MSAI 508 – Natural Language Processing

Assignment #4: Identify Keywords, Search for RRL and make Matrix.

I. **RESEARCH TOPIC**
Multilingual Chatbot for Industrial Robotics Support

II. **KEYWORDS and SYNONYMS SEARCH FOR RELEVANT LITERATURE WITH BOOLEAN OPERATORS**

KEYWORDS SEARCH	Year Range	NUMBER OF HITS
General Search Queries:		
("Multilingual Chatbot" OR "Multilingual Virtual Assistant") AND ("Industrial Robotics" OR "Factory Automation")	2019 - 2025	**3**
("Chatbot" OR "Conversational AI") AND ("Multilingual" OR "Cross-Language") AND ("Industrial" OR "Manufacturing")	2019 - 2025	**4,310**
("Industrial Robotics" OR "Manufacturing Automation") AND ("Chatbot" OR "Virtual Assistant") AND ("Natural Language Processing" OR "NLP")	2019 - 2025	**306**
("Multilingual NLP" OR "Cross-Language NLP") AND ("Technical Support" OR "Troubleshooting") AND ("Industrial Robots")	2019 - 2025	**1**
("Conversational AI" OR "AI Chatbot") AND ("Manufacturing" OR "Factory") AND ("Multilingual" OR "Machine Translation")	2019 - 2025	**1,300**
Focused on NLP and Chatbot Development		
("Natural Language Processing" OR "NLP") AND ("Multilingual Chatbot" OR "Multilingual AI") AND ("Industry 4.0" OR "Smart Manufacturing")	2019 - 2025	**26**
("Speech Recognition" OR "Voice Assistant") AND ("Manufacturing" OR "Industrial Robotics") AND ("Multilingual AI")	2019 - 2025	**9**
("BERT" OR "Transformer Models") AND ("Multilingual NLP" OR "Cross-Language NLP") AND ("Technical Support")	2019 - 2025	**15**
For Performance and Evaluation Studies		
("Chatbot Evaluation" OR "Conversational AI Performance") AND ("Multilingual" OR "Cross-Language") AND ("Industrial Application")	2019 - 2025	**0**
("Machine Translation" OR "Multilingual NLP") AND ("Robotics Assistance" OR "Factory Worker Support")	2019 - 2025	**1**

KEYWORDS SEARCH	Year Range	NUMBER OF HITS
General Search Queries		
("Multilingual Chatbot" OR "Multilingual Virtual Assistant") AND ("Industrial Robotics" OR "Factory Automation")	2019 - 2025	**3**
("Chatbot" OR "Conversational AI") AND ("Multilingual Support" OR "Cross-Language Assistance") AND ("Industrial Robotics" OR "Manufacturing Processes")	2019 - 2025	**25**

("Industrial Robotics" OR "Manufacturing Automation") AND ("Chatbot" OR "Virtual Assistant") AND ("Natural Language Processing" OR "NLP") AND ("Support" OR "Troubleshooting")	2019 - 2025	**289**
("Multilingual NLP" OR "Cross-Language NLP") AND ("Technical Support" OR "Troubleshooting") AND ("Industrial Robots")	2019 - 2025	**1**
("Conversational AI" OR "AI Chatbot") AND ("Manufacturing" OR "Factory") AND ("Multilingual" OR "Machine Translation") AND ("Technical Support" OR "Operator Assistance")	2019 - 2025	**101**
Focused on NLP and Chatbot Development		
("Natural Language Processing" OR "NLP") AND ("Multilingual Chatbot" OR "Multilingual AI") AND ("Industry 4.0" OR "Smart Manufacturing")	2019 - 2025	**26**
("Speech Recognition" OR "Voice Assistant") AND ("Manufacturing" OR "Industrial Robotics") AND ("Multilingual AI")	2019 - 2025	**9**
("BERT" OR "Transformer Models") AND ("Multilingual NLP" OR "Cross-Language NLP") AND ("Technical Support")	2019 - 2025	**15**
For Performance and Evaluation Studies		
("Chatbot Evaluation" OR "Conversational AI Performance") AND ("Multilingual" OR "Cross-Language") AND ("Industrial Application")	2019 - 2025	**0**
("Machine Translation" OR "Multilingual NLP") AND ("Robotics Assistance" OR "Factory Worker Support")	2019 - 2025	**1**

