaré **admis** au niveau
M2 Enterprise engineering
au titre de l'année universitaire 2024/2025 avec la **mention Bien**
et a acquis 60 crédits européens.

Fait le 30/09/2025

Christophe CHAMPION

Christophe CHAMPION

شماره ٤٧٤٤٢٤

50072694995
ردیف دفتر ثبت
هزینه تمبر 900000 ریال

جمهوری اسلامی ایران
قوه قضائیه - اداره مترجمین رسمی

شیوا حیدری
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In the Name of God, the Almighty

Emblem of the Islamic Republic of Iran
Ministry of Science, Research & Technology

Babol Noshirvani University of Technology

Photo of the holder
Affixed and sealed

Ref.: 2/402/464
Date: 9 April 2023
(Hologram of university is attached)

Bachelor's Degree Study Completion Certificate

In view of the approvals ratified on Dec.-Jan., 2007 by Development Council of Higher Education whereas,

Mr. Mousa ALIYARI,

Son of Ehsan, holder of national ID card No. 2210174295 issued in Tonekabon, born in 1993, has successfully completed the course of study at this university on 22 September 2015, the present certificate of **Bachelor's Degree** in field of

Industrial Engineering

is hereby conferred upon him.

The faculty members wish the above-said alumna all the best in mingling knowledge with practice, virtue, and fear of God and in gaining God's blessing by serving the mankind.

[QRCODE]
http://portal.saorg.ir/inquiry?code=14022630888202377457

Signed and sealed by:
Academic Deputy of the University

Signed and sealed for:
Chancellor of the University

Overleaf:
A 10,000/-IRR revenue stamp attached and duly canceled.

True translation from the original Persian text certified.
15 June 2023

Shiva Heydari
شیوا حیدری
مترجم رسمی زبان انگلیسی قوه قضائیه تهران
شماره پروانه ۱۲۷۳
Translator with the Judiciary Of I.R. Iran

نام صاحب سند: موسی علی یاری - هزینه ترجمه و خدمات دفتری: 2602500 ریال بابت ترجمه دانشنامه (کارشناسی) و ریز نمرات هر ترم (کارشناسی) - تعداد کل دروس: 0 و تعداد ترم: 0

آدرس: میدان انقلاب خیابان آزادی نبش کوچه جنتی پلاک 2 طبقه سوم واحد 12
Address:
Email: shiva.heydari90@gmail.com Mobile: (+98) 9124896042 Tel: (+98) 021 09124333860

IELTS™

Test Report Form

ACADEMIC

NOTE *Admission to undergraduate and post graduate courses should be based on the ACADEMIC Reading and Writing Modules.*
*GENERAL TRAINING Reading and Writing Modules are **not** designed to test the full range of language skills required for academic purposes.*
*It is recommended that the candidate's language ability as indicated in this Test Report Form be re-assessed **after two years** from the date of the test.*
To find out more about IELTS, IELTS band scores and the CEFR levels, please visit ielts.org/scores

Centre Number	IR120	Date	31/DEC/2023	Candidate Number	502753

Candidate Details

Family Name	ALIYARI
First Name(s)	MOUSA
Candidate ID	P59417663

Date of Birth	25/06/1993	Sex (M/F)	M	Scheme Code	Private Candidate

Country or Region of Origin	
Country of Nationality	IRAN(ISLAMIC REPUBLIC OF)
First Language	FARSI

Test Results

Listening	Reading	Writing	Speaking	Overall Band Score	CEFR Level
6.0	6.5	6.0	6.5	6.5	B2

Administrator Comments

Recognising organisations must verify this score at ielts.org/verify

Validation stamp

VALIDATION STAMP
IELTS
CAMBRIDGE ENGLISH/BRITISH COUNCIL/IDP:IA

Date	03/01/2024	Test Report Form Number	23IR502753ALIM120A

BRITISH COUNCIL idp Cambridge Assessment English

SECTION 06

Relevés de Notes (*)

Relevés de notes:

- Formation(s) niveau Bac+5

- Toutes années universitaires à partir du Bac+3 (inclus)

(Français, Anglais ou traduction française)

■ REQUIS pour pré-acceptation (*)

Fichier(s) inclus:

• 22415465-2024-releve-M2 Enterprise engineering.pdf

• Bachelor's Grades - T - Mousa Aliyari.pdf université de BORDEAUX

Année universitaire
2024-2025

Relevé de notes et résultats

M2 Enterprise engineering

Page 1/1

Nom :	Mousa ALIYARI
Numéro étudiant :	22415465
INE étudiant :	233371741HE
Né(e) :	25/06/1993 **à** TONEKABON (IRAN)

Formation suivie : M2 Enterprise engineering

Notes et résultats

	Note/Barème	Pts Jury	Résultat	Session	Crédits	Rang
M2 Enterprise Engineering	150.67 / 200		Admis	S1		
Semestre 9 Enterprise Engineering	143.34 / 200		Admis	S1	30	
- Supply Chain Management and Networked Enterprise	147.5 / 200		Admis	S1	6	
- Performance and Continuous Improvement	140.4 / 200		Admis	S1	6	
- Production Management	150 / 200		Admis	S1	6	
- Enterprise Modelling	152 / 200		Admis	S1	6	
- Information System and Interoperability	126.8 / 200		Admis	S1	6	
Semestre 10 Enterprise Engineering	158 / 200		Admis	S1	30	
- Stage Recherche	155 / 200			S1	24	
- Conférences scientifiques et/ou projets	170 / 200			S1	6	

Résultat global

Résultat d'admission :	15.067 / 20		Admis	Bien	60	1 / 10

Fait le 30/09/2025
Le Directeur du collège Sciences et Technologies

Christophe CHAMPION

Christophe CHAMPION

La délibération du jury peut être contestée auprès du tribunal administratif de Bordeaux dans le délai de 2 mois à compter du 30/09/2025.

شماره ۲۷۴۶۲۵
ردیف دفتر ... ۱۸۸۲۶۱۹۹۵

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تأیید

Islamic Republic of Iran
The Emblem

Babol Noshirvani University of Technology
ACADEMIC COMPREHENSIVE SYSTEM
Bachelor's Degree Transcript of Records

Date & Time: 8 April 2023, 09:59 AM *Report No.: 100* *Photo of the holder*

Name & Surname: **Mr. Mousa ALIYARI**	Student No.: 903130087
Father's Name: Ehsan	Faculty: Materials & Industrial Engineering
ID Card No.: 2210174295	Academic Group: Industries
National ID Card No.: 2210174295	Program: **Bachelor's Degree Program-Daily (State-funded)**
Date of Birth: 25 June 1993	Type of Admission: Dist. 3
Place of Issue: Tonekabon	Type of Entrance in University: SANJESH (Collection)
Major: **Industrial Engineering**	

1st Semester 2011-2012 (Studying – Normal)

Course No.	Course Title	Credits	Grade	Effect
1111001	General Mathematics I	3	11.5	-
1111003	Physics I	3	12.75	-
1111017	Persian	3	19.5	-
1611016	Thematic Interpretation of Quean	2	16	-
2121001	General Economics I	2	14.5	-
2121030	Industrial Drawing	2	20	-

Semester →	Average: 15.48	Credits Attempted: 15	Effective Passed Credits: 15
	Failed: 0	Point: 232.25	
Cumulative →	Average: 15.48	Credits Attempted: 15	Effective Passed Credits: 15
	Failed: 0	Point: 232.25	

2nd Semester 2011-2012 (Studying – Normal)

Course No.	Course Title	Credits	Grade	Effect
1111002	General Mathematics II	3	9.5	1
1111004	Physics II	3	9.5	1
1111009	Differential Equations	3	10	-
1111019	Physical Education I	1	18	-
1611001	Islamic Thoughts I – Origin & Resurrection	2	17.5	-
2121002	General Economics II	2	14	-
2121003	Machineries Workshop I	1	16.5	-
2121010	Materials Science	3	15.3	-

Semester →	Average: 12.8	Credits Attempted: 18	Effective Passed Credits: 12
	Failed: 6	Point: 230.4	
Cumulative →	Average: 14.02	Credits Attempted: 33	Effective Passed Credits: 27
	Failed: 6	Point: 462.65	

1st Semester 2012-2013 (Studying – Normal)

Course No.	Course Title	Credits	Grade	Effect
1111002	General Mathematics II	3	16.25	-
1111012	Computer Programming	3	17.2	-
1111018	English Language	3	16.5	-
1611013	Analytical History of Early Islam	2	18	-
2121005	Production Methods	3	13.5	-
2121008	Engineering Economics	3	16	-
2121020	Statics & Strength of Materials	3	13	-

Semester →	Average: 15.67	Credits Attempted: 20	Effective Passed Credits: 20
	Failed: 0	Point: 313.35	
Cumulative →	Average: 14.64	Credits Attempted: 53	Effective Passed Credits: 47
	Failed: 6	Point: 776	

Shiva Heydari
شیوا حیدری

آدرس: میدان انقلاب [illegible] آزادی نبش کوچه [illegible] پلاک 2 طبقه سوم واحد 12
Address:
Email: shiva.heydari90@gmail.com Mobile: [illegible] Tel:(+98) 021 09124333860

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۴۷۴۴۲۶

50072694995
ردیف دفتر ترجمه تمبر 900000 ریال

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2nd Semester 2012-2013 (Studying – Normal)

Course No.	Course Title	Credits	Grade	Effect
1111004	Physics II	3	11.25	-
1111006	Physics II Lab.	1	18.5	-
1111011	Numerical Analysis	2	13	-
1111020	Physical Education II	1	20	-
1111021	Population & Family Planning	1	20	-
1611002	Islamic Thoughts II – Prophecy & Imamate	2	17	-
2121006	Work and Time Study	3	10.75	-
2121007	Theory of Probabilities & its application	3	11.5	-
2121011	Linear Algebra	3	11.25	-

Semester ➔	Average: 13.3	Credits Attempted: 19	Effective Passed Credits: 19
	Failed: 0	Point: 252.75	
Cumulative ➔	Average: 14.29	Credits Attempted: 72	Effective Passed Credits: 66
	Failed: 6	Point: 1028.75	

1st Semester 2013-2014 (Studying – Normal)

Course No.	Course Title	Credits	Grade	Effect
2111009	Fundamentals of Electrical Engineering	3	10	-
2121012	Operations Research I	3	11.5	-
2121013	Engineering Statistics	3	11	-
2121015	Principles of Management & Organization Theory	2	16	-
2121016	Industrial Units Design	3	11.25	-
2121050	Management Information System	3	14	-
2121052	Human Factors Engineering	3	15	-

Semester ➔	Average: 12.51	Credits Attempted: 20	Effective Passed Credits: 20
	Failed: 0	Point: 250.25	
Cumulative ➔	Average: 13.9	Credits Attempted: 92	Effective Passed Credits: 86
	Failed: 6	Point: 1279	

2nd Semester 2013-2014 (Studying – Normal)

Course No.	Course Title	Credits	Grade	Effect
1111005	Physics I Lab.	1	16	-
1611007	Way of Life – Applied Ethics	2	18	-
2121014	Operations Research II	3	11.2	-
2121017	Welding General Workshop	1	15.5	-
2121021	Statistical Quality Control	3	9.9	1
2121022	Inventory Programming & Control I	3	12.9	-
2121023	Project Control	3	17.5	-
2121053	Systems Analysis	3	14.3	-

Semester ➔	Average: 13.94	Credits Attempted: 19	Effective Passed Credits: 16
	Failed: 3	Point: 264.9	
Cumulative ➔	Average: 13.91	Credits Attempted: 111	Effective Passed Credits: 102
	Failed: 9	Point: 1543.9	

1st Semester 2014-2015 (Studying – Normal)

Course No.	Course Title	Credits	Grade	Effect
2111018	Fundamentals of Electrical Engineering	1	19.7	-
2121021	Statistical Quality Control	3	12.5	-
2121051	Maintenance & Repairs Planning	3	20	-
2121054	Transportation Planning	3	16	-
2121060	Inventory Programming & Control II	3	14.1	-
2121064	Technical Project	3	16	-

Semester ➔	Average: 15.97	Credits Attempted: 16	Effective Passed Credits: 16
	Failed: 0	Point: 255.5	
Cumulative ➔	Average: 14.17	Credits Attempted: 127	Effective Passed Credits: 118
	Failed: 9	Point: 1799.4	

Shiva Heydari
شیوا حیدری

نام صاحب سند: موسی علو یاری جهزینه ترجمه و خدمات دفتری: 2602500 ریال بابت ترجمه دانشنامه (کارشناسی) و ریز نمرات هرترم (کارشناسی)-تعداد کل دروس: 0 و تعداد ترم: 0

آدرس: میدان انقلاب خیابان آزادی نبش کوچه چمن پلاک 2 طبقه سوم واحد 12
Address:
Email: shiva.heydari90@gmail.com Mobile: (+98) 9121896842 Tel: (+98) 021 09124333860

2nd Semester 2014-2015 (Studying – Normal)

Course No.	Course Title	Credits	Grade	Effect
1111007	General Chemistry	3	15.5	-
1611009	Islamic Revolution of Iran	2	17	-
2121019	Casting Workshop	1	15	-
2121024	Production Planning	3	14.6	-
2121025	Principles of Simulation	3	10	-
2121026	Principles of Accounting & Costing	3	10	-
2121056	Quality & Productivity Management	3	15	-
2121059	Decision-making Analysis	3	18	-

Semester ➔	Average: 14.2	Credits Attempted: 21	Effective Passed Credits: 21
	Failed: 0	Point: 298.3	
Cumulative ➔	Average: 14.17	Credits Attempted: 148	Effective Passed Credits: 139
	Failed: 9	Point: 2097.7	

Summer Semester 2014-2015 (Studying – Normal)

Course No.	Course Title	Credits	Grade	Effect
2121063	Apprenticeship	1	20	-

Semester ➔	Average: 20	Credits Attempted: 1	Effective Passed Credits: 1
	Failed: 0	Point: 20	
Cumulative ➔	Average: 14.21	Credits Attempted: 149	Effective Passed Credits: 140
	Failed: 9	Point: 2117.7	

Status of the Credits Passed Based on Type of Course
Total Credits Attempted: 149

Course Type	Credits Passed	Average
General	21	17.76
Basic	22	13.52
Main	66	13.15
Optional	27	15.77
Apprenticeship (effective in average & credit)	1	20
Practical	3	15.67

Grades are between zero to 20 and the minimum passed grade is 10.

Summary of Academic Status:
Last Academic Status: graduated on 22 September 2015

Grade Point Average:	**The Student**	**14.21 (out of 20)**
	The University	**14.19**
	The Faculty	**14.35**
	The field of Study	**14.94**

Remarks: In "effect" column, number 1 implies that the respective course isn't taken into account in total number of credits passed, number 2 implies that the respective course isn't taken into account in Cumulative GPA, and number 3 implies that the respective course isn't taken into account both in total number of credits passed and Cumulative GPA.
In the 'Grade" column, student's grade in the course is included in digit or letter format.

Signed & Sealed:
Education Director General of the University

Shiva Heydari
Certified English Translator with the Judiciary Of I R Iran License No 1273

True translation from the original Persian text certified.
15 June 2023

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SECTION 07

Lettres de Recommandation (*)

Lettres attestant des qualités et capacités de recherche:

- Minimum: Responsable formation Bac+5

- Minimum: Responsable stage recherche

- Optionnel: Autres recommandations

■ REQUIS pour pré-acceptation (*)

Fichier(s) inclus:

• Recommendation Letter - ALIYARI Mousa.pdf

Mamadou Kaba TRAORE
Professeur des universités
IMS CNRS 5118
351 Cours de la Libération – Bat A31
Bureau 2.26, 33400 Talence
Tel. 05 40 00 83 95
mamadou-kaba.traore@u-bordeaux.fr

RECOMMENDATION LETTER

To Whom It May Concern,

I am pleased to recommend Mr. Mousa ALIYARI for admission to your esteemed program. As his professor in courses such as Enterprise Modelling and Supply Chain Management, in the Master's program in Enterprise Engineering at the University of Bordeaux, I have had the pleasure of closely observing Mousa's academic and professional growth.

Mousa is currently pursuing a master's degree in Enterprise Engineering in Bordeaux, France, and already holds a Bachelor degree in Industrial Engineering. This multidisciplinary background highlights his ability to handle various majors with ease and proficiency.

Mousa has consistently shown enthusiasm, diligence, and a straight understanding of complex concepts, with an evidence-based capacity of problem-solving.

In conclusion, I highly recommend Mousa for your program. His multidisciplinary expertise, research abilities, and dedication make him an excellent candidate. I am confident that he will be a valuable asset to your institution.

Please do not hesitate to contact me if you have any further questions.

Sincerely,

Mamadou K. Traoré

SECTION 08

Lettre de Motivation (*)

Lettre datée et signée exprimant:

- Intérêts pour activités de recherche

- Liens profil candidat / domaines thèse

- Motivations et objectifs

■ REQUIS pour pré-acceptation (*)

Fichier(s) inclus:

• Cover Letter - Towards a Methodology for Co-constructing Digital and Sociotechnical Commons in Social Organizations - ALIYARI Mousa.pdf

Cover Letter for PhD Position in Towards a Methodology for Co-constructing Digital and Sociotechnical Commons in Social Organizations

Dear PhD Selection Committee,

I am excited to apply for the PhD position in the **SYMBIOSIS** project at **Université de Technologie de Tarbes**. As a Master's student in **Industrial Engineering** at the **University of Bordeaux** (first semester grade: 14.34/20, ranked **1st**) with expertise in **digital twin** technology, **model-based systems engineering** (MBSE), and participatory research, I am eager to contribute to your interdisciplinary approach to co-constructing digital commons and operational methodologies for sustainable value chains.

My academic and research experiences align closely with the SYMBIOSIS project's focus on action research and participatory design. During my current research internship at **IMS Laboratory** and **ITERG** in Bordeaux, I am developing digital twin prototypes for sustainable vegetable oil production, using **AnyLogic** and **OpenModelica** to **model socio-technical interactions** and **optimize material flows**. My academic project on a digital twin for a **sustainable aviation fuel** (SAF) **supply chain** involved engaging stakeholders to map system requirements and model multi-actor coordination, synthesizing insights from over 30 peer-reviewed articles. These experiences equip me to conduct qualitative and quantitative surveys, map irritants, and co-construct solutions within the **Living Lab** framework outlined in your action plan.

My professional background further supports my candidacy. As **Production Manager** at Delfan Offroad, I scaled production from 100 to 300 units annually by fostering collaborative process improvements, demonstrating my ability to mobilize diverse teams. At YallTCo, I implemented **Kaizen** to reduce inventory discrepancies by 15%, engaging workers in iterative problem-solving. My technical skills in **Python**, **Java**, **C++**, **AnyLogic**, **OpenModelica**, and **MBSE** (e.g., SysML), combined with my **ISO 9001:2008 Internal Audit** certification, enable me to develop and evaluate digital tools while ensuring ethical data handling (e.g., GDPR compliance). My interdisciplinary background bridges technical and social dimensions, aligning with your requirement for candidates who understand both.

I am particularly inspired by the SYMBIOSIS project's participatory approach to transforming digital irritants into actionable use cases through agoras and Living Labs. My autonomy, **English proficiency** (IELTS 6.5), and A2-level French (with ongoing improvement) position me to thrive in UTT's collaborative environment, contributing to interdisciplinary publications and transposable methodologies. I am eager to engage with the UTTOP community to formalize evaluation grids and disseminate results.

Thank you for considering my application. I am available for an interview at your convenience and can be reached at mousa.aliyari@etu.u-bordeaux.fr . I look forward to contributing to the SYMBIOSIS project's vision of sustainable digital commons.

Sincerely,
Mousa Aliyari

SECTION 09

Expérience Recherche (*)

Rapport(s) de stage recherche et tout élément permettant d'apprécier:

- Stages de recherche

- Publications

- Activités professionnelles recherche

■■ Si trop volumineux: fichier séparé → edsys@laas.fr

■ REQUIS pour pré-acceptation (*)

Fichier(s) inclus:

• Internship Report - Mousa ALIYARI.pdf

■ *Fichier volumineux (6.9 MB) - Peut être envoyé séparément à edsys@laas.fr*

Objet: 'Expérience recherche - ALIYARI Mousa'

THESIS MANUSCRIPT: AGRI-FOOD DIGITAL TWIN: AI AND SYSTEM EXPERTS FOR DESIGN AND MODELLING

Designing a Sustainable Digital Twin for Vegetable Oil Processing Using AI and System Experts

Author: Mousa ALIYARI

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Supervisor: Simon GORECKI

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minh-phuoc.doan@ims-bordeaux.fr

March – August 2025

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1) Introduction

1.1 The UMT OLEODIGIT project and its targets

The UMT (Unité Mixte Technologique - Mixed Technological Unit) OLEODIGIT project is an interdisciplinary collaboration among ITERG, IMS, and Terres Inovia, with a mission to innovate oilseed processing through high digitalisation, focusing on small and medium-sized enterprises (SMEs) and mid-sized enterprises (ETIs). The following lines show the project's goals:

1. Innovate Tailormade Digital Technologies
2. Enhance Competitiveness
3. Promote Environmental Sustainability
4. Emphasis on Key Physical Mechanisms
5. Target Relevant Markets
6. Improve Product Quality Control
7. Support Process Management and Decision-Making
8. Scientific and Technical Goals:

- WP1: Data Identification
- WP2: Sensor Deployment
- WP3: Data Engineering
- WP4: Digital Twin Development
- WP5: Knowledge Capitalization and Transfer
- **DIGIT2DEHULL** (1 year, starting January 2025, WP1/WP2)
- **SunNMeal** (3 years, starting 2025, WP2/WP3/WP4)
- M2 Internship – Sensor Mapping (6 months, starting April 2025, WP1/WP2/WP3/WP4)
- L3 Internship – Data Specification (2 months, starting May 2025, WP3/WP4)
- M2 Internship – Digital Twin Modelling (6 months, starting March 2025, WP3/WP4)

The following Gantt chart (Figure 1) illustrates the work packages and their key tasks, including specific projects and internships. The timeline reflects task durations and deliverables. (Here, there are 2 different internships for the Master M2 programs, which are defining my internship timeline and overall information in this chart. Additionally, two PhD programs follow these internships. On the other side of the academic part, there is the full timeline schedule for the Work Packages.)

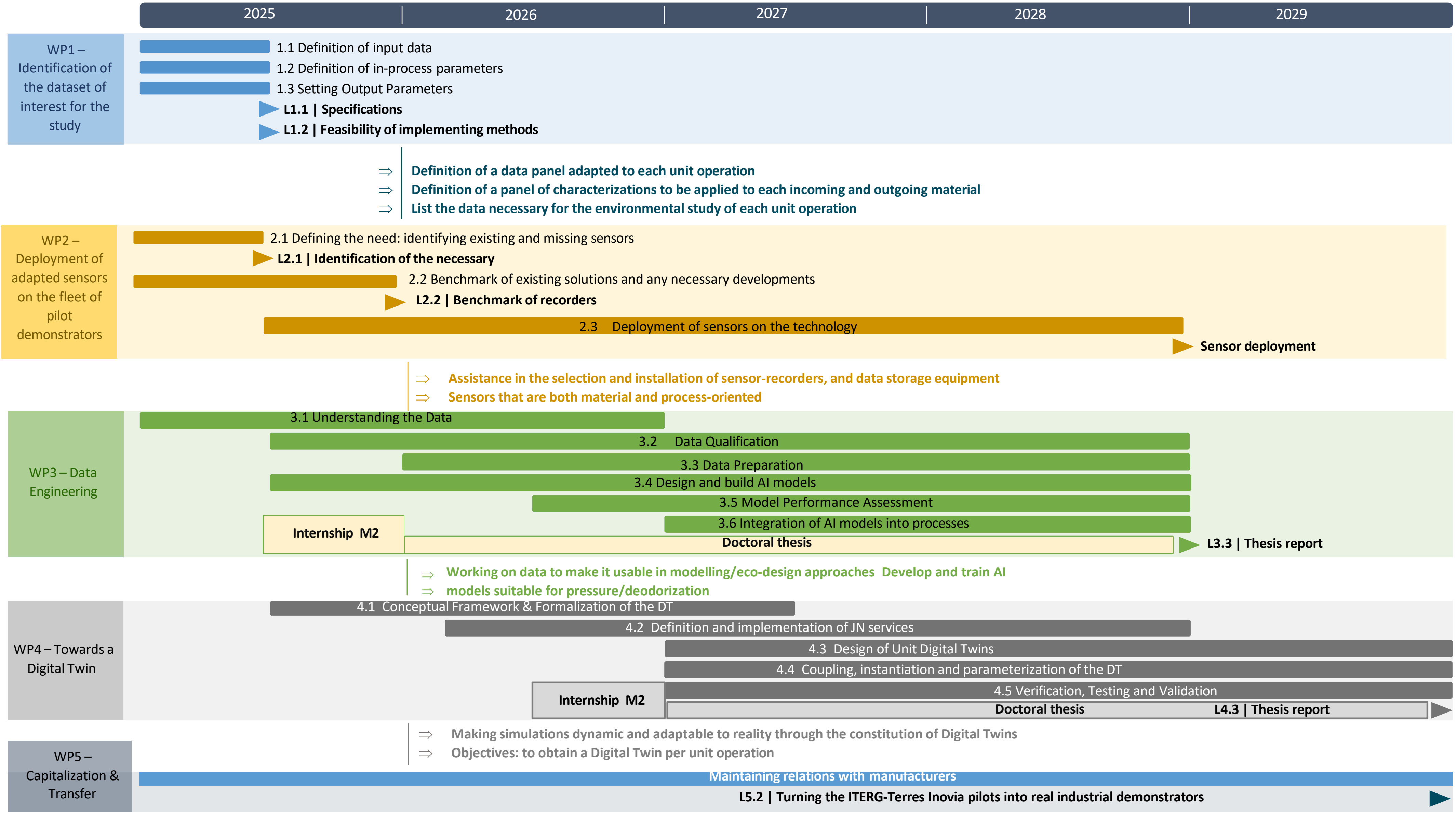

Figure 1: Gantt Chart - whole project

1.2 Introduction to the Digital Twin Designing Internship Project

This six-month M2 internship at UMT started in March 2025, where worked on Work Package 4 Digital Twin Development and contributed to Work Package 3 Data Engineering. The main goal of this work involves studying industrial digital twin applications and creating an AI-powered and knowledge-based digital twin system that models oilseed processing operations, including trituration and dehulling. The project aims to create dynamic, real-time adaptable simulations through this work, which will improve diagnostic capabilities and process control and multicriteria optimisation (e.g., yield, cost, energy). The work integrates AI models to forecast product quality, process breakdowns and energy usage levels, which will create a base for developing extensive digital twin systems. By focusing on data organisation and AI system integration, it supports the project's mission to create ITERG-Terres Inovia pilots as industrial demonstration sites, which will lead to wider industrial adoption and improved sustainability and operational efficiency in oilseed processing.

The main scientific question that should be answered in this term is “How can artificial intelligence and system experts’ knowledge be integrated to design and implement a sustainable digital twin for optimising vegetable oil processing?”. The following sections and subsections will answer this question and the corresponding ones.

For the starting point, let to know what the fundamental concept of a digital twin is and its applications in manufacturing?

1.3 The Digital Twin and Its Applications in Manufacturing

A digital twin (DT) is a virtual replica of what is produced, physical entities and processes which can simulate and analyse their variants in real time, without impacting the physical environment. It would optimise production and support decision-making. (Alfaro-Viquez, et al., 2025) Digital twin is a dynamic link between the physical and digital world by a two-way connection in real time, enabling ongoing synchronisation of data and their analysis for process optimisation and informed decision-making. Note here that the main actor in this is the data, which may have various sources and various sensors. This two-way connection can be achieved by a set of communication protocols, which will vary depending on the use case. (Dihan, et al., 2024) (Negria, et al., 2017) as shown in Figure 2:

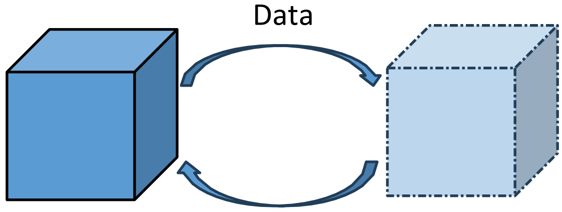

Figure 2: General concept of digital twin.

After understanding better the concept of Digital Twin, we can go through the role of it in the manufacturing systems and its three main dimensions by answering "What are the key dimensions and case studies of digital twin in manufacturing?"

Based on (Alfaro-Viquez, et al., 2025), there are three dimensions of architecture of digital twin in manufacturing: process, operator, and product.

1- **Process**: The process dimension focuses on optimising the core activities of manufacturing, from production planning and execution to real-time control and adjustments.
2- **Operator**: This dimension centres on enhancing the human element in manufacturing by prioritising safety, ergonomics, and performance.
3- **Product**: The product dimension is dedicated to improving the tangible outcomes of manufacturing by enhancing design, quality, and lifecycle management.

According to (Alfaro-Viquez, et al., 2025), there are 75 case studies of the implementation of digital twins in manufacturing in this review. Appendix 1 merges three different sections of this paper, which can illustrate three dimensions, subcategories (classification), AI type in implementation, visualisation tool or application, data types, and network protocols:

The cases illustrate how DTs integrate data from sensors and other AI tools to address challenges unique to each dimension. For instance, in process optimisation, a DT might simulate some operations to enhance the final quality of the products, while in quality control, it could monitor some parameter levels in real time. The table is also a good database when we are searching for a specific dimension which DT implemented there before. Now we can start to talk about DT designing and addressing the question: "What are the steps to design a manufacturing digital twin?"

The 5 Steps to Design the Manufacturing Digital Twin

In this article (Resman, et al., 2021), a five-step method is explained for leading users from initial system analysis through to a fully functioning, data-fed digital twin. A digital twin here is an interactional, real-time coordinated model (as differentiated from one-way "digital shadow" or human-inputted "digital model"). It uses data from the real system (e.g., sensors) to simulate, optimise, and control processes, enabling "what-if" scenarios for agility and sustainability. To understand better the idea of data transferring and integration, Figure 3 can be useful:

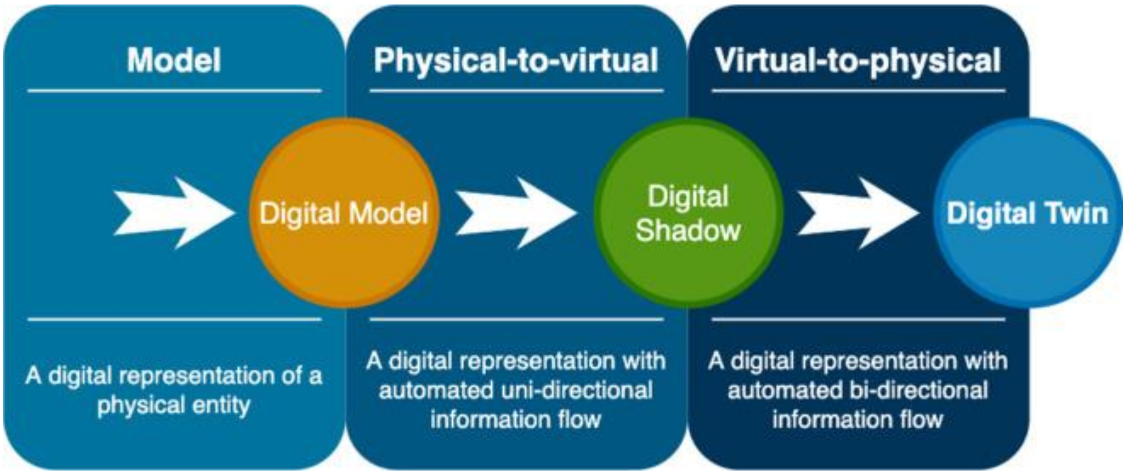

Figure 3: Digital Twin: Data integration (Purcell & Neubauer, 2023)

The steps generalise the four-group classification and are evaluated in a case study of a factory that makes mosaics with robots and conveyors. The approach assumes equipment like simulation software (e.g., Siemens Plant Simulation) and focuses on discrete-event models for manufacturing.

- **Step 1: Decompose the Manufacturing System**

Categorise all building blocks into the above four categories (e.g., assembly stations as "Fabrication", robots as "Logistics"). This determines major characteristics and limitations.

- **Step 2: Define the Sequence of Processes**

Draw a functional diagram of process flow, inputs/outputs, and feedback loops. Begin with the initial process (e.g., raw material loading) and trace the sequence using rectangular boxes and arrows. Add building blocks, engaged, materials/parts required, and outputs.

- **Step 3: Build the Digital Model by Specifying Parameters**

Establish parameters for each building block based on its group (e.g., velocity/coordinates for "Logistics", cycle time for "Inspection"). Use simulation software to build the model: enter layout/dimensions, connect blocks as per Step 2, and validate (check that it looks like real behaviour). Include general information, for instance, raw material quantities, orders, and calendars.

- **Step 4: Merge the Digital Model with the Actual System to Create the Digital Twin**

Incorporate a bi-directional feedback loop using sensors (e.g., RFID, cameras) and interfaces (e.g., OPC UA protocol). The digital model is fed with real-time data (e.g., parts availability), simulates or optimises (using "digital agents" for activities like scheduling), and provides back control signals (like order sequences). Real-time adaptation becomes feasible.

- **Step 5: Presentation and Visualisation for Different Participants**

Envision outputs tailored to be person-specific (e.g., operators see buffer levels; planners see Gantt charts/OEE). Use tools like SCADA software to display real and simulated data on devices or screens. For recognising these steps as a framework, Figure 4 would be helpful:

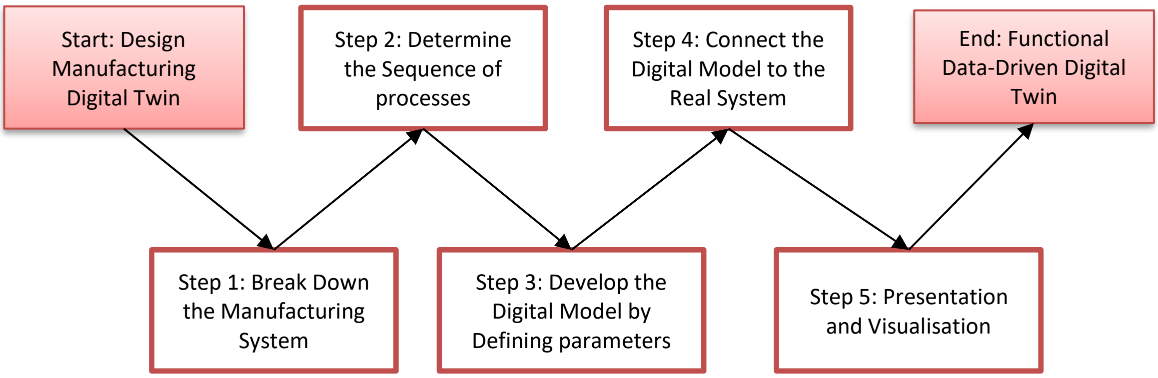

Figure 4: 5 Steps of designing a digital twin in manufacturing

Now, after understanding the design of a DT in manufacturing, it is time to start the State-of-the-Art section by answering the question: “How is a knowledge-based digital twin framework structured, and how does it incorporate experts’ knowledge?”

2) State of the Art

2.1 The Knowledge-Based Digital Twin

In (Su, et al., 2024) a three-layer framework for a knowledge-based DT is presented:

- **Data Layer**: In this layer, there are all the data resources like expert experiences, device resources, sensor data, and geometric data as a **two-dimensional database**. Also, the operation manual and design drawings are the **raw manufacturing data**.
- **Data Preprocessing**: This layer involves cleaning, integration, representation, and manufacturing process ontology development. It transforms raw data into structured information, incorporating historical data for further analysis.
- **Knowledge Framework**: The core of the system, this layer includes a Knowledge Model, Inference Engine, and Knowledge-Driven Modelling components. It integrates **expert**

knowledge, processes data feedback, and uses the Inference Engine to match and update knowledge, driving the construction and refinement of the digital twin model.

- **Knowledge Graph-Based Application Platform**: This layer facilitates the practical application of the knowledge framework. It includes scheduling, algorithm modelling, a server, a switch, and a client, enabling interaction between the knowledge-driven model and real-time manufacturing data.
- **Knowledge-Based Digital Twin System**: The final output, this layer shows the digital twin model interacting with the physical manufacturing process. It uses knowledge-driven geometry and decision-making to provide a virtual representation that continuously updates based on real-time data, ensuring accurate control, prediction, and optimisation of the manufacturing process.
- **Flow and Interaction**: Arrows indicate the flow from raw data through preprocessing and knowledge integration to the DT system, with feedback loops ensuring continuous improvement and adaptation. and adaptability in Industry 4.0. As shown in Figure 5:

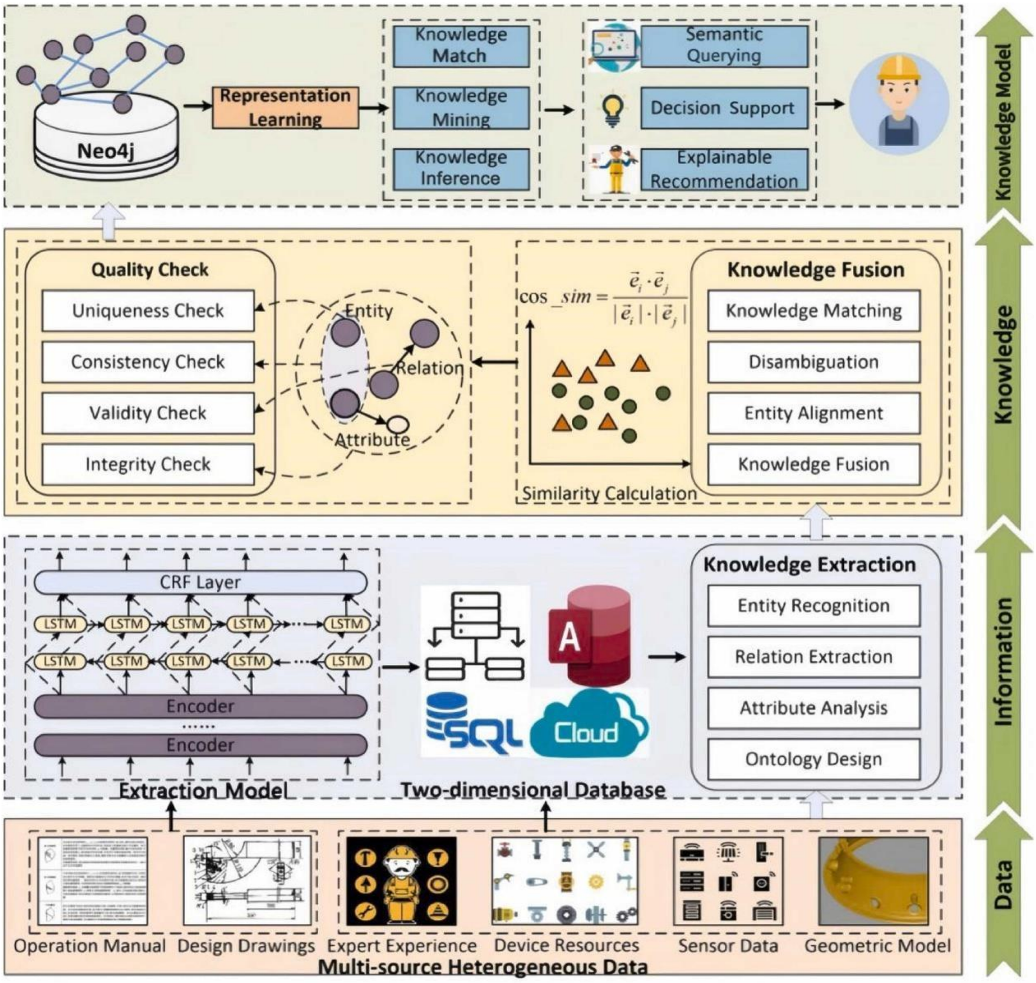

Figure 5: Bottom-up modelling of the complex industrial components manufacturing process. (Su, et al., 2024)

2.1.1 Using System Experts' Knowledge to Make a Digital Twin in Manufacturing

Based on this article (Su, et al., 2024), system experts' knowledge (interpreted as domain experts' insights, such as process rules, historical experiences, and manufacturing standards) is integrated into the knowledge model via knowledge graphs to drive the creation and evolution of a digital twin. Here's a step-by-step explanation derived from the methodology:

1. **Extract and Structure Experts' Knowledge**: Start by identifying experts' knowledge as structured elements (e.g., regulations like guidelines/protocols, features like material properties, and processes like operational steps). Use bottom-up modelling: Extract raw insights from experts (e.g., via interviews or documents) in the data layer, then transform them into triplets (entity-relationship-entity) in the information layer. For instance, an expert's rule on tool wear could be encoded as "Tool (entity) - Affects - Process Efficiency (relationship-entity)."
2. **Build the Knowledge Model with Ontology**: Incorporate experts' knowledge into the Manufacturing Process Ontology (MPO), categorising it under classes like Continuant (static: objects, features, regulations) and Occurrent (dynamic: processes, events, decisions). Experts' insights populate relationships (e.g., how a regulation constrains a process), enabling semantic representation. This creates a KG (Knowledge Graph) that unifies experts' tacit knowledge with data, ensuring the model captures domain-specific logic (e.g., safety protocols or optimisation rules).
3. **Drive Model Integration and Inference**: Use the KG to infer new knowledge from experts' inputs (e.g., by knowledge matching and representation learning algorithms). It links experts' knowledge to geometry (e.g., updating virtual models based on expert-defined material behaviours) and decision models (e.g., case-based reasoning from historical expert decisions). The inference engine continuously refines the KG, allowing self-evolution-e.g., an expert's anomaly-handling rule triggers predictive updates.
4. **Enable DT Self-Update and Decision-Making**: Experts' knowledge in the KG facilitates real-time DT functions: It drives geometry model updates (e.g., simulating changes based on expert process parameters) and decision support (e.g., recommending optimisations from inferred expert cases). This creates a closed-loop where the DT learns experts' accumulated knowledge, adapting to production changes without manual intervention.
5. **Implementation in Framework Layers**: In the ontology layer, experts' knowledge acts as the "core driver" for consistency across models. In the service layer, it supports DT services

like prediction (like using expert rules for failure forecasting) and optimisation (like process adjustments). Validation on the blade line showed experts' process knowledge, enabling accurate mapping and iterative improvements. As shown in Figure 6, the final prediction model is:

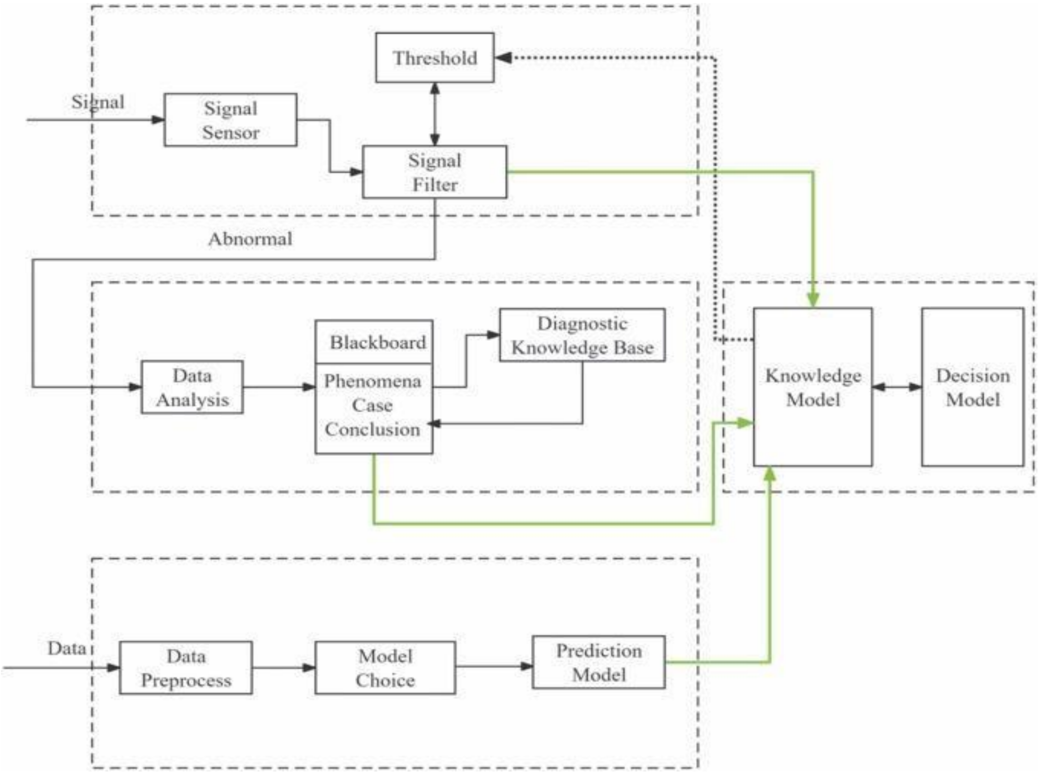

Figure 6: Intelligent prediction decision module in actual machining: assessment, diagnosis, evaluation, decision support. (Su, et al., 2024)

2.1.2 The Expert Twin (Digital Twin with Expert Knowledge) Framework

By facilitating coordination among engineering professionals, data science professionals, and specific industries, industries can hasten the adoption of digital twin technology and fuel innovations in predictive maintenance, real-time monitoring, and operating efficiency. Further investment in research and development, coupled with strategic partnership development, is crucial to tap the full potential of digital twin technology in shaping industrial ecosystems. (Kaur & Bhatia, 2025)

The authors of (Monek & Fischer, 2024) detail the Expert Twin framework, designed for bilateral communication via OPC-UA (OPC Unified Architecture), using DES (Discrete Event Simulation) and FL (Fuzzy Logic).