KEYWORDS SEARCH	Year Range	NUMBER OF HITS
General Search Queries		
("Chatbot" OR "Conversational AI") AND ("Multilingual" OR "Cross-Language") AND ("Industrial Robotics" OR "Manufacturing Automation") AND ("Natural Language Processing" OR "NLP")	2019 - 2025	**58**
("Industrial Robotics" OR "Factory Automation") AND ("Chatbot" OR "Virtual Assistant") AND ("Multilingual NLP" OR "Machine Translation") AND ("Human-Robot Interaction")	2019 - 2025	**25**
("Conversational AI" OR "AI Chatbot") AND ("Manufacturing" OR "Factory") AND ("Multilingual Support" OR "Cross-Language Communication") AND ("Technical Troubleshooting")	2019 - 2025	**0**

TITLE AND AUTHORS	PUBLICATION VENUE AND YEAR	RESEARCH PROBLEM AND OBJECTIVES	METHODOLOGY USED	KEY FINDINGS AND CONTRIBUTIONS	RESULTS	RECOMMENDATION/ CONCLUSION
□ Title: *A Speech-Enabled Virtual Assistant for Efficient Human–Robot Interaction in Industrial Environments*	**□ Journal: *The Journal of Systems & Software* □ Year: 2023**	**□ Problem: Lack of efficient human-robot interaction (HRI) in industrial settings, which affects productivity and user engagement. □ Objective: To develop and evaluate a natural language-**	**□ Architecture: Client-server-based VA with a language service and industrial robot service. □ Intent Recognition: Fine-tuning of BERT (Bidirectional Encoder Representations from**	**□ The VA successfully supports real-time industrial robot operation through natural language commands.**	**Completion Rate: 0.60 to 0.76, depending on the task complexity. munication Time: 15.28s to 24.70s, influenced by error rates. r Rates: Intent and slot errors increase under high ambient noise (69 dB), affecting performance**	**□ Future work should focus on reducing ambient noise effects and improving speech recognition accuracy. □ The study confirms that a natural language-enabled VA enhances HRI in industrial**

Authors: Chen Li, Dimitris Chrysostomou, Hongji Yang		enabled virtual assistant (VA) named *Max* to enhance communication between human operators and industrial robots	Transformers) for user intent identification. Deployment: Implemented in Aalborg University’s learning factory, using Raspberry Pi 4 for voice support. Evaluation Metrics: Intent error rate (IER), slot error rate (SER), task success rate (TSR), communication time, and parallel request handling	Demonstrates high accuracy in intent recognition but faces challenges due to ambient noise and user accents. Enables humanized communication, improving user engagement and task efficiency in manufacturing settings		environments, but additional refinement is needed for real-world factory deployment
TITLE AND AUTHORS	PUBLICATION VENUE AND YEAR	RESEARCH PROBLEM AND OBJECTIVES	METHODOLOGY USED	KEY FINDINGS AND CONTRIBUTIONS	RESULTS	RECOMMENDATION/ CONCLUSION
Title: *Assessment of a Large Language Model-Based Digital Intelligent Assistant in Assembly Manufacturing* **Authors:** Silvia Colabianchi, Francesco Costantino, Nicolò Sabetta	Journal: *Computers in Industry* Year: 2024	Problem: The study addresses the lack of intelligent assistants in manufacturing that can support assembly workers in reducing cognitive workload and improving operational efficiency. Objective: To evaluate the applicability of a Large Language Model (LLM)-based Digital Intelligent Assistant (DIA) in an industrial assembly process through a multi-dimensional evaluation criteria, including technical robustness, usability, and impact on operators	Experimental Design: Laboratory-based qualitative experiment in a real assembly manufacturing setting. Independent Variable: Use of a Digital Intelligent Assistant (DIA) for assembly tasks. Dependent Variables: • Technical robustness (accuracy and reliability of responses). • Cognitive workload (NASA TLX index). • Usability and user experience (System Usability Scale, Chatbot Usability Questionnaire, and User Experience Questionnaire). • Process performance (assembly time, error rates, and defect analysis). Technology Used: LLM-based chatbot with GPT-4 Turbo, FAISS retriever, and Google Speech Recognition	The DIA improved operator experience by reducing cognitive workload and enhancing process efficiency. 93% of the chatbot's responses were accurate, with 97% of those being exhaustive for operators' questions. Error Reduction: The chatbot helped reduce human errors in assembly tasks, leading to fewer defects and higher product quality. Challenges: Some responses contained hallucinations (3%), and the system struggled in noisy environments	Reduction in Assembly Time: The DIA significantly reduced assembly time and improved process efficiency. Cognitive Workload: Operators reported a lower cognitive load, improving their overall experience. Usability Score: The DIA received an average System Usability Scale (SUS) score of 80, indicating a good usability rating	Future improvements should focus on reducing hallucinations, enhancing speech recognition in noisy environments, and adapting the chatbot to different operator profiles. Further testing in real-world industrial environments is needed to validate findings. The study demonstrates the potential of LLM-based DIAs to improve manufacturing efficiency and worker experience, supporting Industry 4.0 and 5.0 transitions
TITLE AND AUTHORS	PUBLICATION VENUE AND YEAR	RESEARCH PROBLEM AND OBJECTIVES	METHODOLOGY USED	KEY FINDINGS AND CONTRIBUTIONS	RESULTS	RECOMMENDATION/ CONCLUSION
Title: *ToD4IR: A Humanised Task-Oriented Dialogue*	➢ Journal: *IEEE Access* ➢ Year: 2022 ➢	Problem: Existing task-oriented dialogue (ToD) systems for industrial robots are limited due to a	Dataset: Introduced IRWoZ (Industrial Robots Wizard-of-Oz dataset), covering four	First industrial robot dialogue dataset (IRWoZ) for training NLP models in manufacturing.	➢ BLEU Scores: ToD4IR-GPT2-large achieved BLEU-1 to BLEU-4 scores of 0.6013, 0.5349, 0.5032,	➢ The system improves task efficiency and human-robot communication, making