- **Proposed Expert Twin Framework**: Combines DES optimisation with FL based on expert knowledge. It links real systems (ERP (Enterprise Resource Planning), MES (Manufacturing Execution System), production) to a digital shadow (DS) and a Decision-making module

(DMM). Real-time data flows bidirectionally, triggering optimisations for uncertainties (e.g., rescheduling). Figure 7 shows the structure: Real System → Data Acquisition → Digital Shadow/Triggers → DMM (Simulation + Fuzzy Logic) → Control back to real system.

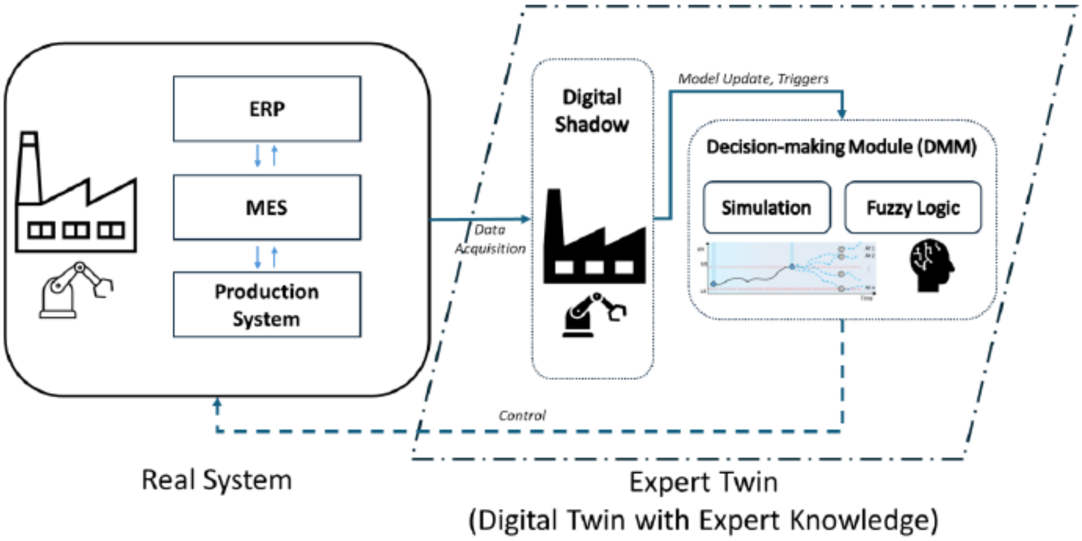

Figure 7: The Expert Twin Framework. (Monek & Fischer, 2024)

- **Digital Shadow Module**: Maps the physical system in DES (e.g., Siemens Tecnomatix Plant Simulation). Events are triggered by PLC (Programmable Logic Controller) signals via OPC-UA for real-time monitoring. Hardware: OPC-UA-enabled PLCs (e.g., Siemens S7-1200/1500). Skills needed: DES/PLC programming, OPC-UA modelling.
- **Decision-Making Module:**
  - **Simulation Submodule**: Builds on DS but adds logic for predictions. Uses genetic algorithms to optimise sequences (e.g., minimise production time or maximise on-time deliveries).
  - **Fuzzy Logic Submodule**: Turns DS into DT with bidirectional auto-exchange. Uses Sugeno-Fuzzy (SF) inference for handling nonlinearities.
- **Framework Operation**: ERP/MES send tasks to PLC. Simulation optimises the initial plan. DS monitors real-time; if deviations (e.g., failures) occur, FL evaluates the need for re-optimisation. If yes, the simulation updates and intervenes via PLC.

In the case of the absence of expert knowledge, how can AI and machine learning methods handle big data to architect a digital twin?

2.2 AI and Its Role in Designing and Modelling the Digital Twin

Artificial Intelligence (AI) plays a vital role in the designing and modelling of DTs, enabling the creation of dynamic, data-driven virtual replicas that enhance simulation accuracy, predictive capabilities, and real-time adaptability. AI facilitates the integration of complex data streams from physical systems, allowing for advanced analytics that go beyond traditional modeling approaches. In the design phase, AI algorithms, such as machine learning (ML) and deep learning, assist in constructing high-fidelity models by processing large datasets to identify patterns, optimise parameters, and simulate "what-if" scenarios without disrupting physical operations. For instance, AI supports the development of DT architectures by automating the mapping of physical-to-virtual connections, ensuring bidirectional data flow for continuous synchronisation and feedback. However, there are problems related to AI-based DTs like a large number of modelling approaches levels are high and never follow the modelling languages (Kreuzer, et al., 2024) . The Figure 8 can show a general theme of AI-based DT:

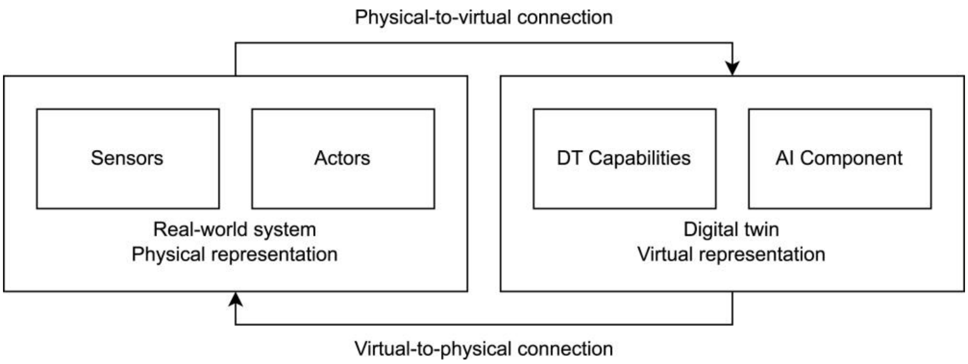

Figure 8: Schematic model of a digital twin with an AI component. (Kreuzer, et al., 2024)

In modelling, AI enhances DTs through predictive modelling and optimisation techniques. Supervised and unsupervised learning methods are commonly employed to handle uncertainties and non-linear relationships in system behaviours, while reinforcement learning enables adaptive decision-making within the DT framework. This is particularly evident in manufacturing contexts, where AI-driven DTs categorise applications across operator, process, and product dimensions, using tools like convolutional neural networks (CNNs) for real-time monitoring and genetic algorithms for process optimisation (Alfaro-Viquez, et al., 2025). Generative AI further contributes by creating synthetic data to train models, filling gaps in real-world datasets and accelerating the iterative design process. In maintenance scenarios, AI-enhanced DTs leverage deep learning for fault prediction and anomaly detection, bridging gaps between research and practice through modular architectures that incorporate edge-cloud computing for scalable modelling. (Rojek, et al., 2025) The main structure of architecting the generative AI-based DTs is shown in Figure 9:

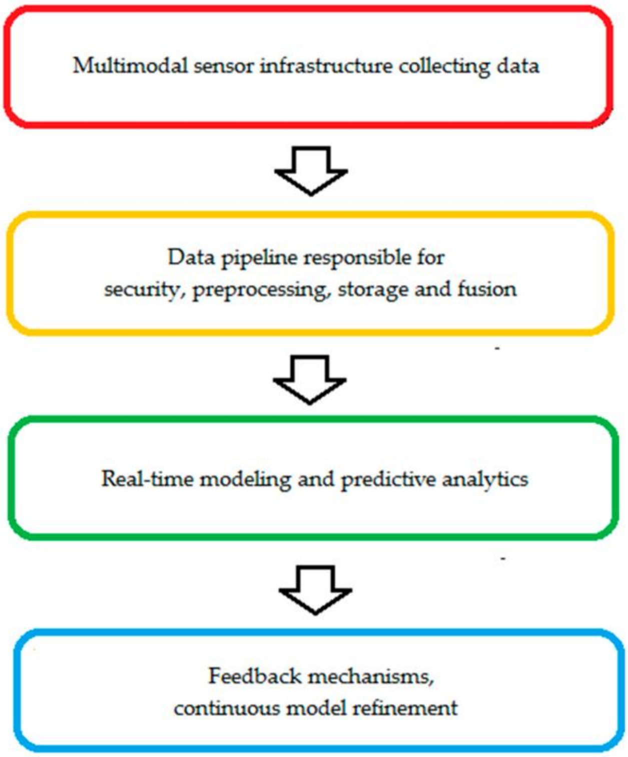

Figure 9: Layered architecture of generative AI-based DTs. (Rojek, et al., 2025)

Overall, AI's role extends to improving interpretability and efficiency in DT modelling by combining data-driven insights with simulation tools, reducing reliance on manual configurations and enabling robust, scalable designs. This integration not only minimises errors in virtual representations but also supports advanced functionalities like predictive analytics and autonomous optimisation, making DTs more viable for complex industrial applications (Chaparro-Cárdenas, et al., 2025).

In case of machine learning methods, based on (Aghbashlo, et al., 2021), the Artificial Neural Networks (ANNs) models obtain their knowledge using various training or optimisation algorithms in which numerical weights transferred by synapses are adjusted to minimise the error between real and simulated data. In general, developing ANN models is not straightforward due to many critical steps like data compilation, data processing, topology selection, training and testing the selected model, and applying the developed ANN models for simulation and validation. Figure 10 portrays the typical main steps involved in the development of ANN models. Among the mentioned steps, data preparation is one of the most essential and crucial stages in ANN modelling of complex systems.

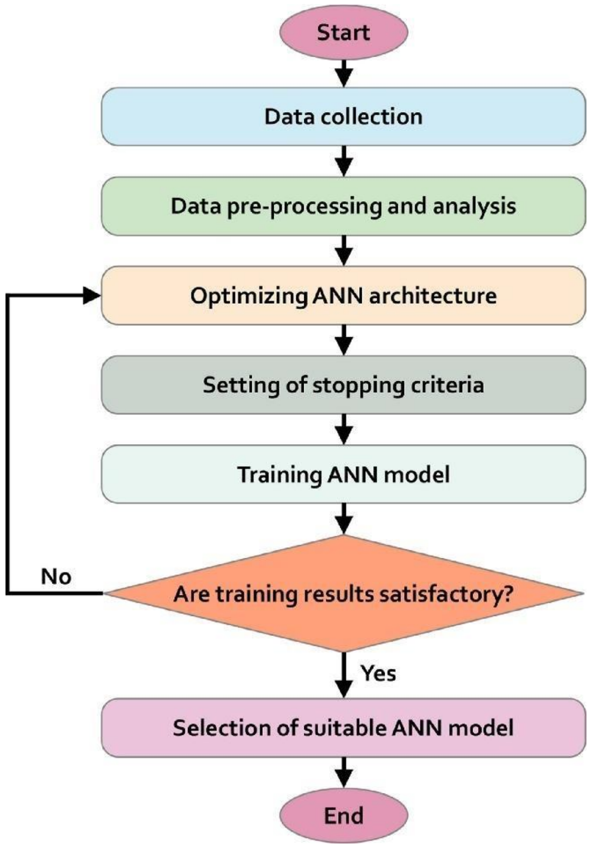

Figure 10: A general flowchart depicting the procedure of ANN model development. (Aghbashlo, et al., 2021)

Or when we are facing a complex system, the structure below would be useful in terms of modelling. (Figure 11) (Kumari & Sarangi, 2024)

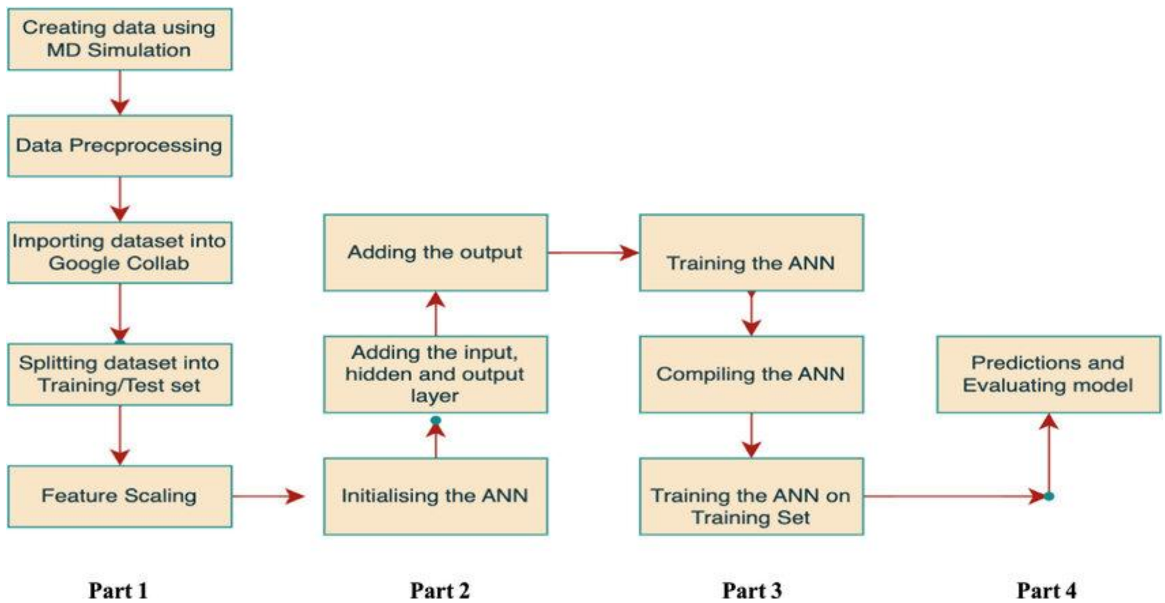

Figure 11: Flowchart of the general procedure of ANN modelling. (Kumari & Sarangi, 2024)

For instance, artificial neural networks (ANNs) have been widely applied to model and predict biodiesel yield from waste vegetable oils, capturing intricate dependencies among input variables. In a comprehensive review, (Awogbemi & Von Kallon, 2023) highlighted how **ANN**, **response surface methodology** (RSM), and **adaptive neuro-fuzzy inference systems** (ANFIS) optimise parameters like alcohol-to-oil molar ratio, catalyst concentration, reaction temperature, residence time, and agitation speed, achieving biodiesel yields between 84% and 98%. The study emphasised ANN's superiority in modelling non-linear relationships, with Pearson correlation coefficients and coefficients of determination approaching 1, demonstrating high predictive accuracy. Appendix 2 can concisely show the impacts of using each ML model in the different case studies:

Similarly, in heterogeneous catalytic biodiesel production from waste cooking oil, multiple ML models—including boosted linear regression, boosted multi-layer perceptron (MLP), and forest of randomised trees—were developed to optimise yield based on reaction temperature, time, catalyst loading, and methanol-to-oil ratio. The whole parameters and final yields numbers that were used in this article comes from Table 1: (Yahya, et al., 2020)

RUN	X1=Temperature (°C)	X2=Reaction time (h)	X3=Catalyst loading (weight%)	X4=Methanol: oil molar ratio	Y=Actual yield (%)
1	125	4.5	3	10	62.93
2	175	4.5	3	10	66.13
3	125	7.5	3	10	65.36
4	175	7.5	3	10	66
5	125	4.5	5	10	63.72
6	175	4.5	5	10	68.92
7	125	7.5	5	10	68.81
8	175	7.5	5	10	70.25
9	125	4.5	3	14	64.34
10	175	4.5	3	14	60.25
11	125	7.5	3	14	65.2
12	175	7.5	3	14	58
13	125	4.5	5	14	74.52
14	175	4.5	5	14	75.31
15	125	7.5	5	14	78.24
16	175	7.5	5	14	73.13
17	100	6	4	12	62.02
18	200	6	4	12	64.7

19	150	3	4	12	60.24
20	150	9	4	12	68.12
21	150	6	2	12	58.59
22	150	6	6	12	79.79
23	150	6	4	8	71.44
24	150	6	4	16	73.15
25	150	6	4	12	97.53
26	150	6	4	12	95.75
27	150	6	4	12	95.26
28	150	6	4	12	96.41
29	150	6	4	12	96.23
30	150	6	4	12	97.78

Table 1:The whole used dataset for simulation of biodiesel production used in this work. (Yahya, et al., 2020)

After learning the role of using machine learning, AI, and system experts in modelling and designing the DTs, it is the time to go through the fusion structure of them and addressing the question: “ In case of using AI and system experts, how would be our designing framework?”

2.3 The Hybrid approaches, based on AI and system experts, for the design and modelling of a sustainable DT

Hybrid approaches to Digital Twin design combine AI (data-driven) methods with structured system-expert knowledge (symbolic/rule-based and physics-based models) to obtain models that are simultaneously accurate, interpretable and robust to changing operating conditions. Two complementary research threads illustrate this: (1) hybrid Knowledge-Based Systems (HKBS) that organise multiple knowledge families and compose hybrid functions to estimate KPIs and support decision making; and (2) hybrid expert systems that encode practitioner know-how in rules and ontologies while using machine learning (ML) to update or extend the rule base. Together they provide the technical foundations for sustainable, Industry-5.0-oriented DTs. (Traini, et al., 2024) (Müller, et al., 2021)

2.3.1 Architecture and Modelling Patterns of Hybrid Approaches

Hybrid DTs typically adopt one of two structural patterns. In a serial configuration a physics or white-box model produces intermediate features or parameters that feed an AI model (for example a mechanistic model computes a stress field that is then mapped to remaining useful life by an ML regressor). In a parallel configuration two (or more) diverse models run concurrently and their outputs are fused (e.g., weighted ensemble or decision-level fusion) so that data-driven components correct or complement the mechanistic model where it lacks fidelity. Both patterns are usefully managed inside an HKBS that treats models and knowledge sources as "knowledge edges" connecting feature nodes; the HKBS orchestrates selection, fusion and retraining so the DT can estimate KPIs in real time and under counterfactual scenarios. These patterns and the rationale for choosing them are described in detail in Traini et al.; they form the basis for resilient, explainable DT architectures. (Traini, et al., 2024) (Müller, et al., 2021) (Figure 12)

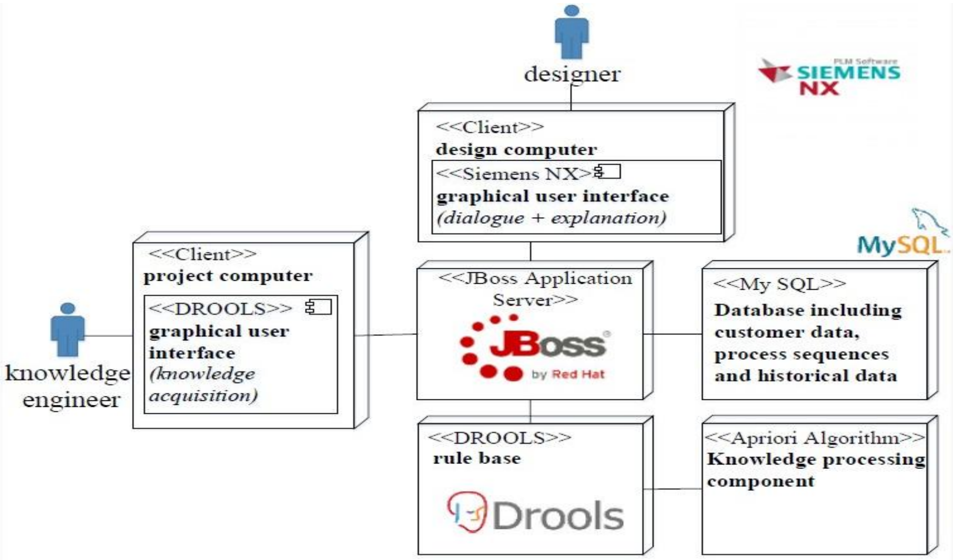

Figure 12: Architecture of the developed expert system. (Müller, et al., 2021)

Types of knowledge and how they integrate

A practical hybrid solution recognises multiple knowledge families and encodes them differently: domain knowledge and standards as ontologies/rules; heuristic and tacit knowledge as elicited rules or case libraries; explicit knowledge as physics equations, surrogate/simulation models, and measured sensor streams; and data-driven knowledge as ML/DL models or learned surrogate models. (Traini, et al., 2024) propose managing these in a unified HKBS so any KPI function $Y = f(X)$ can be composed from sub-functions drawn from different families (physics, ML, simulation, rules) and fused with explicit Data Quality Assessment (DQA) to weigh sources according to trustworthiness and context. This layered handling preserves interpretability (via rules/ontologies) while exploiting ML's capacity to model complex, nonlinear relationships. (Traini, et al., 2024)

Role of expert systems + ML (practical mechanisms)

(Müller, et al., 2021) show how classic expert-system components (dialogue/ explanation/ knowledge-acquisition, rule base and reasoning engine) can be extended with ML to create hybrid expert systems that (a) automate rule discovery from historical data, (b) prefill dialogues using similarity search, and (c) keep the knowledge base current via an interactive loop with shop-floor actors. Practically, this means deploying a rule engine (e.g., DROOLS) and an ML layer that proposes candidate rules or parameter updates which are then validated by experts — a workflow that preserves traceability and human oversight while reducing knowledge-engineering bottlenecks. Such a setup is directly transferable to DT design: rules and ontological constraints guide AI models, ML proposes model refinements, and experts validate or correct automated suggestions.

Sustainability, human-centricity and Industry-5.0 benefits

Hybrid DTs support sustainability objectives in three complementary ways. First, physics and rule components encode constraints and design limits that prevent optimisation from sacrificing safety or environmental criteria (for example limiting temperatures that cause higher emissions or food spoilage). Second, ML components extract efficiency gains from large datasets (energy reductions, yield improvements) that experts then contextualise and validate. Third, the HKBS / hybrid expert-system pattern fosters human-in-the-loop operations: explainable outputs, rule provenance and an interactive knowledge-acquisition path increase user trust and enable socially and environmentally aware decision-making — a core Industry-5.0 aim described by (Traini, et al., 2024).

Implementation recommendations and practical challenges

To implement a sustainable hybrid DT the literature suggests the following pragmatic steps: (1) construct a manufacturing ontology and a feature database (KG) to capture entities, constraints and typical operational rules; (2) deploy a modular HKBS that can register heterogeneous knowledge sources (physics models, simulators, ML models, rules) and perform runtime fusion with a DQA layer; (3) use expert-system components (dialogue, explanation, knowledge acquisition) to capture tacit knowledge and to validate ML-proposed rules; and (4) establish continuous retraining + governance loops so that ML updates are peer-reviewed by domain experts before becoming part of the operational knowledge base. Two recurring challenges must be addressed: (a) knowledge elicitation and rule maintenance (capturing tacit expertise is labour-intensive), and (b) data veracity and covariate shift (ML models can degrade if seed quality, equipment wear or material batches change). Both papers recommend iterative prototyping and human validation as mitigation strategies. (Traini, et al., 2024) (Müller, et al., 2021)

2.3.2 The Structure of Digital Twin for Integration of Data and Expert Knowledge

In the article (Jungmann & Lazarova-Molnar, 2024), the authors proposed a new comprehensive structure of DTs when the system is dealing with data and expert knowledge. (Figure 13)

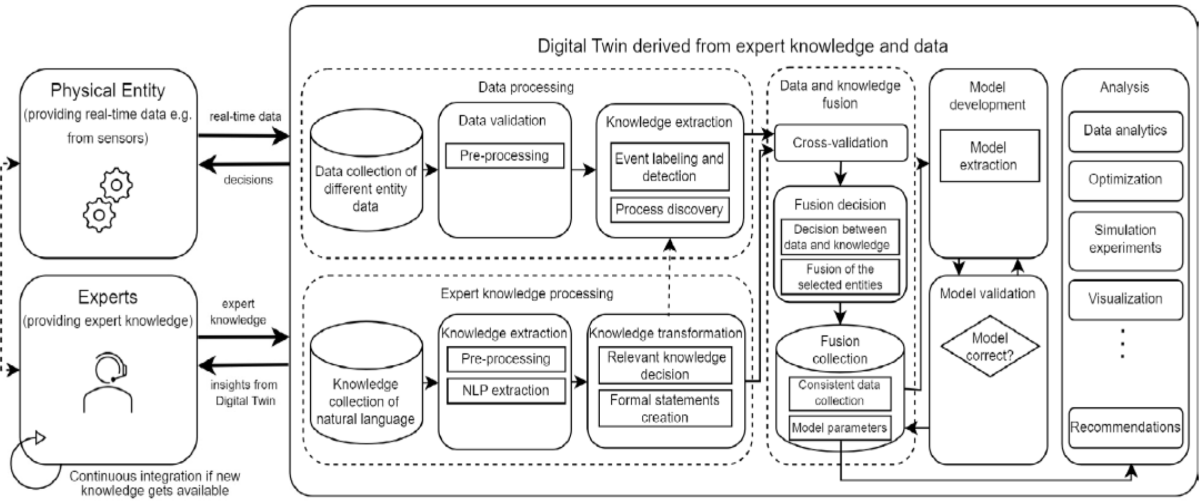

Figure 13: Fusion DT Framework derived from both expert knowledge and data. (Jungmann & Lazarova-Molnar, 2024)

The first task here is the generalization of the DT framework in the data-driven way for a Fusion DT Framework and describing the innovative elements making it possible to furnish, process, and accumulate expertise. The respective novel components are the experts, the expert knowledge processing component, the data and knowledge fusion component and the related links and feedback connections.

To integratively combine data with expert insights, the tangible entity that supplies real-time information, such as sensor data, is supplied by the experts. The DT is given the expert knowledge of the physical entity by the experts in the form of natural or domain-specific language and can also access the insights of the DT in a user interface. In the specialist knowledge processing component, supplied expert knowledge is stored and further processed for knowledge extraction, consisting of pre-processing and Natural Language Processing (NLP).

The extracted relevant knowledge is then subsequently transformed in formal statements to enable a fusion with real-time data from the physical entity. Experts need to continuously and manually update the provided knowledge to ensure consistency between the physical entity and its digital replica as soon as new knowledge is discovered or the physical entity adapts, as changes occur frequently.

Once knowledge and data elements are processed through the corresponding processing components and tasks, the data and knowledge fusion component performs cross-validation of data and knowledge. This is especially important if data and knowledge do not match, contradict each other or the sides have an unequal amount of information about a given aspect of a system of interest. In such cases, a decision algorithm has to decide which element is more trusted, correct, or more important and, therefore, selected. This step is processed in the fusion decision sub-component. The fusion decision step is especially important and can have a high influence on the performance of the DT models. After the decision is made on which data and knowledge entities are taken, the chosen entities are merged into the fusion collection.

The fusion collection is the consistent storage of the previously selected data and expert knowledge. In addition to data and knowledge, model parameters extracted from previous developed models can also be contained in the fusion collection. For the Fusion DT Framework, the fusion collection is the data foundation for the model development and validation components. Extracted DT models are able to provide DT capabilities for further analysis, such as optimizations or simulations that can support decisions for the physical entity.

2.3.3 The suggested AI and Expert Knowledge-Based Digital Twin Environment:

By an inspiration of the conceptual framework proposed by (Traoré, et al., 2024), the ecosystem of AI and experts integrated digital twin environment is illustrated in Figure 14:

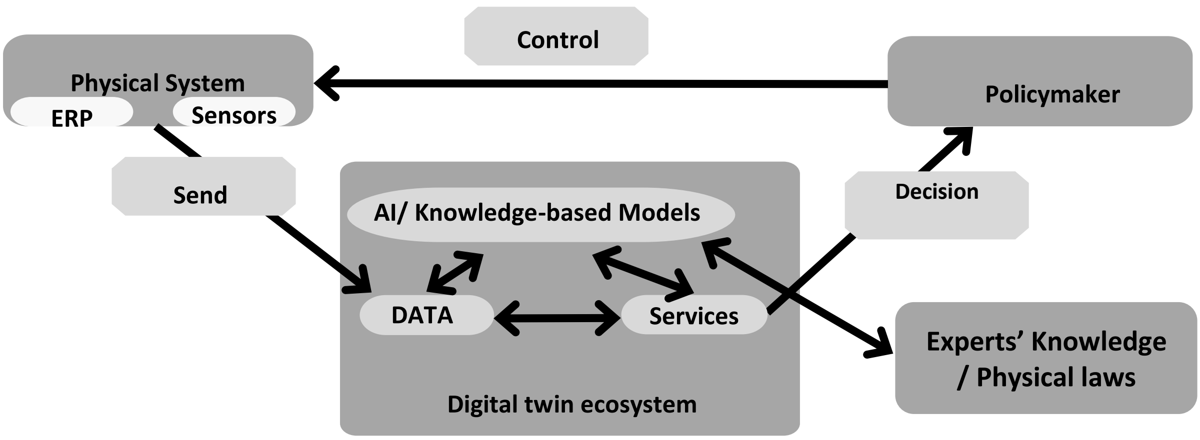

Figure 14: The AI-integrated DT ecosystem. (Traoré, et al., 2024)

2.4 The Hybrid Approaches, Special Focus on Agri-Food Industry

In the agri-food industry, hybrid approaches to digital twin (DT) design and modeling integrate AI-driven techniques with domain-specific expert knowledge to address the sector's unique challenges, such as variability in biological systems, environmental factors, and supply chain complexities. These methods combine data-driven ML models with physics-based simulations and expert-derived ontologies, enabling accurate predictions of crop growth, food quality degradation, and process efficiencies while incorporating agronomic rules for sustainability and traceability. Physics-based models, informed by expert knowledge on thermodynamics or biological processes, provide interpretable foundations, while AI handles non-linear data patterns from sensors, improving scalability and real-time optimization (Melesse, et al., 2023).

So, by getting the idea form this article (Melesse, et al., 2023) the following steps of architecting the DT and the role of system experts are shown in Figure 15:

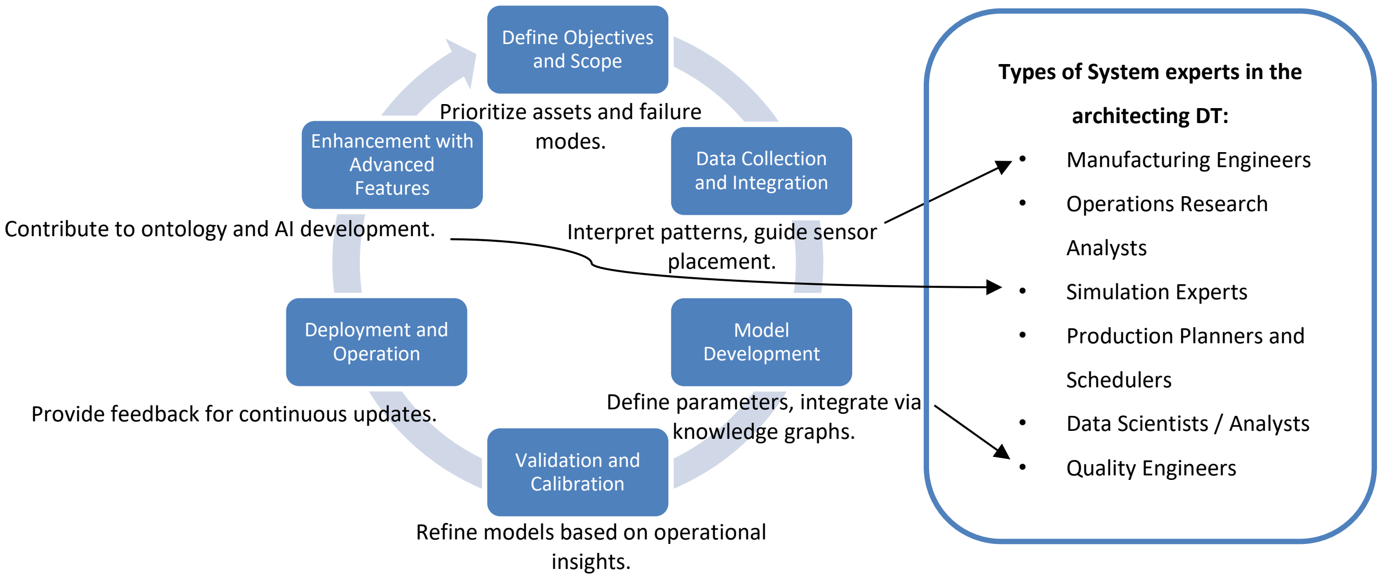

Figure 15: Architecting the DT in a manufacturing system and system expert roles.

Key applications include post-harvest supply chains, where hybrid DTs use statistical and data-driven models to monitor thermophysical behaviors of produce, fusing expert insights on storage conditions with ML for anomaly detection and predictive maintenance. In food processing, hybrid modeling employs computational fluid dynamics (CFD) alongside neural networks to optimize operations like pasteurization or cooling, reducing energy consumption and waste through multi-objective algorithms that balance expert-defined constraints (e.g., quality thresholds) with AI-optimized parameters (Abdurrahman & Ferrari, 2025). Greenhouse and aquaponic systems benefit from reinforcement learning integrated with expert rules for resource allocation, adapting to demand fluctuations while ensuring compliance with sustainability standards.

Implementation involves mapping processes, selecting technologies like IoT sensors and cloud platforms, and establishing bidirectional data links for synchronization. Challenges such as data quality, interoperability, and rural connectivity are addressed through modular architectures that prioritize expert validation, fostering resilient DTs for personalized food design and risk management. These hybrid strategies enhance agri-food resilience by promoting resource efficiency and human-in-the-loop decision-making, aligning with Industry 4.0 goals. As its beneficial sides shown in Figure 16 (Pylianidis, et al., 2021).

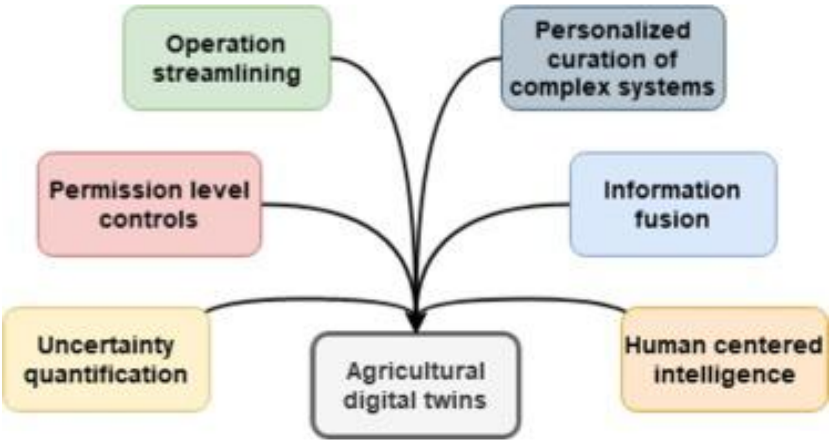

Figure 16: The characteristics of DT that can benefit agricultural applications.

2.5 Concluding Remark

In short, the hybrid strategy advocated by (Müller, et al., 2021) (Traini, et al., 2024) combines structured expert knowledge (ontologies, rules, simulations) with adaptive AI components (surrogates, ML/DL) inside a modular HKBS / hybrid expert-system architecture. That combination yields Digital Twins that are accurate, explainable and aligned with sustainability goals — provided a disciplined knowledge-engineering process and strong expert oversight are maintained. The practical design choices (serial vs parallel hybridisation, rule-learning loop, DQA thresholds) should be selected according to available data, critical KPIs and the degree of acceptable automation for the specific unit operation you are modelling. (Traini, et al., 2024) (Müller, et al., 2021)

After reaching the enough maturity level, it should be answered that “How is the real case study manufacturing line and how we can conceptualize model it based on our information?”

3) Case Study of a Vegetable Oil Manufacturing Company

3.1 Case Description

The physical system targeted was a pilot-scale trituration line at ITERG, involving seed preparation (dehulling), pressing, and initial refining. Real-time data was collected from sensors (e.g., optical cameras for dehulling rates as in DIGIT2DEHULL, temperature/pressure sensors for pressing). Historical datasets from SunNMeal (e.g., protein digestibility variations) supplemented big data inputs. The DT aimed to simulate process flows, predict oil yield and meal quality, and optimize parameters like screw speed, moisture content, and energy use for reduced environmental impact.

As you can see in the Figure 17, the all process has been drawn and the current and future sensors that should be deployed are shown:

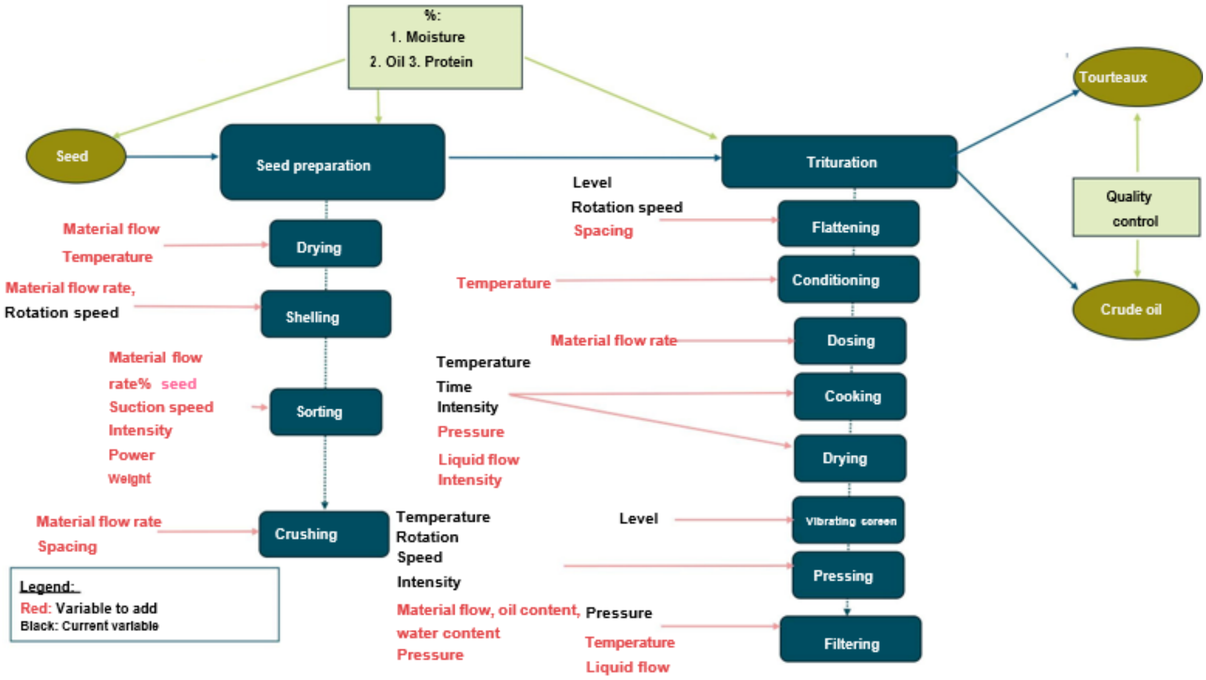

Figure 17: ITERG Manufacturing line (Before the Refining), current and future sensors.

The Production Lines in Detail and Conceptual Models

This manufacturing line uses several seed types to extract the final crude oil and tourteaux (meal) as the products before refining. To simplify the system, three seed types has been chosen (sunflower, rapeseed (Colza), and camelina). Based on three main examples of the manufacturing line these details below and Appendix 6 are given:

1- Cold Pressing: 6 tons of Sunflower (oil production that goes to refining) for a period of 3 days (24 hours a day)

2- Pressure Cooking: 500kg of rapeseed (oilseed cake production with a fat content of <6%) for a period of 1-2 days (The green words show the future sensors)

3- Flattening-cooking-pressure: 20 tons of Camelina (Oil Production) duration is 3 days 24 hours a day.

Then based on these steps and dividing the processes, as we know the sequences among the all processes, the lowest layer of BPMN (Business Process Model and Notation) could be completed and other sections in ITERG can confirmed the other three layers of it to manage the production orders (Appendix 3). The logical diagram to illustrate better the different production method is shown by the full details BPMN based on user selection (Appendix 4). And finally, by having the exact duration of each process, and machines details the final VSM (Value Stream Mapping) is shown in Appendix 5.

According to Appendix 6, we know that there are several processes to clean, rise the quality rate of the seeds, and dehull them like drying, shelling, sorting, and crushing. Also, some phases to pre-press and press the seeds such as flattening, conditioning, dosing, cooking, drying, vibrating, pressing, and final filtering. In each seed types that user want to select, some processes (machines) are ready, and some processes (machines) are idle. In our two cases, the factory uses the Big Press Machine (Olexa MBU75) to extract the oil. Because of importance of this stage and machine, it has been selected for first machine and process to model. The outer side of this machine is shown in Figure 18, and a close schematic of inner side is illustrated in Figure 19.

Figure 18: The Olexa MBU75-Big Press Machine – outside. (www.olexapress.com)

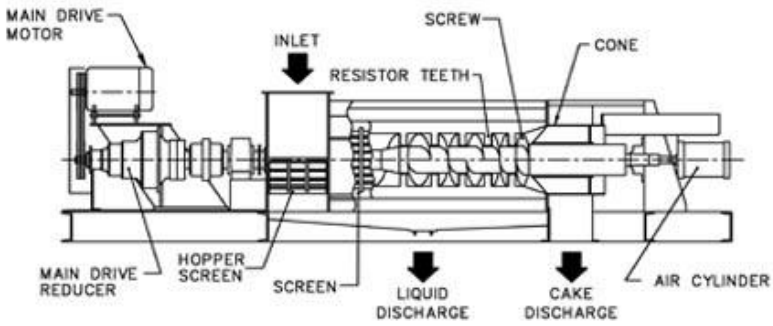

Figure 19: The Olexa MBU75-Big Press Machine – inside. (www.vincentcorp.com)

The technical information of this machine is:

Performances

With rapeseeds, or sunflower

- Capacity: 350 to 450 Kg/hr (nominal flow: 400 Kg/hr)
- Oil flow: 105 to 130 Litres / hr
- Residual oil content (R.O.C.): 10 to 12 %

Dimensions

- Length: 3900 mm
- Width: 1450 mm
- Height: 1830 mm

Installed capacity: electric motor = 22 kW at 380 volts and three phases 50 Hz + earth

Weight

- Empty weight: around 3600 kg
- Operating weight: 3690 kg

By having these details can we start to find the relationships between the different parameters in the Big Pressing process and start the simulation by formulization?

3.2 The Early Steps of The Simulation

3.2.1 Formulation of the model

The correlation between the parameters for the similar case studies is shown below: (Table 2) (Kabutey, et al., 2023) (Lobur, et al., 2024) (Ionescu, et al., 2016) (Ajibola, et al., 1990) (Allay, et al., 2025) (Veljković, et al., 2011) (Hasanov, et al., 2022)

Input Parameter	Crude Oil Yield	AO	PV	Residual Oil	Tourteaux Protein Insolubility	Fiber
Oil Content	++	N/A	+	++	+	+
Moisture Content	++	++	+	++	+	+
Hardness	++	N/A	N/A	++	N/A	+
Protein Content	N/A	N/A	N/A	+	++	N/A
Dehulling Rate (Sunflower)	++	N/A	N/A	++	+	++
Screw Speed	--	+	+	+	+	+
Backpressure (Nozzle size)	--	+	+	N/A	+	+
Feed Rate	-	+	+	++	+	+
Temperature	++	++	++	++	+	+
Pressure	+	N/A	N/A	--	N/A	N/A

Table 2: The correlation between the different parameters of a screw press machine.