System for Industrial Robots Authors: Chen Li, XiaoChun Zhang, Dimitrios Chrysostomou, Hongji Yang		lack of domain-specific conversational datasets and insufficient human-like interaction capabilities. Objective: To develop ToD4IR, a humanized task-oriented dialogue system that improves human-robot interaction (HRI) in industrial environments using a novel dataset (IRWoZ), enhancing both task efficiency and user experience	industrial robotics domains with 401 dialogues. Models: Developed ToD4IR using GPT-2 and GPT-Neo models for task-oriented conversations. Evaluation Metrics: Used BLEU scores (BLEU 1-4) for dialogue performance, along with human evaluation assessing engagement, fluency, and knowledgeability	ToD4IR model outperforms other task-oriented dialogue systems in dialogue state tracking, dialogue act generation, and response generation. Incorporates small talk and human-like conversation strategies, enhancing natural language interaction between workers and industrial robots	and 0.4763, outperforming other models. ➢ Human Evaluation: Rated high on engagement, fluency, and knowledgeability by domain experts and factory workers ➢	industrial robots more user-friendly. ➢ Future work should focus on expanding the dataset, improving adaptability to different industrial scenarios, and enhancing multilingual capabilities ➢
TITLE AND AUTHORS	**PUBLICATION VENUE AND YEAR**	**RESEARCH PROBLEM AND OBJECTIVES**	**METHODOLOGY USED**	**KEY FINDINGS AND CONTRIBUTIONS**	**RESULTS**	**RECOMMENDATION/ CONCLUSION**
Title: *Responsible Multilingual Large Language Models: A Survey of Development, Applications, and Societal Impact* Authors: Junhua Liu, Bin Fu	• Preprint Repository: *arXiv* • Year: 2024 •	Problem: The development of Multilingual Large Language Models (MLLMs) is challenged by linguistic diversity, low-resource languages, and deployment complexities. Objective: To provide a comprehensive framework for developing and optimizing MLLMs, addressing issues like data pre-processing, multilingual training, and societal impact	➢ Pipeline Approach: Presents a step-by-step guide for MLLM development, from data preprocessing to deployment. ➢ Case Study: Uses Llama2 to evaluate curriculum learning, tokenization, and multilingual fine-tuning strategies. ➢ Interdisciplinary Analysis: Combines technical, linguistic, and cultural perspectives to assess MLLM performance ➢	➢ 88.38% of world languages are low-resource, affecting over a billion speakers. ➢ Optimization techniques like curriculum learning, tokenization, and sampling improve multilingual model performance. ➢ Applications in customer service, search engines, and machine translation show practical benefits of MLLMs ➢	MLLMs improve linguistic inclusivity, but low-resource languages remain underserved. Cross-lingual transfer learning helps bridge gaps in underrepresented languages. Ethical concerns like bias, cultural adaptation, and fairness remain significant challenges	➢ Further research should focus on enhancing linguistic diversity, reducing bias, and adapting models for real-world applications. ➢ Calls for standardized evaluation benchmarks to measure MLLM effectiveness across languages. ➢ Stresses the importance of responsible AI practices in multilingual model deployment

TITLE AND AUTHORS	PUBLICATION VENUE AND YEAR	RESEARCH PROBLEM AND OBJECTIVES	METHODOLOGY USED	KEY FINDINGS AND CONTRIBUTIONS	RESULTS	RECOMMENDATION/ CONCLUSION
• ? Title: *Inferring Multilingual Domain-Specific Word Embeddings From Large Document Corpora* • ? Authors: L. Cagliero, M. La Quatra •	• ? Journal: *IEEE Access* • ? Year: 2021 •	• ? Problem: Many low-resource languages lack sufficient domain-specific corpora for training NLP models. • ? Objective: Develop a method to adapt general-purpose multilingual word embeddings to a domain-specific context while improving cross-lingual alignment •	• ? Word Embeddings Model: Uses Word2Vec as the core embedding model for multilingual adaptation. • ? Two-Step Inference Process: • (1) Automatic identification of domain-specific words. • (2) Supervised inference of new word vectors in the domain-specific hyperspace of the target language. • ? Bilingual Alignment Approach: Aligns multilingual embeddings using supervised bilingual lexicon-based methods •	? First benchmark dataset combining general-purpose, multi-domain, and multilingual word embeddings. ? Demonstrates effective domain adaptation of multilingual word embeddings. ? Enhances low-resource language representation in NLP applications	? Deep neural network models outperform linear models in multilingual word retrieval tasks. ? Domain-specific embeddings significantly improve accuracy compared to general-purpose embeddings. ? Cross-lingual alignment proves effective, enabling better NLP performance for low-resource languages	? Future work should explore contextualized embeddings for even better performance. ? Encourages further research into cross-lingual domain adaptation for industry-specific applications. ? Suggests expanding datasets to improve model generalizability
TITLE AND AUTHORS	PUBLICATION VENUE AND YEAR	RESEARCH PROBLEM AND OBJECTIVES	METHODOLOGY USED	KEY FINDINGS AND CONTRIBUTIONS	RESULTS	RECOMMENDATION/ CONCLUSION
? Title: *Natural-Language-Instructed Robot Execution Systems: A Survey* ? Authors: Multiple authors	• ? Journal: AI Journal • ? Year: 2024 •	• ? Problem: Many industrial robotic systems lack natural language (NL) capabilities, making them difficult for non-expert users to operate. • ? Objective: To survey existing natural-language-instructed robot execution systems, categorize their functionalities, and propose directions for improvement in industrial applications •	• ? Comprehensive Literature Review: Analyzes existing NL-based robot control systems in manufacturing and automation. • ? Categorization of Systems: Breaks down NL-assisted robotic execution into control, interactive execution, training, and social execution systems. • ? Comparative Analysis: Evaluates different methods of integrating NLP into robotics •	? Framework for NL-Based Robotic Execution: Establishes a taxonomy for understanding how robots process NL commands. ? Application in Industry: Discusses task-oriented dialogue systems for industrial automation. ? Identifies Challenges: Highlights accuracy, adaptability, and user intent recognition as key areas for improvement	? NL-assisted robots enhance usability in industrial settings but require more advanced contextual understanding. ? Hybrid systems (rule-based + deep learning) perform better in understanding and executing complex instructions. ? Multilingual support remains limited, requiring cross-lingual NLP improvements	? Further research should focus on multilingual NLP for industrial robotics. ? Adaptive learning and user feedback mechanisms should be integrated to improve real-time interaction with factory workers. ? Hybrid NLP architectures combining rule-based logic and machine learning are suggested for optimal performance