According to the given details and the related peer reviewed articles, there are these equations for design the model in this step:

Throughput in Screw Press Oil Extraction: (Ionescu, et al., 2016)

$$Q_u = K.Q_a.(\frac{d.p}{Q_a.n})^{\alpha_1}.U^{\alpha_2}.q_c{}^{\alpha_3}.\theta^{\alpha_4}$$

k*, α1, α2, α3, α4 are constant coefficients

Material feed rate, Qa (kg/s);

The moisture content of the material, u (%);

The shelling degree of the material, qc (%);

The chamber press temperature, θ (°C);

The screw speed, n;

The diameter of the nozzle for cake discharge, d (m);

The pressure from the pressing chamber, p (Pa).

The pressing process efficiency is assessed by the extracted oil flow, Qu (kg/s)

- $E = \left(\frac{M}{W}\right) \times 100$ Determining oil extraction efficiency (Mansuri, et al., 2025)

E is the oil extraction efficiency (%), M represents the weight of oil obtained (g), and W shows the weight of initial seeds.

- $A = \frac{(2.82 \times V)}{W}$ Acidity measurement

V is the volume of sodium hydroxide used (mL), W shows the weight of the sample (g), and A represents the free fatty acids as oleic acid per 100 g of the sample.

- $P = \frac{S \times M \times 100}{W}$ Peroxide value determination

S shows the volume of sodium thiosulfate used (mL), M is the molarity of sodium thiosulfate, W represents the weight of oil (g), and P is the peroxide value (meq O2 per kg of oil).

The question here is AI can play vital roles in designing this complex system?

3.2.2 An Example of Testing ANN Which Is Close to The Internship Project

If we move closer to our project, in the context of vegetable oil mills, where large datasets encompass parameters such as seed moisture content, pressing temperature, screw speed, and inputting speed, AI and machine learning (ML) techniques offer powerful tools for uncovering complex relationships and predicting outcomes like final oil yield. These methods excel at handling big data by identifying non-linear patterns, optimising processes, and enabling predictive modelling, which is crucial for enhancing efficiency in oil extraction and processing.

According to a sample in (Deli, et al., 2011), there is a quite similar table to the internship project which is given below: (Table 3)

No	Nozzle Size (mm)	Shaft Screw Diameter (mm)	Rotational Speed (rpm)	Oil yield (%) M ± SD
1	6	8	21	22.27
2	6	8	54	19.2
3	6	8	65	17.85
4	6	8	98	15.62
5	6	11	21	13.01
6	6	11	54	17.84
7	6	11	65	17.92
8	6	11	98	17.67
9	10	8	21	18.58
10	10	8	54	16.21
11	10	8	65	17.13
12	10	8	98	14.72
13	10	11	21	8.73
14	10	11	54	11.45
15	10	11	65	14.17
16	10	11	98	12.02
17	12	8	21	18.37
18	12	8	54	17.79

19	12	8	65	16.94
20	12	8	98	15.88
21	12	11	21	19.05
22	12	11	54	15.47
23	12	11	65	14.96
24	12	11	98	13.46

Table 3: Percentage of oil yields from N. sativa seed pressed at 60°C with different nozzle sizes, diameter of shaft screw and speed of screw press machine. (Deli, et al., 2011)

After defining the best optimised parameters, the authors tried to find the best temperature also to maximise the final oil yield. As it is shown in Table 4:

Temperature (°C)	50	60	70	80	90	100
Oil Yield (%)	22.68	22.16	20.02	17.97	16.35	15.21

Table 4: The impact of temperature on the final oil yield. (Deli, et al., 2011)

Also, the thresholds and ranges of parameters in ITERG are:

- Temperature range (pressing process): 30–130°C
- Entrance temperature: 20–90°C
- Motor intensity: 10–37 (assumed to be kW, typical for motor power in screw presses)
- Motor speed: 9–50 Hz (likely corresponding to screw rotational speed, to be correlated with rpm)
- Material flow (tourteaux out of press): 50–200 kg/h
- Tourteaux temperature (out of press): 40–120°C

The most accurate formula for predicting oil yield (Y , in percent) of Nigella sativa seeds, based on nozzle size (N), shaft screw diameter (S), and rotational speed (R), is given by a degree-3 polynomial regression model:

$$Y = 101.5858068421 - 11.5553840934N - 2.5338428226S + 0.0739495861R$$
$$+ 0.5664946701N^2 + 0.0875757576S^2 - 0.0007343996R^2$$
$$+ 0.0290671351NS - 0.0032833921NR - 0.0001470588SR$$
$$- 0.0093517510N^3 + 0.0003050505S^3 + 0.0000029816R^3$$
$$+ 0.0014366722N^2S + 0.0001123743N^2R - 0.0009848485NS^2$$
$$- 0.0000084967NSR - 0.0000019608S^2R + 0.0000014556NR^2$$

Variables

- Y : Oil yield (%)
- N : Nozzle size (mm, e.g., 6, 10, 12)
- S: Shaft screw diameter (mm, e.g., 8, 11)
- R: Rotational speed (rad min−1, e.g., 21, 54, 65, 98)

Coefficients Performance

- R^2: 0.9622 (tested on all 24 data points)
- Root Mean Squared Error (RMSE): 0.6147
- Mean Squared Error (MSE): 0.3779

Notes

- The formula was derived using a degree-3 polynomial regression model, fitted to 24 data points with nozzle size, shaft screw diameter, and rotational speed.
- The model captures linear, quadratic, cubic, and interaction effects, providing high accuracy.
- The formula is valid within the tested ranges: N ∈ [6, 12] mm, S ∈ [8, 11] mm, R ∈ [21, 98] rad min−1. Extrapolation may reduce accuracy.
- Coefficients for R3, NSR, S2R, and NR2 are very small but are reported with exact values for precision.

3.2.3 Simulating and Testing the First Oil Yield Prediction

These tests python codes are available in Appendix 7,8, and 9 . Also, the final result of the testing is shown in the Figure 20-21-22:

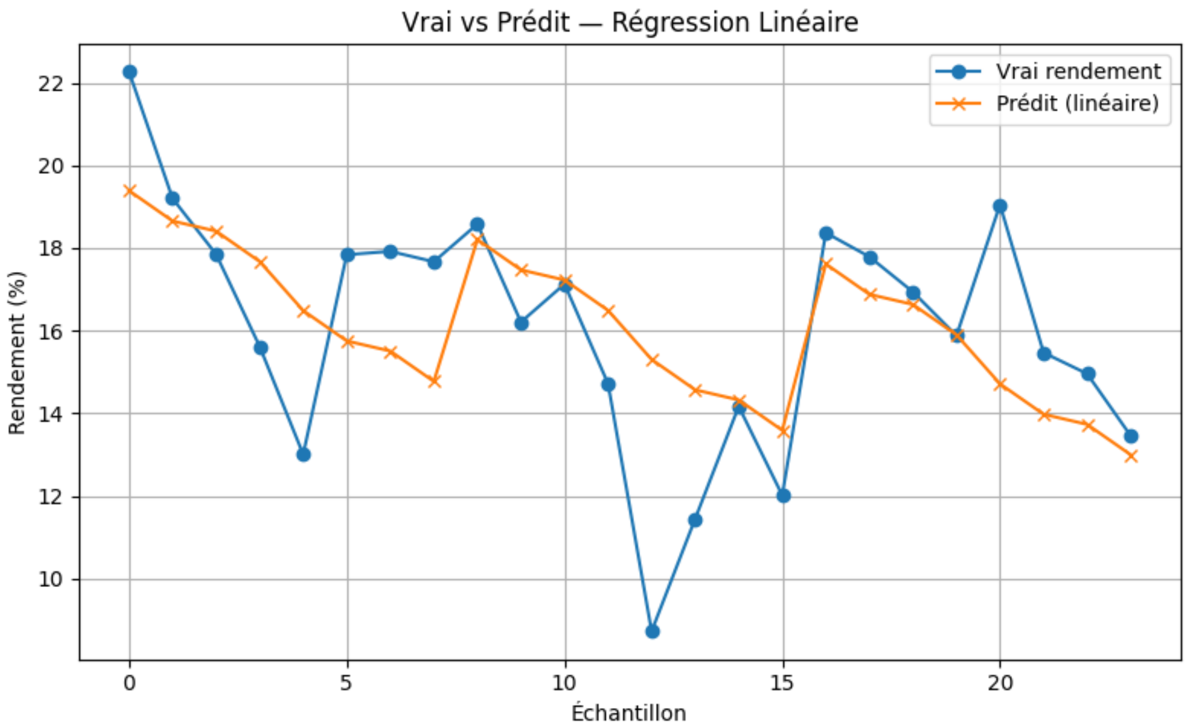

Figure 20: Testing the Example by Polynomial Regression Degree 1. (Code in Appendix 7)

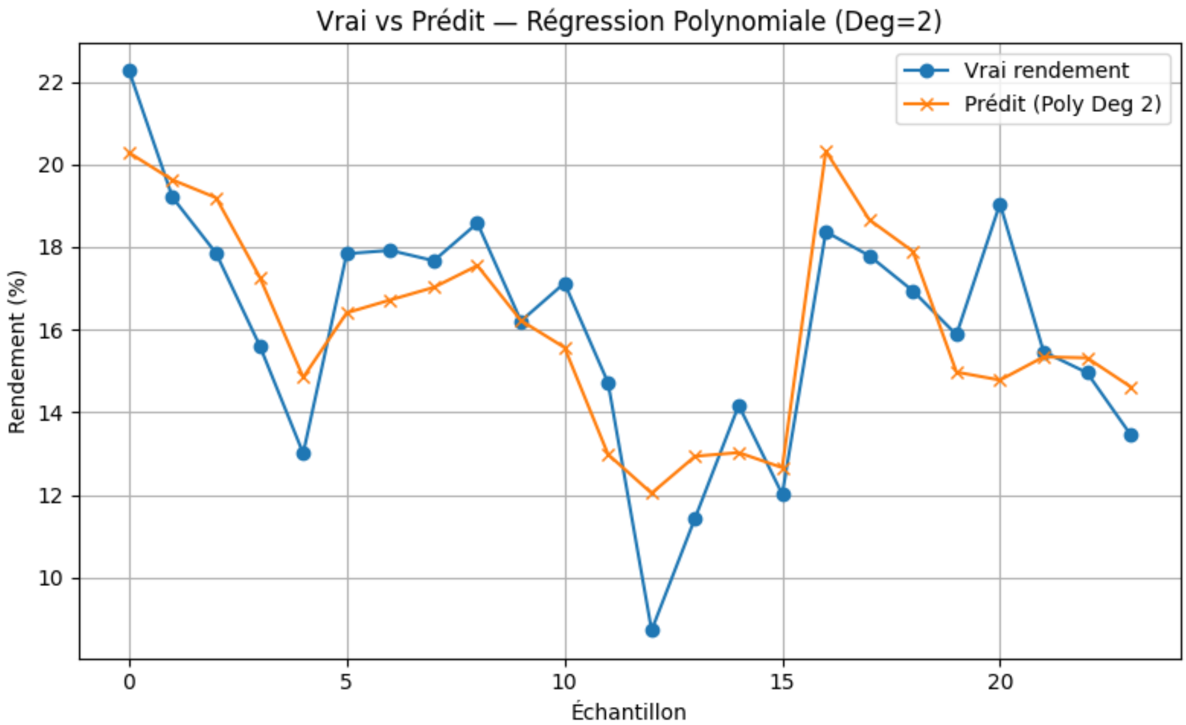

Figure 21: Testing the Example by Polynomial Regression Degree 2. (Code in Appendix 8)

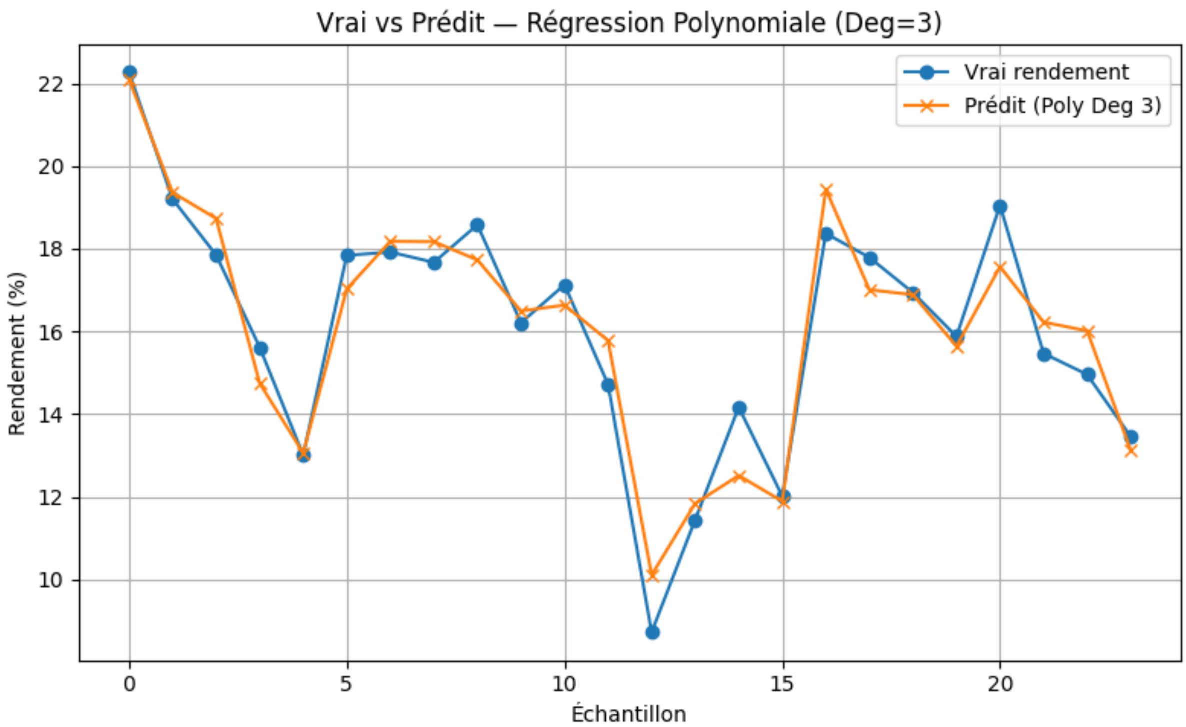

Figure 22: Testing the Example by Polynomial Regression Degree 3. (Code in Appendix 9)

After adding some other methods, we found the polynomial regression degree 3 might overfit the data. So, finally the comparison of the different methods that were used in this step is given in table below: (Table 5)

Model	Configuration	Test R^2	Comments
Polynomial Regression	Degree 1 (Linear)	0.524	Captures linear trends but misses nonlinear interactions. Moderate performance.
Polynomial Regression	Degree 2 (Quadratic)	0.672	Improves over degree 1 with some nonlinear capture; risks overfitting with 10 features.
Polynomial Regression	Degree 3 (Previous)	0.389	Overfits severely; 20 features overwhelm 19 train points, reducing generalization.
Polynomial Regression	Degree 3 (Provided)	0.9998	Nearly perfect fit on train data; likely overfits due to 20 parameters for 19 points. Test R^2 inflated; real generalization likely lower (e.g., ~0.4).
MLPNN	1 Layer, 2 Neurons	0.75	Underfits; too simple for complex interactions.
MLPNN	1 Layer, 4 Neurons	0.85	Good balance; captures basic nonlinearity.
MLPNN	1 Layer, 6 Neurons	0.92	Best model; optimal complexity for capturing interactions, good generalization.
MLPNN	1 Layer, 8 Neurons	0.88	Slight overfitting: minor R^2 drop vs. 6 neurons.
MLPNN	1 Layer, 10 Neurons	0.82	Overfits; excessive parameters reduce generalization.
MLPNN	2 Layers, [2,2] Neurons	0.78	Too simple for 2 layers; limited pattern capture.
MLPNN	2 Layers, [4,2] Neurons	0.86	Decent; captures more nonlinearity but not optimal.
MLPNN	2 Layers, [6,3] Neurons	0.89	Good performance; slight overfitting vs. 1 layer, 6 neurons.
MLPNN	2 Layers, [8,4] Neurons	0.84	Overfits; too many parameters for small data.
MLPNN	2 Layers, [10,5] Neurons	0.80	Significant overfitting; poor test performance.

Table 5: Comparison the different model to find the best formula to calculate the oil yield

Based on the dataset, and the experts' opinion we can choose the best method to model and simulate the oil yield extraction. In a simple way we can use the code in Appendix 10 and the results would be the Figure 23:

```
OLEXA MBU75 Oil Press Model
===========================
Enter the seed type (sunflower or Camelina): Sunflower
Enter the pressing temperature (°C, 30-130): 60
Enter the motor speed (Hz, 9-50): 20
Enter the pressure (MPa, 10-37): 20
Enter the nozzle diameter (mm, 6-12): 6
Enter the screw shaft diameter (mm, 8 or 11): 8
Enter the feed rate (kg/h, 50-200): 100

Results for Sunflower:
Feed Rate (kg/h): 100.00
Screw Shaft Diameter (mm): 8.00
Screw Speed (rpm): 41.66
Oil Yield: 52.28%
Free Fatty Acid (FFA): 1.50%
Peroxide Value (PV): 4.22 meq/kg
```

Figure 23: The first test of the simulation of Big Press Machine. (Code in Appendix 10)

4) Results

This literature review and early steps of modelling the digital twin (DT) for oilseed processing was developed during the internship project, with a focus on trituration and dehulling operations within the UMT OLEODIGIT framework. AI models, such as artificial neural networks (ANNs), were integrated with system experts' knowledge to simulate key parameters including oil yield, meal quality, and energy consumption. Historical datasets from SunNMeal and real-time sensor data from DIGIT2DEHULL, such as temperature, pressure, and optical cameras, were utilized. Polynomial regressions for oil yield, based on variables like nozzle size, screw diameter, and rotational speed, were explored using examples from related studies. Hybrid approaches, incorporating data-driven ML techniques and expert-derived rules, were employed to enable multicriteria optimization, thereby aiming to reduce energy use and enhance sustainability. The manufacturing system was broken down into building blocks—fabrication, logistics, storage, and inspection—to facilitate modular DT design, which was validated on ITERG's pilot-scale line for sunflower, rapeseed, and camelina processing.

Adaptability of the DT was further explored through bidirectional data flows and knowledge graphs, with potential for real-time process control and failure prediction. In case studies involving big pressing with the Olexa MBU75 machine, equations for throughput and oil extraction efficiency were formulated, incorporating factors such as moisture content, screw speed, and temperature ranges (30–130°C). Uncertainties were handled via ontologies and fuzzy logic with expert involvement ensuring interpretability, alongside environmental assessments. Data veracity challenges were mitigated through fusion components, illustrating the DT's potential for adoption in SMEs and ETIs in alignment with Industry 5.0's human-centric focus.

Also based on (Abdurrahman & Ferrari, 2025),the implementation of DTs in the Agri-food industry has some potential issues. The Figure 24 easily shows us the cause and effects diagram of these challenges for the future works:

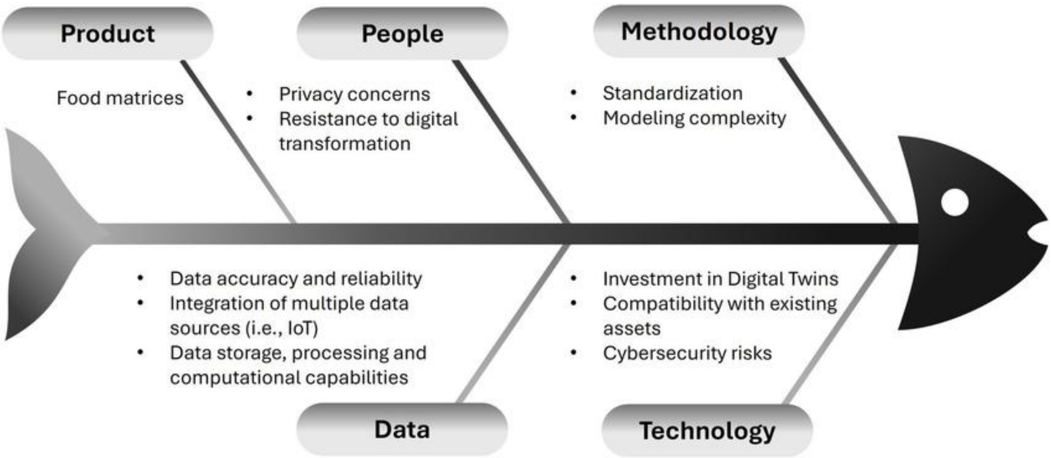

Figure 24: The main cased that have the potential struggles with the implementation of DTs in the Agri-food industry. (Abdurrahman & Ferrari, 2025)

5) Conclusion

The integration of AI with system experts' knowledge was demonstrated to enable the design of sustainable digital twins for vegetable oil processing, optimizing efficiency, quality, and environmental impact. A scalable foundation for real-time monitoring and decision-making in oilseed trituration was provided by the proof-of-concept DT, supporting UMT OLEODIGIT's goals of innovation and transferability to agri-food sectors. Expansion to full-scale implementations and additional processes like refining should be considered in future work to ensure broader industrial applicability and long-term sustainability. However, in this project due to the time shortage, the complete simulation did not run, in the future work it is definitely possible to spend time and collecting data from the whole processes and machines to model the system.

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7) Appendix

Dimension	Reference	Classification	AI Type	Visualization Tool	Data Types	Network Protocols
Process	(Helman, 2022)	MS	-	-	-	-
Process	(Onaji, 2022)	MS	-	Siemens Tecnomatix	RTD	OPCUA, TCP/IP, Ethernet
Process	(Mo, 2023)	PO	GA	Siemens Tecnomatix	RTD	OPC-UA, MQTT, and TCP/IP
Process	(Latsou, 2024)	PO	-	-	RTD	REST-API
Process	(Urgo, 2024)	MS	CNN	-	RTD	-
Process	(Zhou, 2023)	MS	-	-	RTD	-
Process	(Ding, 2023)	MS	-	-	RTD	-
Process	(Kirner, 2024)	PPC	-	Rhinoceros 3D	RTD	MQTT
Process	(Liu, 2024)	MS	RNN	-	RTD	-
Process	(Zhong, 2023)	MS	RNN	MapleSim	RTD	TCP/IP
Process	(Xia, 2021)	MS	VAE	Simulink Simscape	RTD	-
Process	(Naqvi, 2022)	MS	GAN	-	HD	REST-API
Process	(Zhang, 2024)	MS	CNN, SVM	OpenGL	RTD	OPC-UA and MTConnect
Process	(Liu, 2022)	MS	-	-	RTD	OPC-UA
Process	(Wen, 2024)	MS	-	Simulink Simscape	RTD	OPC-UA
Process	(Bonci, 2024)	MS	-	-	RTD	OPC-UA
Process	(Zhang, 2022)	MS	-	Plant Simulation	RTD	-
Process	(Pantelidakis, 2022)	MS	-	Unity	RTD	REST API
Process	(Shoshi, 2024)	MS	-	-	RTD	-
Process	(Li, 2022)	MS	CNN and GAN	Unity	RTD	OPC-UA
Process	(Singh, 2024)	MS	-	Unity	RTD	Ethernet/IP
Process	(Zhou, 2022)	MS	DNN	-	HD	-
Process	(Xie, 2023)	MS	Math Models	-	RTD	OPC-UA
Process	(Castañé, 2023)	PPC	RLN	-	RTD	REST-API
Process	(Ragazzini, 2024)	PPC	-	Siemens Tecnomatix	RTD	OPC-UA
Process	(Latsou, 2023)	PPC	-	-	RTD	REST-API
Process	(Liu, 2024)	PPC	SVM	-	RTD	OPC-UA
Process	(Mu, 2024)	PPC	RNN	-	SD/RTD	-
Process	(Li, 2023)	PPC	IMOLSA Algorithm	AnyLogic 8.7	RTD	-
Process	(Eunike, 2022)	PPC	GA	-	RTD	TCP/IP and Modbus
Process	(Cai, 2024)	PPC	RNN	-	RTD	RFID
Process	(Tang, 2023)	PPC	ENN	-	HD/RTD	-
Process	(Ding, 2022)	PPC	LVQ	Unreal Engine	RTD	-
Process	(Alsakka, 2024)	PPC	DNN	Simio	RTD	-
Process	(Li, 2023)	PPC	GNN	Unity	HD/RTD	-

Process	(Yang, 2024)	PPC	-	-	RTD	ZigBee, Bluetooth, NFC, REST API
Process	(Catti, 2024)	PPC	LR	Three.js	HD/RTD	MQTT
Process	(Link, 2025)	PPC	CNN	-	SD	EtherCAT
Process	(Wanner, 2023)	PPC	Math Models	-	RTD	-
Process	(Liu, 2022)	PPC	CNN	-	HD	Ethernet, TCP/IP, and REST API
Process	(Chancharoen, 2023)	PPC	-	CoppeliaSim	RTD	-
Process	(Wang, 2023)	PPC	RLN	Unity	-	Ethernet
Process	(Yang, 2022)	PO	-	-	RTD	TCP/IP
Process	(Song, 2023)	PO	RLN	Blender and Unity3D	RTD	OPC-UA,Ethernet/IP
Process	(Tahiri, 2022)	PO	-	CellFlex4.0	-	Profinet
Process	(Abouzid, 2023)	PPC	-	ProModel	HD/RTD	-
Process	(Papacharalampopoulos, 2023)	PO	-	-	RTD	-
Process	(Slot, 2024)	MS	-	Arena Simulation	RTD	-
Operator	(Zhang, 2024)	OS	ST-GCN	SMPL Model	RTD	-
Operator	(Ramasubramanian, 2022)	OS	-	Unity	RTD	-
Operator	(Löcklin, 2021)	OS	-	-	RTD	WLAN, Profinet
Operator	(Wang, 2024)	OS	R-CNN	Unreal Engine	RTD	ROS framework
Operator	(Shi, 2022)	OS	CNN, LSTM	-	RTD	-
Operator	(Dallel, 2023)	OS	ST-GCN	-	RTD	-
Operator	(Gkournelos, 2024)	OS	LLM	-	RTD	-
Operator	(Berti, 2023)	OS	-	-	RTD	-
Operator	(Sharotry, 2022)	OS	-	-	RTD	-
Operator	(Davila-Gonzalez, 2024)	OS	LLM	-	RTD	APIs
Operator	(Park, 2024)	OS	-	Unity	RTD	ROS framework
Operator	(Chand, 2024)	OS	LSTM	-	RTD	-
Operator	(Cimino, 2022)	SA	-	-	RTD	-
Operator	(Marchi, 2023)	SA	-	-	RTD	-
Operator	(Modoni, 2023)	SM	CNN, RNN, LSTM	-	RTD	-
Operator	(Balaji, 2023)	SA	-	-	RTD	TCP/IP
Operator	(Mordaschew, 2024)	PP	-	-	RTD	-
Product	(Chen, 2024)	PD	SVM	-	RTD	OPC-UA
Product	(Araque, 2024)	PD	-	Simulink/Simscape	-	-
Product	(Khalaj, 2024)	PD	ANN	-	HD	-
Product	(Huang, 2022)	PD	-	-	RTD	-
Product	(Dietrich, 2024)	PD	-	ISG Virtuos	RTD	OPC-UA
Product	(Lehner, 2024)	PD	-	-	RTD	-
Product	(Arnemann, 2023)	PD	-	-	RTD	OPC-UA

Product	(Mourtzis, 2022)	PD	-	Unity	RTD	FTP
Product	(Farsi, 2021)	PD	-	-	RTD	-
Product	(Rojek, 2021)	PD	-	-	RTD	-

Appendix 1: The Digital Twin applications in manufacturing. (Alfaro-Viquez, et al., 2025)

To understand better this table, below there are the corresponding abbreviations:

From "Classification" Column:

- MS: Monitoring and Simulation
- PO: Process Optimization
- PPC: Production Programming and Control
- OS: Operator Safety
- SA: Smart Assistance
- SM: (Likely a variant or typo for Smart Assistance, based on context)
- PP: Production Planning
- PD: Product Development

From "AI Implementation" Column:

- GA: Genetic Algorithm
- CNN: Convolutional Neural Network
- RNN: Recurrent Neural Network
- VAE: Variational Autoencoder
- GAN: Generative Adversarial Network
- SVM: Support Vector Machine
- DNN: Deep Neural Network
- RLN: Reinforcement Learning Network
- IMOLSA: (Specific algorithm name, likely "Improved Multi-Objective Local Search Algorithm")
- ENN: Elman Neural Network
- LVQ: Learning Vector Quantization
- GNN: Graph Neural Network
- LR: Linear Regression
- ST-GCN: Spatio-Temporal Graph Convolutional Network
- R-CNN: Region-based Convolutional Neural Network
- LSTM: Long Short-Term Memory
- LLM: Large Language Model
- ANN: Artificial Neural Network

From "Data Types" Column:

- RTD: Real-Time Data
- HD: Historical Data
- SD: Simulation Data

From "Network Protocols" Column:

- OPC-UA: Open Platform Communications Unified Architecture
- TCP/IP: Transmission Control Protocol/Internet Protocol
- MQTT: Message Queuing Telemetry Transport
- REST-API: Representational State Transfer Application Programming Interface
- RFID: Radio-Frequency Identification
- ZigBee: (Wireless communication protocol)
- NFC: Near Field Communication
- EtherCAT: Ethernet for Control Automation Technology
- WLAN: Wireless Local Area Network
- ROS: Robot Operating System
- APIs: Application Programming Interfaces
- FTP: File Transfer Protocol

Feedstock	Research aim(s)	No. Of data	ML model used	Model inputs	Model output	Remark	Ref
Jatropha oil	To model biodiesel yield using ANN model	15	ANN	M:O ratio = 6:1–12:1CC=0.5–1.0 wt%Rt=30–90 min	Biodiesel yield 85.2%	ANN predicted biodiesel yield	Tan S. X. et al. (2019)
Waste cooking oil	Prediction of biodiesel yield using ANN	27	ANN	M:O ratio=9:1–18:1CC=0.5–2.0 wt%Rt=10–20 minSS=300–700 rpm	Biodiesel yield 84.1%	Accurate prediction of biodiesel yield by ANN	Fangfang et al. (2021)
Canola oil	Using ANN to predict biodiesel yield	42	ANN	M:O ratio=20:1–40:1Rt=3–30 minRT=270°C–400°C	Biodiesel yield 97.26%	ANN was successful in predicting biodiesel yield	Farobie et al. (2015)
Nannochloropsis sp. Biomass	Prediction and optimization of biodiesel yield by RSM	25	RSM	M:O ratio=0.5:1–1:1CC=0.5–2.0 wt%RT=65°C–95°CRt=5–25 min	Biodiesel yield 40.9%	Low biodiesel yield	Wahidin et al. (2018)
Mustard seed oil	Application of RSM to predict and optimize the reaction parameters of	30	RSM	M:O ratio=2:1–10:1CC=0.2–1.0 wt%RT=50°C–	Biodiesel yield 96.695%	RSM is a suitable statistical technique to optimize and	Yesilyurt et al. (2019)

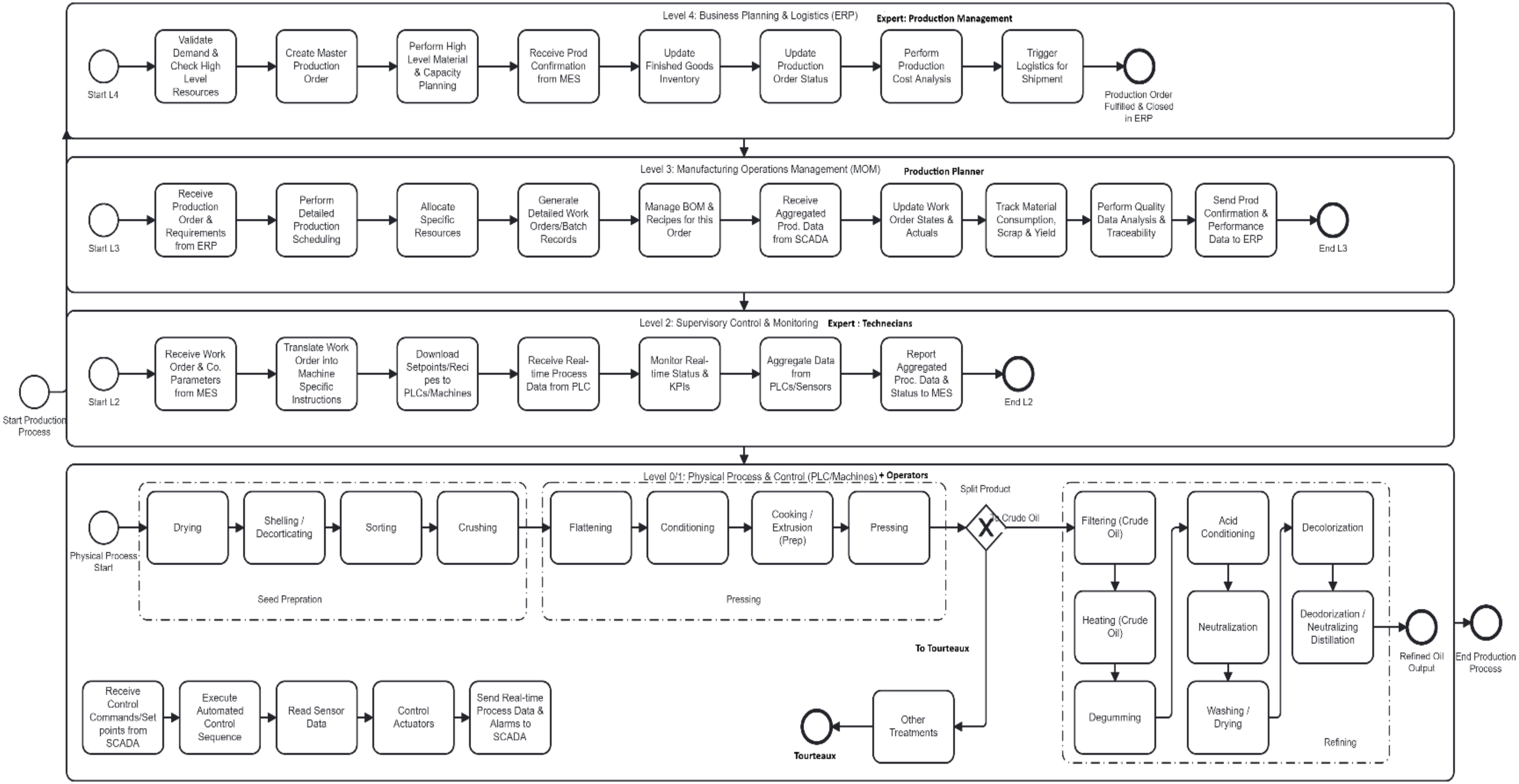
Feedstock	Research aim(s)	No. Of data	ML model used	Model inputs	Model output	Remark	Ref
	biodiesel production			70°CRt=30–90 min		maximize biodiesel yield	
Stone fruit seed oil	Modelling and optimization of biodiesel production by RSM	15	RSM	M:O ratio=4:1–6:1CC=0.5–1.5 wt%RT=45°C–65°C	Biodiesel yield 95.9%	Effective and easy to use technique	Anwar et al. (2018)
Oleic acid	Modelling and optimization of biodiesel production by RSM	30	RSM	M:O ratio=6:1–18:1CC=1.0–5.0 wt%RT=60°C–180°CRt=60–300 min	Biodiesel yield 97.94%	RSM was effective in predicting biodiesel yield	Hashemzehi et al. (2022)
Kusum oil	Modelling and optimization of transesterification process by RSM	31	RSM	M:O ratio=1:1–12:1CC=0–2.0 wt%RT=50°C–70°CRt=30–180 min	Biodiesel yield 98.48%	Actual experiment and predicted data are close	Singh et al. (2021)
Waste sunflower oil	Investigation and comparing RSM and GWO for biodiesel production	20	RSM and GWO	M:O ratio=4:1–8:1CC=0.5–1.5 wt%Rt=40–80 min	Biodiesel yield 97.1%	Effective predictive capabilities of the techniques	Samuel et al. (2020)
Chicken fat oil	Application of RSM and GA to optimize and model biodiesel production	15	RSM and GA	M:O ratio=4:1–8:1CC=0.75–1.25 wt%Rt=3–9 min	Biodiesel yield 94.8%	Efficient optimization techniques	Fayyazi et al. (2015)
Mahua oil	Use of RSM and GA to optimize biodiesel yield	27	RSM and GA	M:O ratio=4:1–12:1CC=0.3–0.9 wt%RT=45°C–55°CRt=90–150 min	Biodiesel yield 96.28%	GA presented fast, efficient and more accurate results than RSM	Kolakoti et al. (2020)
Waste chicken fat	Modelling and optimization of biodiesel yield by RSM and ANFIS-GA	30	RSM and ANFIS - GA	M:O ratio=4:1–12:1CC=0.5–1.5 wt%RT=45°C–65°CRt=45–65 min	Biodiesel yield: RSM=92.70%ANFIS-GA=94.89%	ANFIS-GA demonstrated better predictive capability and cheaper process than RSM	Chizoo et al. (2022)
Crude rubber seed oil	Evaluate the efficacies of RSM and ANFIS to predict biodiesel yield	30	ANFIS and RSM	M:O ratio=25:1–75:1CC=8–16 wt%Rt=180–240 min	Biodiesel yield: ANFIS=96.25%RSM=91.235%	ANFIS performed better and more accurate than RSM	Jisieike et al. (2023)
H. sabdariffa seeds oil	Modeling the transesterification of H. sabdariffa seeds oil to biodiesel	28	RSM, ANN, and ANFIS	M:O ratio=4:1–12:1CC=0.5–2.5 wt%Rt=15–75 min	Biodiesel yield: RSM=60%ANN=80.01–98.37%ANFIS=80.1–98.3%	ANFIS was the most accurate technique in predicting biodiesel yield	Ishola et al. (2019)
Muskmelon oil	To compare the prediction and simulating efficiencies RSM	30	RSM and ANN	M:O ratio=3:1–9:1CC=0.5–1.5 wt%RT=30°C–50°CRt=10–50 min	Biodiesel yield ANN=97.90%.,RSM=97.56 ± 0.63%	ANN was more accurate and reliable than RSM in	Maran and Priya (2015)

Feedstock	Research aim(s)	No. Of data	ML model used	Model inputs	Model output	Remark	Ref
	and ANN for biodiesel yield					predicting biodiesel yield	
Sesame oil	Investigation and comparison of the capability of ANN and RSM to predict biodiesel yield	27	RSM and ANN	M:O ratio=4.5:1–9:1CC=0.5–2.5 wt%RT=25°C–40°CRt=10–50 min	Biodiesel yield ANN=99.7%.,RSM=98.3%	ANN model demonstrate better accuracy and reliability than RSM model	Sarve et al. (2015)
Neem oil	Model biodiesel yield using RSM and ANN	30	RSM and ANN	M:O ratio=3:1–9:1CC=0.5–1.5 wt%RT=30°C–50°CRt=10–50 min	Biodiesel yield 91.5%	ANN was more robust and accurate than RSM	Prakash Maran and Priya (2015)
Sunflower oil	To investigate and compare the prediction capabilities of ANN and RSM	162	RSM and ANN	M:O ratio=4.5:1–7.5:1CC=0.3–0.7 wt%RT=20°C–40°CRt=40–60 min	Biodiesel yield 89.9%	ANN model was more accurate than RSM	Rajković et al. (2013)
Ceiba pentandra oil	Application of ELM for modeling and optimization of biodiesel production	29	ELM	M:O ratio=50:1–70:1CC=0.6–1.0 wt%Rt=4–12 minSS=600–900 rpm	Biodiesel yield 96.19%	ELM is an effective modelling technique	Silitonga et al. (2020)
Waste cooking oil	Use of ELM-RSM and SVM-RSM to optimize biodiesel production process	28	ELM-RSM and SVM-RSM	M:O ratio=3:1–9:1CC=0.5–1.0 wt%RT=50°C–80°CRt=30–90 minSS=300–900 rpm	Biodiesel yield ELM-RSM=96.86%SVM-RSM=95.5%	ELM and SVM showed high estimation capability	Faizollahzadeh Ardabili et al. (2018)
Mountain almond oil	Optimization of biodiesel production by Artificial Bee Colony Algorithm	14	ABC	M:O ratio=4:1–6:1Rt=3–9 min	Biodiesel yield 96.1%	High accuracy optimization	Rostami et al. (2016)
Waste Sunflower oil	Optimization of biodiesel production by ANN	6	ANN	M:O ratio=6:1–712:1CC=5–15 wt%RT=45°C–65°CRt=60–180 min	Biodiesel yield of 92.17%	Product meets ASTM-D6751 and EN-14214 standards	Kolakoti (2020)
Waste cooking oil	Modelling of biodiesel production by ANN and RSM	30	ANN and RSM	M:O ratio=3:1–7:1CC=0.9–1.3 wt%RT=40°C–60°CRt=40–80 min	Biodiesel yield of 94%	ANN outperform RSM	Soji-Adekunle et al. (2019)
Waste domestic cooking oil	Optimizing biodiesel production using GA	55	GA	M:O ratio=6:1–9:1CC=1.0–2.0 wt%RT=20°C–40°CRt=20–40 minSS=500–1000 rpm	Improved biodiesel yield	Quality biodiesel produced	Corral Bobadilla et al. (2018)
Thevetia peruviana seed oil	Optimization of biodiesel	13	ANFIS and RSM	M:O ratio=4.76:1–12:1CC=0.79–	Biodiesel yield ANFIS=99.8%RSM=98.8%	ANFIS performed	Ogaga Ighose et al. (2017)

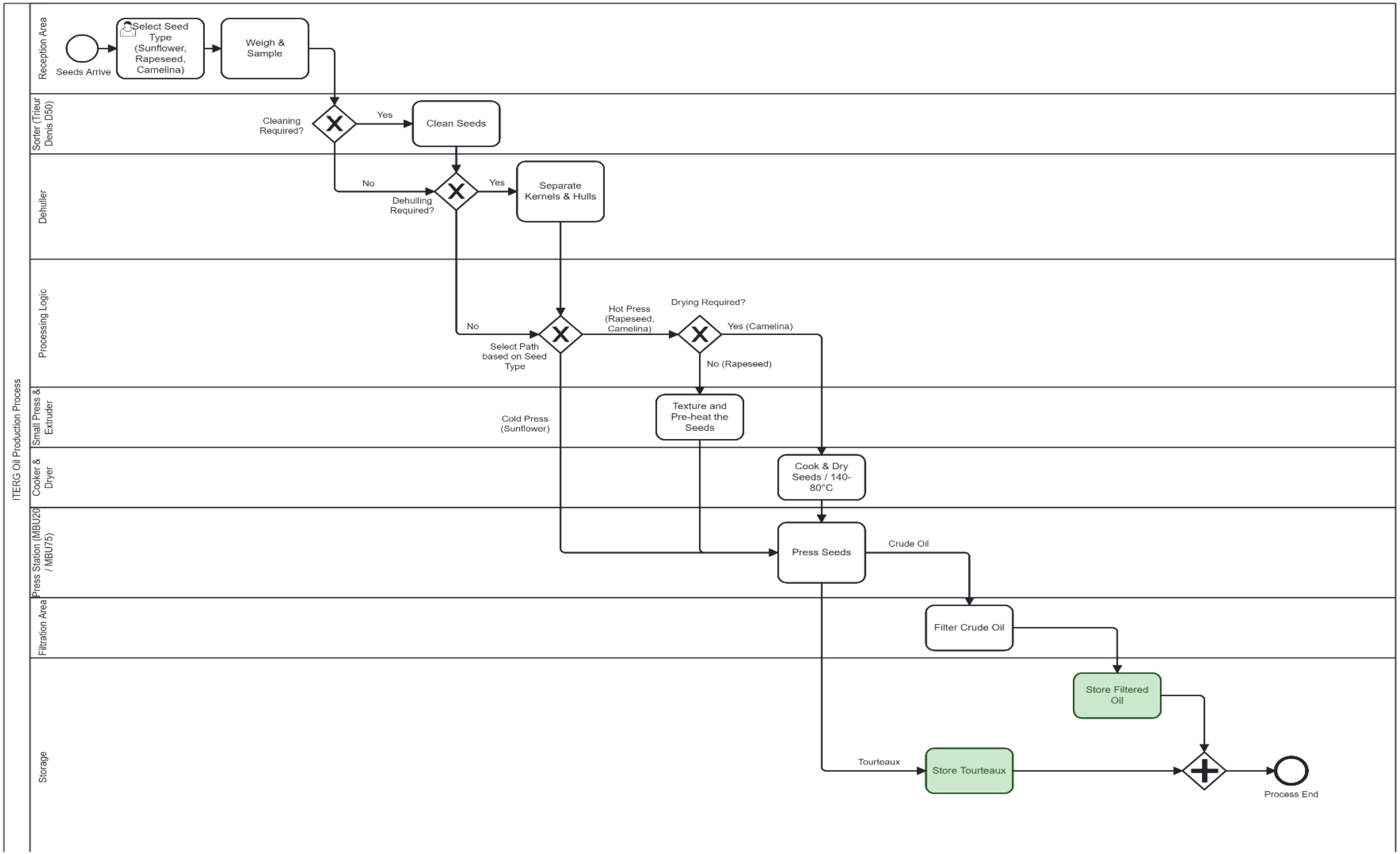
Feedstock	Research aim(s)	No. Of data	ML model used	Model inputs	Model output	Remark	Ref
	production using ANFIS and RSM			2.0 wt%Rt=20–60 min		better than RSM	
Sunflower oil	Optimization of biodiesel production using RSM and ANN-GA	330	RSM and ANN-GA	M:O ratio=6:1–18:1CC=10–20 wt%RT=65°C–75°CRt=360–480 min	Biodiesel yield of 99.2%	ANN-GA more accurate than RSM	Avramović et al. (2015)
Waste sunflower oil	Modelling and optimization of waste sunflower oil conversion into biodiesel	20	RSM	M:O ratio=4:1–6:1CC=0–400 wt%RT=50°C–70°CRt=360–480 min	Biodiesel yield of 96.4%	RSM successfully optimized biodiesel production	Zahed et al. (2021)