TITLE AND AUTHORS	PUBLICATION VENUE AND YEAR	RESEARCH PROBLEM AND OBJECTIVES	METHODOLOGY USED	KEY FINDINGS AND CONTRIBUTIONS	RESULTS	RECOMMENDATION/ CONCLUSION
• Title and Authors: "An Interactive Framework of Cross-Lingual NLU for In-Vehicle Dialogue" Authors: Xinlu Li, Liangkuan Fang, Lexuan Zhang, Pei Cao	• Publication Venue and Year: Journal: *Sensors* Year: 2023	• Addresses the challenge of cross-lingual natural language understanding (NLU) in in-vehicle dialogue systems. • Aims to develop an interactive attention-based contrastive learning (IABCL) framework for better multilingual NLU performance. • Seeks to improve intent detection and slot filling in multilingual dialogue settings. •	• Developed a contrastive learning-based encoder and an interactive attention-based decoder. • Constructed a multilingual in-vehicle dialogue (MIvD) dataset with Chinese, Arabic, Japanese, and English. • Utilized mBERT and XLM-R as pre-trained models for cross-lingual transfer learning. • Compared the IABCL framework with baseline models like CoSDA-ML, Multilingual-ZeroShot, and GL-CLEF. •	Introduced a new dataset (MIvD) for multilingual in-vehicle dialogue systems. Proposed a contrastive learning framework that improves cross-lingual NLU by aligning intent detection and slot filling. Showed that interactive attention mechanisms enhance multilingual model performance.	The IABCL framework outperformed existing models in multilingual NLU tasks. Achieved higher intent accuracy, slot F1 score, and overall accuracy than baseline models across different languages. Demonstrated better performance in language transfer tasks, particularly between Chinese and Japanese due to linguistic similarities.	The study highlights the importance of cross-lingual transfer learning and interactive attention mechanisms in multilingual dialogue systems. Future research should explore more languages and refine negative sample selection in contrastive learning to improve model performance further.

TITLE AND AUTHORS	PUBLICATION VENUE AND YEAR	RESEARCH PROBLEM AND OBJECTIVES	METHODOLOGY USED	KEY FINDINGS AND CONTRIBUTIONS	RESULTS	RECOMMENDATION/ CONCLUSION
Title and Authors: "Large Language Models for Manufacturing" Authors: Yiwei Li, Huaqin Zhao, Hanqi Jiang, Yi Pan, Zhengliang Liu, Zihao Wu, Peng Shu, Jie Tian, Tianze Yang, Shaochen Xu, Yanjun Lyu, Parker Blenk, Jacob Pence, Jason Rupram, Eliza Banu, Ninghao Liu, Linbing Wang, Wenzhan Song, Xiaoming Zhai, Kenan Song, Dajiang Zhu, Beiwen Li, Xianqiao Wang, Tianming Liu	Publication Venue and Year: arXiv Preprint Date: October 30, 2024	Investigates the role of Large Language Models (LLMs) in the manufacturing industry. Explores how LLMs can optimize manufacturing processes, including robotics engineering, quality control, supply chain management, and engineering design. Examines how LLMs enhance robot control systems and facilitate knowledge transfer in smart factories. Evaluates LLM performance in automating text-heavy tasks, such as engineering documentation, coding, and industrial chatbot interactions.	Conducted case studies and evaluations of LLMs (e.g., GPT-4V) in various manufacturing tasks. Analyzed LLM capabilities in robotic task automation, engineering programming, knowledge management, and multilingual support. Explored applications of generative AI in Industry 4.0 and smart factories, including real-time decision-making, predictive analytics, and engineering education.	LLMs can automate engineering support systems, including multilingual chatbot-based assistance for industrial robotics. LLMs enhance robotic task execution by processing natural language commands for machine control. Multimodal LLMs (text + vision models) improve robot perception and interaction capabilities. LLMs streamline technical documentation and engineering workflows, reducing manual effort in industrial automation.	LLMs outperform traditional automation tools in tasks like robotic control support, engineering documentation, and chatbot-based troubleshooting. Real-time chatbot-based assistance helps industrial engineers interact with robotic systems more efficiently. Multilingual capabilities allow for better cross-border collaboration in industrial settings.	LLMs should be further refined to improve domain-specific knowledge for industrial applications. Integrating LLMs with robotics platforms can enhance human-robot collaboration and automated troubleshooting. Future research should focus on fine-tuning LLMs for robotics-specific terminology and real-time language translation in manufacturing environments.