Appendix 2: The case studies that related to the ML models. (Awogbemi & Von Kallon, 2023)

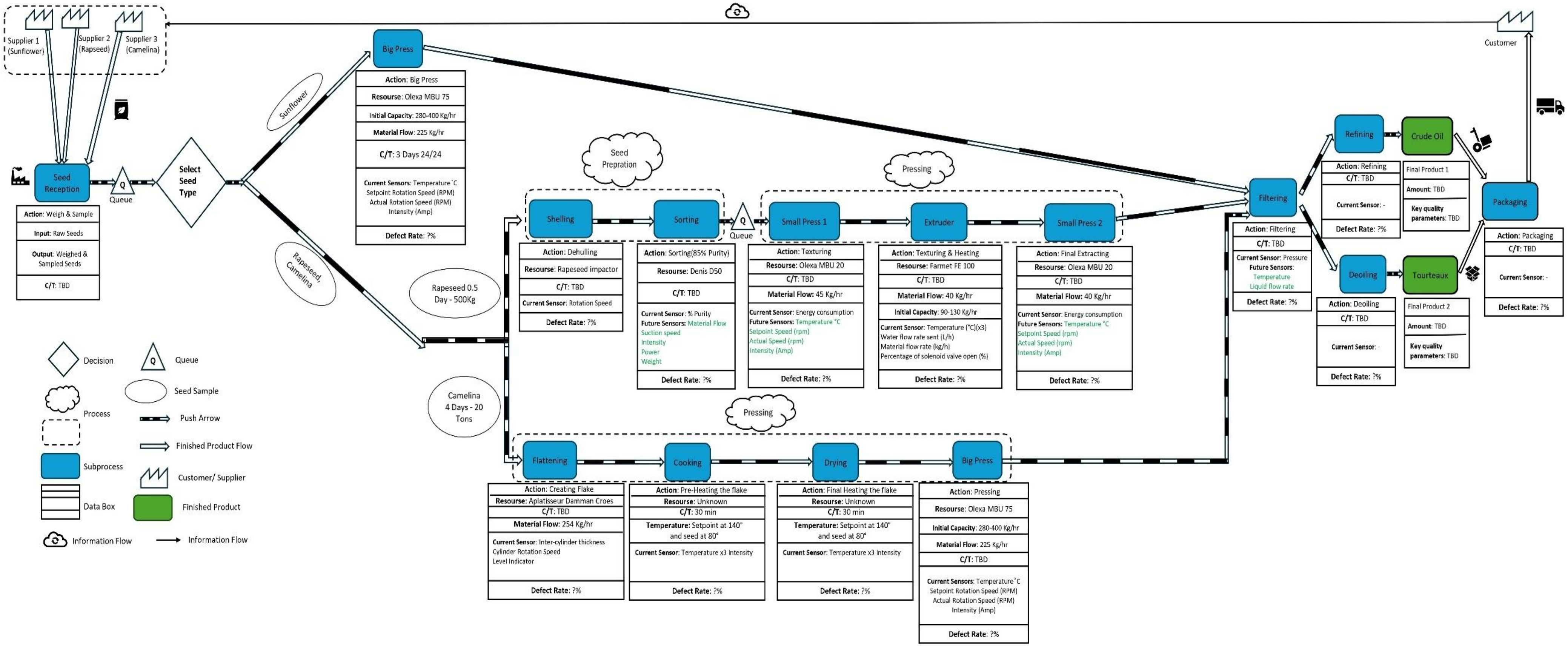
- M:O ratio: Methanol: Oil molar ratio
- CC: Catalyst concentration
- RT: Reaction temperature
- Rt: Reaction time (residence time)
- SS: Agitation speed (stirring speed)
- ANN: Artificial Neural Network
- RSM: Response Surface Methodology
- ANFIS: Adaptive Neuro-Fuzzy Inference System
- GA: Genetic Algorithm
- GWO: Grey Wolf Optimizer
- ELM: Extreme Learning Machine
- SVM: Support Vector Machine
- ABC: Artificial Bee Colony
- R: Pearson correlation coefficient
- R^2: Coefficient of determination
- MSE: Mean Squared Error
- RMSE: Root Mean Squared Error
- APE: Absolute Percentage Error
- MRPD: Mean Relative Percentage Deviation
- MAPE: Mean Absolute Percentage Error
- SEP: Standard Error of Prediction
- SD: Standard Deviation



Appendix 3: General BPMN of ITERG



Appendix 4: The detailed BPMN of ITERG



Appendix 5: VSM of ITERG (3 seed types).

Type	Stage	Initial Capacity	Installed capacity	Reference	Usage	Current parameter measured	Visible/ Recorded/ Handwritten	Mass flow	Parameter to add
Cold Press	Big Press	280 to 400 kg/h	22 kW	Olexa MBU 75	Mechanical Extraction by Pressure	Temperature °c (x2) Setpoint rpm RPM or Hz speed Ampere Intensity	Recorded	225 kg/hour	Material flow rate (kg/h) Product temperature °c Oil and water content (%) Protein (%)
Pressure Cooking	Shelling			Rapeseed impactor	Remove a % of the seed shell	Rotational speed rpm	Recorded		
	Sorter			Denis D50	Sorting the hulls and seeds	% of seed	Recorded (camera)	85% seeds 15% Hulls	
	Small press MBU20	80 to 120 * kg/h	7.5 kW	Olexa MBU 20	Texture the material	Energy consumption Temperature °C Setpoint rpm RPM or Hz speed Amperage	Recorded		45 kg/hour
	Extruder	90 – 130 * kg/h	15 kW	Farmet fe 100	Heat to extract as much oil as possible and texture the material	Temperature (°C)(x3) Water flow rate sent (L/h) Material flow rate (kg/h) solenoid valve open (%)	Recorded	Temperature at 120°	40 kg/h
	Small press MBU20	80 to 120 * kg/h	7.5 kW	Olexa MBU 20	Mechanical extraction by pressing the meal	Energy consumption Temperature °C Setpoint rpm RPM or Hz speed Amperage	Recorded		40 kg/hour
Flattening-cooking-pressure	Flattening			Flatten the seed	Inter-cylinder thickness	Recorded			

					Cylinder speed Level Indicator				
	Cooker			Cook the seed to extract as much oil as possible	Temperature Intensity		Setpoint at 140° and seed at 80°		Liquid flow rate
	Dryer			Dry the seed to remove excess water	Temperature Intensity	Recorded	Setpoint at 140° and seed at 80°		Liquid flow rate
	Big Press	280 to 400 kg/h	22 kW	Mechanical Pressure Extraction	Temperature °c (x2) Setpoint rpm RPM or Hz speed Ampere intensity	Recorded		225 kg/hour	Material Flow-Product Temperature-Oil and Water Content-Protein

Appendix 6: The detailed Processes and Machines of ITERG.

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score
from google.colab import files


print("📁 Veuillez importer votre fichier Excel...")
uploaded = files.upload()
filename = next(iter(uploaded))


df = pd.read_excel(filename)
df.columns = df.columns.str.strip().str.lower()
df = df.loc[:, ~df.columns.str.contains("^unnamed", case=False)]

df.rename(columns={
    "nozzle size": "Nozzle Size",
    "shaft screw": "Shaft Screw Diameter",
    "rotational speed": "Rotational Speed",
    "oil yield": "Oil yield"
}, inplace=True)

df["Oil yield"] = df["Oil yield"].astype(str).str.replace(",",
".").astype(float)
df[["Nozzle Size", "Shaft Screw Diameter", "Rotational Speed"]] = df[
    ["Nozzle Size", "Shaft Screw Diameter", "Rotational Speed"]
].astype(float)


plt.figure(figsize=(6, 4))
corr_matrix = df.corr(numeric_only=True)
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm', fmt=".2f")
plt.title("🔍 Matrice de corrélation")
plt.tight_layout()
plt.show()


X = df[["Nozzle Size", "Shaft Screw Diameter", "Rotational Speed"]]
y = df["Oil yield"]

model = LinearRegression()
model.fit(X, y)
df["Predicted"] = model.predict(X)
df["Error"] = df["Oil yield"] - df["Predicted"]


intercept = model.intercept_
coefs = model.coef_
equation = f"Oil yield = {intercept:.4f}"
for coef, name in zip(coefs, X.columns):
    equation += f" + ({coef:.4f} * {name})"
print("\n📌 Équation de la régression linéaire :\n", equation)
```

```
plt.figure(figsize=(8,5))
plt.plot(y.values, label="Vrai rendement", marker='o')
plt.plot(df["Predicted"].values, label="Prédit (linéaire)", marker='x')
plt.title("Vrai vs Prédit — Régression Linéaire")
plt.xlabel("Échantillon")
plt.ylabel("Rendement (%)")
plt.legend()
plt.grid(True)
plt.tight_layout()
plt.show()


rmse = np.sqrt(mean_squared_error(y, df["Predicted"]))
r2 = r2_score(y, df["Predicted"])
print(f"\n📊 RMSE : {rmse:.4f} | R² : {r2:.4f}")


df.to_excel("oil_yield_with_linear_predictions.xlsx", index=False)
files.download("oil_yield_with_linear_predictions.xlsx")
```

Appendix 7: Python Code of Polynomial Regression, Degree 1.

```
import pandas as pd
import numpy as np
from sklearn.preprocessing import PolynomialFeatures
from sklearn.linear_model import LinearRegression
from sklearn.pipeline import make_pipeline
from sklearn.metrics import mean_squared_error, r2_score
import matplotlib.pyplot as plt
from google.colab import files

print("📁 Importer votre fichier Excel (bardia.xlsx)")
uploaded = files.upload()
filename = next(iter(uploaded))

df = pd.read_excel(filename)
df.columns = df.columns.str.strip().str.lower()
df = df.loc[:, ~df.columns.str.contains("^unnamed", case=False)]

df.rename(columns={
    "nozzle size": "Nozzle Size",
    "shaft screw": "Shaft Screw Diameter",
    "rotational speed": "Rotational Speed",
    "oil yield": "Oil yield"
}, inplace=True)

df["Oil yield"] = df["Oil yield"].astype(str).str.replace(",",
".").astype(float)
df[["Nozzle Size", "Shaft Screw Diameter", "Rotational Speed"]] = df[
    ["Nozzle Size", "Shaft Screw Diameter", "Rotational Speed"]
].astype(float)

X = df[["Nozzle Size", "Shaft Screw Diameter", "Rotational Speed"]]
y = df["Oil yield"]
```

```
model = make_pipeline(PolynomialFeatures(degree=2, include_bias=False),
LinearRegression())
model.fit(X, y)
df["Predicted"] = model.predict(X)
df["Error"] = df["Oil yield"] - df["Predicted"]

poly = model.named_steps["polynomialfeatures"]
linreg = model.named_steps["linearregression"]

features_poly = poly.get_feature_names_out(X.columns)
intercept = linreg.intercept_
coefs = linreg.coef_

equation = f"Oil yield = {intercept:.4f}"
for coef, name in zip(coefs, features_poly):
    equation += f" + ({coef:.4f} * {name})"

print("\n📌 Équation polynomiale (degré 2) trouvée :\n")
print(equation)

rmse = np.sqrt(mean_squared_error(y, df["Predicted"]))
r2 = r2_score(y, df["Predicted"])
print(f"\n📊 RMSE : {rmse:.4f} | R² : {r2:.4f}")

plt.figure(figsize=(8,5))
plt.plot(y.values, label="Vrai rendement", marker='o')
plt.plot(df["Predicted"].values, label="Prédit (Poly Deg 2)", marker='x')
plt.title("Vrai vs Prédit — Régression Polynomiale (Deg=2)")
plt.xlabel("Échantillon")
plt.ylabel("Rendement (%)")
plt.grid(True)
plt.legend()
plt.tight_layout()
plt.show()

df.to_excel("polynomial_oil_yield_predictions.xlsx", index=False)
files.download("polynomial_oil_yield_predictions.xlsx")
```

Appendix 8: Python Code of Polynomial Regression, Degree 2.

```
import pandas as pd
import numpy as np
from sklearn.preprocessing import PolynomialFeatures
from sklearn.linear_model import LinearRegression
from sklearn.pipeline import make_pipeline
from sklearn.metrics import mean_squared_error, r2_score
import matplotlib.pyplot as plt
from google.colab import files

print("📁 Importer votre fichier Excel (bardia.xlsx)")
uploaded = files.upload()
filename = next(iter(uploaded))

df = pd.read_excel(filename)
df.columns = df.columns.str.strip().str.lower()
df = df.loc[:, ~df.columns.str.contains("^unnamed", case=False)]
```

```
df["oil yield"] = df["oil yield"].astype(str).str.replace(",",
".").astype(float)
df[["nozzle size", "shaft screw", "rotational speed"]] = df[
    ["nozzle size", "shaft screw", "rotational speed"]
].astype(float)

X = df[["nozzle size", "shaft screw", "rotational speed"]]
y = df["oil yield"]

model = make_pipeline(PolynomialFeatures(degree=3, include_bias=False),
LinearRegression())
model.fit(X, y)
df["predicted"] = model.predict(X)
df["error"] = df["oil yield"] - df["predicted"]

poly = model.named_steps["polynomialfeatures"]
linreg = model.named_steps["linearregression"]
features_poly = poly.get_feature_names_out(X.columns)
intercept = linreg.intercept_
coefs = linreg.coef_

equation = f"Oil yield = {intercept:.4f}"
for coef, name in zip(coefs, features_poly):
    equation += f" + ({coef:.4f} * {name})"

print("\n📌 Équation polynomiale (degré 3) trouvée :\n")
print(equation)

rmse = np.sqrt(mean_squared_error(y, df["predicted"]))
r2 = r2_score(y, df["predicted"])
print(f"\n📊 RMSE : {rmse:.4f} | R² : {r2:.4f}")

plt.figure(figsize=(8,5))
plt.plot(y.values, label="Vrai rendement", marker='o')
plt.plot(df["predicted"].values, label="Prédit (Poly Deg 3)", marker='x')
plt.title("Vrai vs Prédit — Régression Polynomiale (Deg=3)")
plt.xlabel("Échantillon")
plt.ylabel("Rendement (%)")
plt.grid(True)
plt.legend()
plt.tight_layout()
plt.show()

df.to_excel("poly_deg3_predictions.xlsx", index=False)
files.download("poly_deg3_predictions.xlsx")
```

Appendix 9: Python Code of Polynomial Regression, Degree 3.

```
class SeedParameters:
    def __init__(self, a, ffa_base, ffa_temp_factor, ffa_pressure_factor,
pv_base, pv_temp_factor, pv_speed_factor):
        self._a = a
        self._ffa_base = ffa_base
        self._ffa_temp_factor = ffa_temp_factor
```

```
        self._ffa_pressure_factor = ffa_pressure_factor
        self._pv_base = pv_base
        self._pv_temp_factor = pv_temp_factor
        self._pv_speed_factor = pv_speed_factor

    @staticmethod
    def get_parameters(seed_type):
        if seed_type.lower() == "sunflower":
            return SeedParameters(
                115.0,          # Oil yield constant
                0.5, 0.01, 0.02, # FFA
                2.0, 0.03, 0.01  # PV
            )
        else:
            return SeedParameters(
                110.0,          # Oil yield constant
                0.5, 0.01, 0.02, # FFA
                2.0, 0.03, 0.01  # PV
            )

    @property
    def a(self): return self._a
    @property
    def ffa_base(self): return self._ffa_base
    @property
    def ffa_temp_factor(self): return self._ffa_temp_factor
    @property
    def ffa_pressure_factor(self): return self._ffa_pressure_factor
    @property
    def pv_base(self): return self._pv_base
    @property
    def pv_temp_factor(self): return self._pv_temp_factor
    @property
    def pv_speed_factor(self): return self._pv_speed_factor


class ExtractionResult:
    def __init__(self, oil_yield, ffa, pv, feed_rate, shaft_diameter,
screw_speed_rpm):
        self._oil_yield = oil_yield
        self._ffa = ffa
        self._pv = pv
        self._feed_rate = feed_rate
        self._shaft_diameter = shaft_diameter
        self._screw_speed_rpm = screw_speed_rpm

    @property
    def oil_yield(self): return self._oil_yield
    @property
    def ffa(self): return self._ffa
    @property
    def pv(self): return self._pv
    @property
    def feed_rate(self): return self._feed_rate
    @property
    def shaft_diameter(self): return self._shaft_diameter
    @property
```

```
    def screw_speed_rpm(self): return self._screw_speed_rpm

    def __str__(self):
        return (f"Feed Rate (kg/h): {self.feed_rate:.2f}\n"
                f"Screw Shaft Diameter (mm): {self.shaft_diameter:.2f}\n"
                f"Screw Speed (rpm): {self.screw_speed_rpm:.2f}\n"
                f"Oil Yield: {self.oil_yield:.2f}%\n"
                f"Free Fatty Acid (FFA): {self.ffa:.2f}%\n"
                f"Peroxide Value (PV): {self.pv:.2f} meq/kg")


class OilPressCalculator:
    @staticmethod
    def _hz_to_rpm(screw_speed_hz):
        return 21 + (98 - 21) * (screw_speed_hz - 9) / (50 - 9)

    def calculate(self, seed_type, temperature, screw_speed_hz, pressure,
nozzle_diameter, shaft_diameter, feed_rate):
        params = SeedParameters.get_parameters(seed_type)
        screw_speed_rpm = self._hz_to_rpm(screw_speed_hz)

        # Oil yield calculation
        N = nozzle_diameter
        S = shaft_diameter
        R = screw_speed_rpm

        oil_yield = (params.a
                     - 11.5553840934 * N
                     - 2.5338428226 * S
                     + 0.0739495861 * R
                     + 0.5664946701 * N * N
                     + 0.0875757576 * S * S
                     - 0.0007343996 * R * R
                     + 0.0290671351 * N * S
                     - 0.0032833921 * N * R
                     - 0.0001470588 * S * R
                     - 0.0093517510 * N * N * N
                     + 0.0003050505 * S * S * S
                     + 0.0000029816 * R * R * R
                     + 0.0014366722 * N * N * S
                     + 0.0001123743 * N * N * R
                     - 0.0009848485 * N * S * S
                     - 0.0000084967 * N * S * R
                     - 0.0000019608 * S * S * R
                     + 0.0000014556 * N * R * R)

        # Quality metric calculations
        ffa = params.ffa_base + params.ffa_temp_factor * temperature +
params.ffa_pressure_factor * pressure
        pv = params.pv_base + params.pv_temp_factor * temperature +
params.pv_speed_factor * screw_speed_rpm

        # Ensure realistic bounds
        oil_yield = max(0, min(100, oil_yield))
        ffa = max(0, ffa)
        pv = max(0, pv)
```

```
        return ExtractionResult(oil_yield, ffa, pv, feed_rate,
shaft_diameter, screw_speed_rpm)


class InputValidator:
    def __init__(self):
        pass

    def get_valid_seed_type(self):
        while True:
            seed = input("Enter the seed type (sunflower or Camelina):
").strip()
            if seed.lower() in ["sunflower", "camelina"]:
                return seed
            print("Invalid seed type. Please enter 'sunflower' or
'Camelina'.")

    def get_valid_double(self, prompt, min_val, max_val):
        while True:
            try:
                value = float(input(prompt))
                if min_val <= value <= max_val:
                    return value
                print(f"Value must be between {min_val:.1f} and
{max_val:.1f}. Try again.")
            except ValueError:
                print("Invalid input. Please enter a number.")

    def get_valid_shaft_diameter(self, prompt):
        while True:
            try:
                value = float(input(prompt))
                if value in [8, 11]:
                    return value
                print("Shaft diameter must be 8 or 11 mm. Try again.")
            except ValueError:
                print("Invalid input. Please enter a number (8 or 11).")


class OilPressApp:
    def __init__(self):
        self.calculator = OilPressCalculator()
        self.validator = InputValidator()
        self.model_name = "OLEXA MBU75 Oil Press Model"

    def run(self):
        print(self.model_name)
        print("=" * len(self.model_name))

        seed = self.validator.get_valid_seed_type()
        temp = self.validator.get_valid_double("Enter the pressing
temperature (°C, 30-130): ", 30, 130)
        speed = self.validator.get_valid_double("Enter the motor speed (Hz,
9-50): ", 9, 50)
        pressure = self.validator.get_valid_double("Enter the pressure
(MPa, 10-37): ", 10, 37)
```

```
        nozzle = self.validator.get_valid_double("Enter the nozzle diameter
(mm, 6-12): ", 6, 12)
        shaft = self.validator.get_valid_shaft_diameter("Enter the screw
shaft diameter (mm, 8 or 11): ")
        material_flow = self.validator.get_valid_double("Enter the feed
rate (kg/h, 50-200): ", 50, 200)

        result = self.calculator.calculate(seed, temp, speed, pressure,
nozzle, shaft, material_flow)
        print(f"\nResults for {seed}:")
        print(result)


if __name__ == "__main__":
    app = OilPressApp()
    app.run()
```

Appendix 10: The final test code of big press machine based on the example.

SECTION 10

Contexte Supplémentaire (*)

TOUT élément permettant de mieux apprécier:

- Contexte complet du projet de thèse
- Environnement de recherche
- Spécificités de la candidature

■ REQUIS pour pré-acceptation (*)

Fichier(s) inclus:

• PhD Application-Mousa Aliyari.pptx

PhD Application: Towards a Methodology for Co-constructing Digital and Sociotechnical Commons in Social Organizations

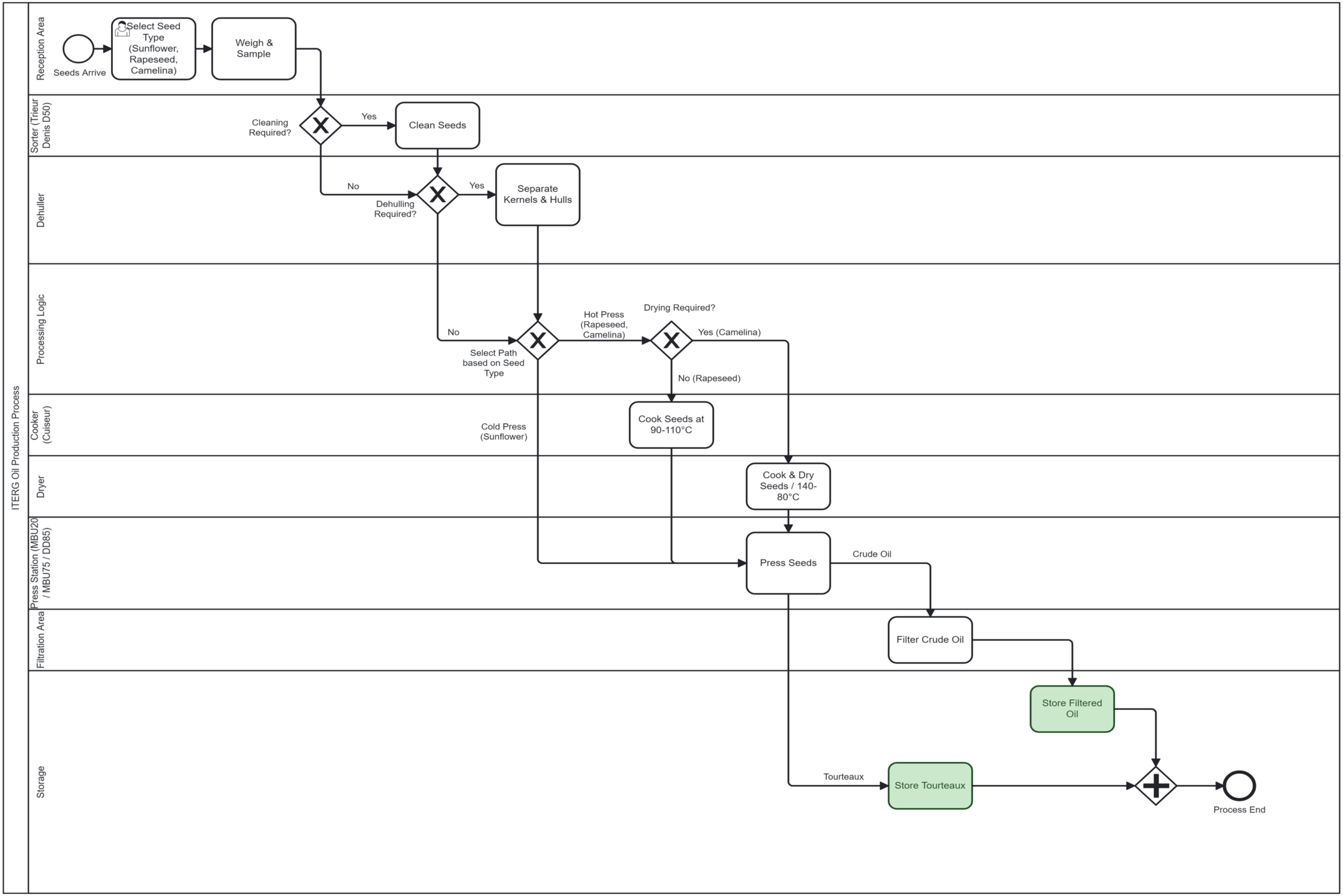
Mousa Aliyari

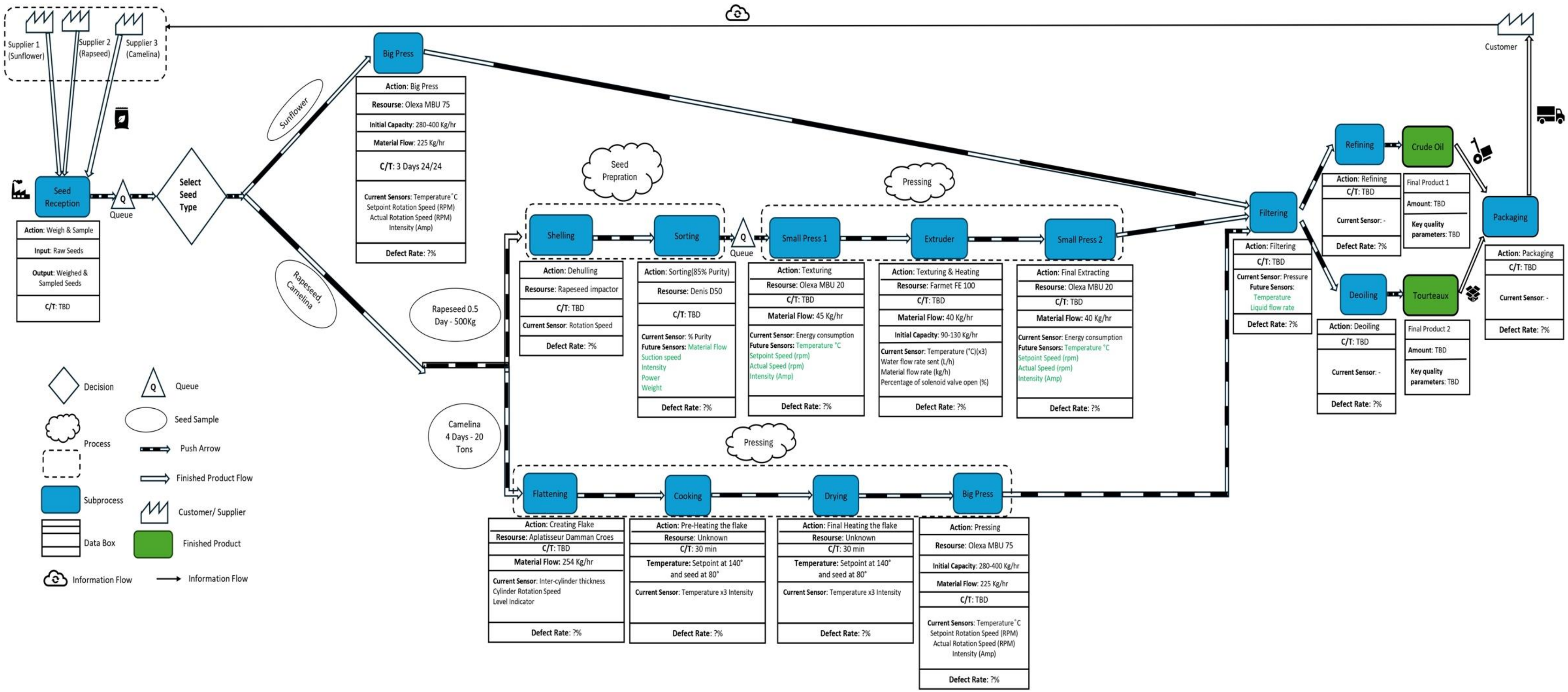
Introduction - Academic Background

- **Education:**
  - Master (M2) of Industrial Engineering (Enterprise Engineering), University of Bordeaux, Bordeaux, France (Sep 2024–Sep 2025) – Ranked 1st in Class.
  - Bachelor of Industrial Engineering, Babol Noshirvani University of Technology, Babol, Iran (Sep 2011–Sep 2015).
- **Certification:** Internal Audit (ISO 9001:2008) from Babol Noshirvani University of Technology & ICIM (2013) – Based on PDCA (Deming cycle)

Professional Experience

- **IMS Laboratory (University of Bordeaux) & ITERG, Bordeaux, France – Intern, Agri-Food Digital Twin (Mar 2025–Aug 2025)**
- **2Nabsh(Real state's advertisement website), Tonekabon – Data Analyst (Nov 2022–Aug 2024)**
- **Delfan Offroad (Automotive industry), Tonekabon – Production Manager (May 2021–Sep 2022)**
- **Sazeh Gostar Tahvieh Araz (Refinery HVAC systems), Asaluyeh – Project Controller (Apr 2019–Apr 2021)**
- **YalitCo (Importing goods), Babol – Industrial Engineer (Jun 2017–Jan 2019)**


ITERG Oil Production Process
Reception Area
Sorter (Trieur Denis D50)
Dehuller
Processing Logic
Cooker (Cuiseur)
Dryer
Press Station (MBU20 / MBU75 / DD85)
Filtration Area
Storage
Seeds Arrive
Select Seed Type (Sunflower, Rapeseed, Camelina)
Weigh & Sample
Cleaning Required?
Yes
Clean Seeds
No
Dehulling Required?
Yes
Separate Kernels & Hulls
No
Select Path based on Seed Type
Hot Press (Rapeseed, Camelina)
Drying Required?
Yes (Camelina)
No (Rapeseed)
Cold Press (Sunflower)
Cook Seeds at 90-110°C
Cook & Dry Seeds / 140-80°C
Press Seeds
Crude Oil
Filter Crude Oil
Store Filtered Oil
Tourteaux
Store Tourteaux
Process End


Supplier 1 (Sunflower)
Supplier 2 (Rapseed)
Supplier 3 (Camelina)
Customer
Seed Reception
Action: Weigh & Sample
Input: Raw Seeds
Output: Weighed & Sampled Seeds
C/T: TBD
Queue
Select Seed Type
Sunflower
Rapeseed, Camelina
Big Press
Action: Big Press
Resourse: Olexa MBU 75
Initial Capacity: 280-400 Kg/hr
Material Flow: 225 Kg/hr
C/T: 3 Days 24/24
Current Sensors: Temperature˚C
Setpoint Rotation Speed (RPM)
Actual Rotation Speed (RPM)
Intensity (Amp)
Defect Rate: ?%
Rapeseed 0.5 Day - 500Kg
Camelina 4 Days - 20 Tons
Seed Prepration
Shelling
Action: Dehulling
Resourse: Rapeseed impactor
C/T: TBD
Current Sensor: Rotation Speed
Defect Rate: ?%
Sorting
Action: Sorting(85% Purity)
Resource: Denis D50
C/T: TBD
Current Sensor: % Purity
Future Sensors: Material Flow
Suction speed
Intensity
Power
Weight
Defect Rate: ?%
Queue
Pressing
Small Press 1
Action: Texturing
Resource: Olexa MBU 20
C/T: TBD
Material Flow: 45 Kg/hr
Current Sensor: Energy consumption
Future Sensors: Temperature °C
Setpoint Speed (rpm)
Actual Speed (rpm)
Intensity (Amp)
Defect Rate: ?%
Extruder
Action: Texturing & Heating
Resourse: Farmet FE 100
C/T: TBD
Material Flow: 40 Kg/hr
Initial Capacity: 90-130 Kg/hr
Current Sensor: Temperature (°C)(x3)
Water flow rate sent (L/h)
Material flow rate (kg/h)
Percentage of solenoid valve open (%)
Defect Rate: ?%
Small Press 2
Action: Final Extracting
Resourse: Olexa MBU 20
C/T: TBD
Material Flow: 40 Kg/hr
Current Sensor: Energy consumption
Future Sensors: Temperature °C
Setpoint Speed (rpm)
Actual Speed (rpm)
Intensity (Amp)
Defect Rate: ?%
Pressing
Flattening
Action: Creating Flake
Resourse: Aplatisseur Damman Croes
C/T: TBD
Material Flow: 254 Kg/hr
Current Sensor: Inter-cylinder thickness
Cylinder Rotation Speed
Level Indicator
Defect Rate: ?%
Cooking
Action: Pre-Heating the flake
Resourse: Unknown
C/T: 30 min
Temperature: Setpoint at 140° and seed at 80°
Current Sensor: Temperature x3 Intensity
Defect Rate: ?%
Drying
Action: Final Heating the flake
Resourse: Unknown
C/T: 30 min
Temperature: Setpoint at 140° and seed at 80°
Current Sensor: Temperature x3 Intensity
Defect Rate: ?%
Big Press
Action: Pressing
Resourse: Olexa MBU 75
Initial Capacity: 280-400 Kg/hr
Material Flow: 225 Kg/hr
C/T: TBD
Current Sensors: Temperature˚C
Setpoint Rotation Speed (RPM)
Actual Rotation Speed (RPM)
Intensity (Amp)
Defect Rate: ?%
Filtering
Action: Filtering
C/T: TBD
Current Sensor: Pressure
Future Sensors:
Temperature
Liquid flow rate
Defect Rate: ?%
Refining
Action: Refining
C/T: TBD
Current Sensor: -
Defect Rate: ?%
Crude Oil
Final Product 1
Amount: TBD
Key quality parameters: TBD
Deoiling
Action: Deoiling
C/T: TBD
Current Sensor: -
Defect Rate: ?%
Tourteaux
Final Product 2
Amount: TBD
Key quality parameters: TBD
Packaging
Action: Packaging
C/T: TBD
Current Sensor: -
Defect Rate: ?%
Decision
Queue
Process
Seed Sample
Push Arrow
Finished Product Flow
Subprocess
Customer/ Supplier
Data Box
Finished Product
Information Flow
Information Flow

Key Projects

- **Digital Twin for Sustainable Aviation Fuel Supply Chain, University of Bordeaux, Bordeaux, France (2025):**
  - Simulated SAF supply chain using AnyLogic, supporting EU sustainability goals.
  - Relevant: Demonstrates ability to model complex systems.
- **MBSE for Digital Twin Systems, University of Antwerp & Bordeaux, Belgium/France (2024):**
  - Developed harbour infrastructure digital twin using OpenModelica.

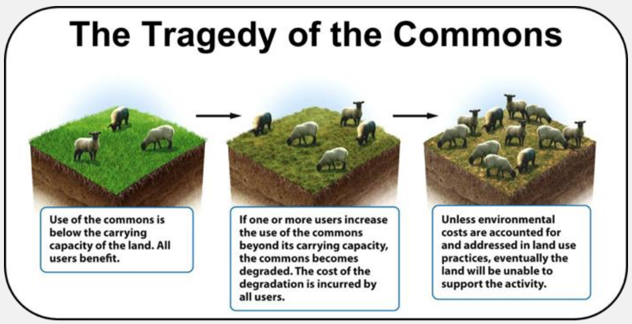
Skills

Programming: Java, C++, Python, R – Used in data analysis and simulation projects for efficient tool development.

Software: AnyLogic, OpenModelica, SCADA LAquis, AutoCAD, Microsoft Office, Microsoft Project – Expertise in modeling and prototyping digital twins, essential for experimenting with commons in the PhD.

Engineering: Project Management, Supply Chain Management, Lean Manufacturing, Data Analysis, Six Sigma, Kaizen, 5S – Proven in professional roles for continuous improvement and participatory design, aligning with PDCA cycles and user-centered co-construction.

A quick brief of “Governing the commons” (Ostrom, 1990)

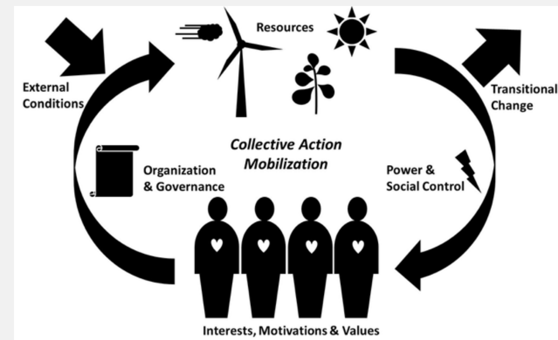


sustainable-environment.org.uk

The tragedy of the commons

mindhealth.com.au

The prisoner's dilemma game



(sterling, et al. 2020)

The logic of collective action

Design principles illustrated by long-enduring CPR institutions (Chapter 3)

1. **Commons need to have clearly defined boundaries.** (Collecting data – Defining the entities and the relationships – Course : Enterprise Modelling - Master)
2. **Rules should fit local circumstances.** (Creating rules, guidelines, and policy in the agoras)
3. **Participatory decision-making is vital.** (Agora/Agile/Scrum – Control Project Experience) (Zanjera)
4. **Commons must be monitored.** (PDCA – ISO 9001:2008)
5. **Sanctions for those who abuse the commons should be graduated.** (Smooth guidelines)
6. **Conflict resolution should be easily accessible.** (Agora – Act in PDCA–Flexibility in Control Project)
7. **Commons need the right to organise.** (Nova Scotia)
8. **Commons work best when nested within larger networks.** (Proof of concepts – Internship)(Meta)

Action 1: Observation and Continuous Collection

1. **Define Boundaries and Participants (Design Principle 1: Clea**

Collecting the data with surveys (by using google forms, etc

2. **Incorporate Contingent Strategies and Norms (Com**

By starting with anonymous tools (e.g., online forms)

3. **Use Low-Cost Monitoring and Iteration (Design P**

Begin small (e.g., pilot in one department) to test and

4. **Ethical and Facilitative Regime (External Variables f**

Ensure GDPR/consent to avoid fragility (e.g., like Nova Scoti

rules)

My last professional experience: **Creating online surveys, analysing the users demands, and running the beta versions of some applications**

Action 2: Co-construction, Experimentation and Capitalization

1. **Establish Collective-Choice Arenas (Design Principle 3: Collectiv**

Using agoras and scrum as low-cost forums for users to discuss

2. **Incorporate Monitoring and Graduated Sanctions (Prin**

Voting in the living labs for the guidelines.

3. **Iterative PDCA with Contingent Strategies (Incremen**

Testing prototypes in small pilots (e.g., one digital tool), u

4. **Address Supply and Commitment (Problems from Ch**

Motivating via shared benefits (e.g., "Better commons mean

conflict-resolution (Principle 6: e.g., mediated discussions) to pr

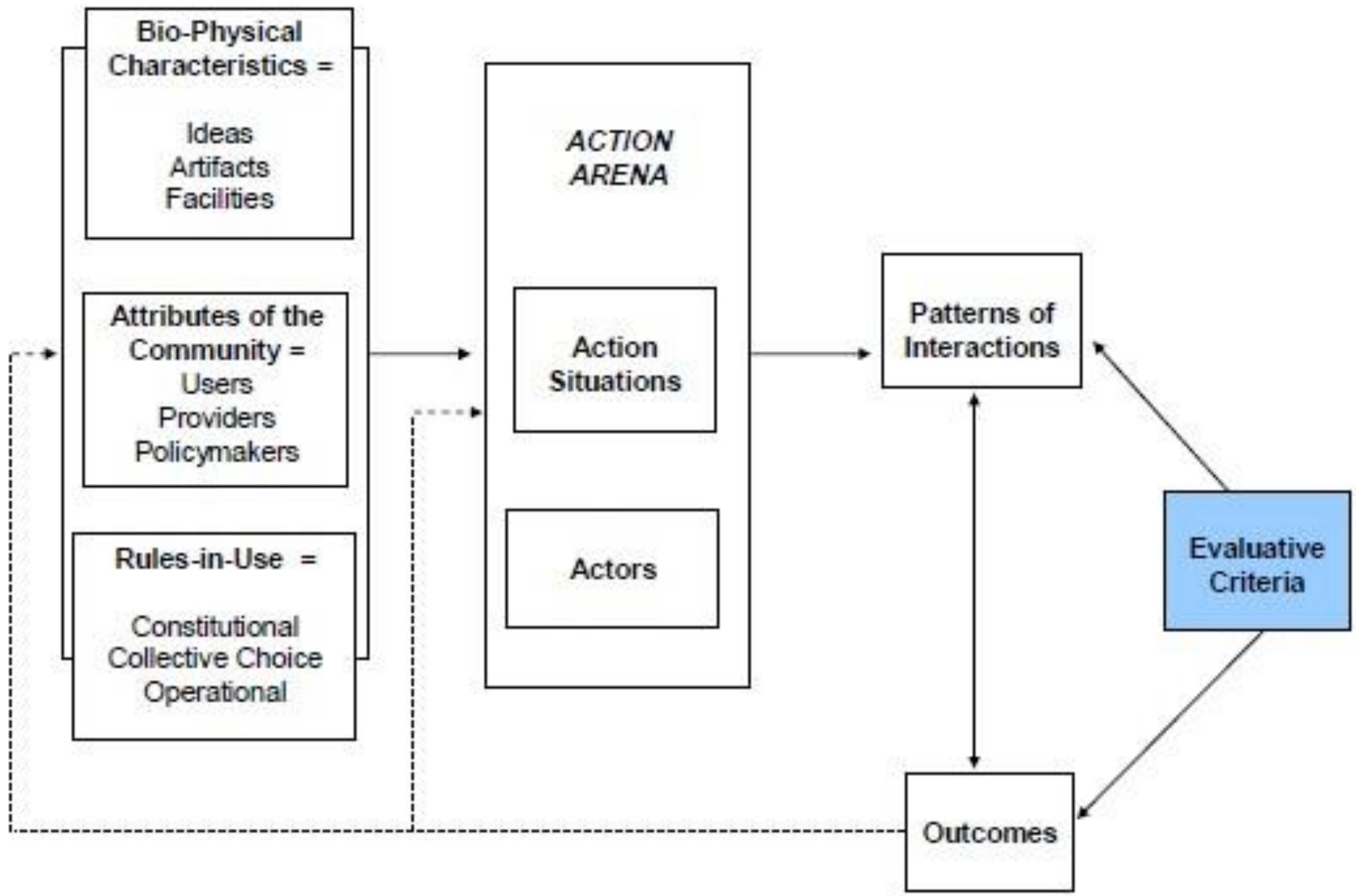
cases.

Using **PDCA** (Like ISO 9001) for testing and getting feedbacks from the users. / Creating the conceptual and pilot **prototypes** like the internship project

Action 3: Consolidation and Generalization

1. **Evaluate Using Ostrom’s Framework (Benefits/C**
2. **Build Nested Enterprises and Autonomy (P**
3. **Formalize Incremental Change (From Chapt**
4. **Disseminate with Conflict-Resolution in Mind (Pr**

Evaluating the final variables like Project Controlling in the HVAC system of the refinery / Creating a proof of concept of the final results and developing the model like the internship project



Hess & Ostrom (2007)