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Translating AI Exposure Indices into a Work-based Training Framework for Supply Chain and Maritime Industry

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Abstract

AI exposure indices provide a systematic work activity-level diagnostic tool that moves beyond generic automation risk assessments to identify which specific work activities within industries are most susceptible to AI-driven displacement or augmentation. This granularity is essential for designing a targeted and role-specific training intervention framework. Without such measurement, organizations risk investing in broad upskilling initiatives that fail to address the precise capability gaps that AI adoption creates, leaving organizations poorly equipped to capture the operational benefits of AI while managing its workforce disruption. In this paper, we present an *AI training priority index* for work-based activities in the supply chain and maritime industry.

Keywords
Artificial Intelligence, AI exposure, supply chain, maritime and AI transition training.

1. Introduction
Rapid advances in Artificial Intelligence (AI) have intensified concerns about job displacement, with published estimates of AI-exposed occupations ranging from 14% to 70% (Colombo et al. 2024; Gimbel et al. 2025; Tamayo et al. 2025). "AI exposure" is a well-researched metric that quantifies the degree to which specific occupational activities or tasks align with current AI capabilities. Foundational research on AI exposure indices (Acemoglu et al. 2021; Felten et al. 2021) has established AI exposure indices, providing a macro-economic lens for predicting overall labor market shifts and potential workforce displacement. While existing research confirms that AI exposure is real, its distribution across occupations is uneven – current research identifies *which* occupations are exposed to AI, yet the question of *how* this exposure should guide workforce upskilling efforts remains an open question. For example, an exposure index of 0.8 for "operational planning" provides little guidance for a supply chain manager or transportation manager on what type of AI-related training the worker may need (prompt engineering, AI output evaluation, regulatory compliance evaluation, etc.). In sum, there is a lack of granular industry-specific mechanisms to translate AI exposure indices into practical workforce training framework. This study complements a growing body of research examining

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detailed data from generative AI models to measure AI's impact on different aspects of work-based activities within organizations.

1.1 Objectives

The objective of this research is to bridge this disconnect through the development of an *AI training priority index* based on the O*NET occupational classification and the existing large language models' (LLMs) usage data in different work-related tasks. We apply this index to a set of 151 key work activities in 31 main occupations in the supply chain and maritime industry. The significance of this study is twofold. Academically, it extends the utility of labor economics indices into the realm of supply chain and maritime industry. Practically, it provides a roadmap for supply chain and maritime firms to proactively set their training priorities for AI-driven workforce transition while strategically managing human resources.

2. Literature Review

2.1. *AI Exposure Indices: Foundations and Measurement*

The measurement of occupational exposure to artificial intelligence has emerged as a critical research domain for understanding labor market transition under this new technology. The AI exposure measurement has matured considerably, with multiple studies capturing the impact through the AI capabilities or its user applications. Foundational work by Acemoglu et al. (2021) and Felten et al. (2021) established task-based approaches, while recent innovations refined methodologies to distinguish between theoretical capability and actual use (Vasilauskas et al 2026; Fenoaltea et al. 2026; Massenkoff et al. 2026; Eloundou et al. 2023; Putka et al. 2026).

Several studies have focused on observing the activities by real-world users of LLMs (i.e. GPT-4 or Copilot) (Eloundou et al. 2023; Tomlinson et al. 2025; Richmond 2026). Eloundou et al. (2023) developed a rubric assessing tasks classified as "exposed" if GPT access would reduce task completion time by at least 50%. This assessment was done using human annotators and GPT-4. The scores were aggregated to generate multiple occupation-level exposure scores. Tomlinson et al. (2025) analyzed 200,000 anonymized Bing Copilot conversations separating the user goals from LLM actions. For each work activity, the authors measured how AI assists with the task and how it broadly contributes to the task. Richmond (2026) used ChatGPT conversations to assess where the AI has technical capabilities. It was found that many of the most exposed jobs were more likely to be expanded or reorganized.

Kacha et al. (2026) noted that AI integration requires systematic workforce development approaches accounting for technical competencies and adaptive capabilities. However, comprehensive frameworks linking AI exposure measurement to training prioritization in supply chain contexts remain underdeveloped (Kacha et al. 2026). Massenkoff et al. (2026) refined AI exposure measurements with "observed exposure" measure, combining theoretical capability with real-world usage data and demonstrating that actual AI coverage remains a fraction of technical feasibility (Massenkoff et al. 2026).

In sum, the research has shown that AI exposure is not a uniform predictor of occupational growth or displacement (Vasilauskas et al. 2026; Richmond, 2026). Manning et al. (2026) concluded that AI exposure and adaptive capacity were positively correlated: many highly exposed occupations are held by workers with strong means to manage job transitions. This paradox reflects AI's dual nature - as both a substitute for and a complement to human labor (Manning et al. 2026). Additionally, the studies concerned with AI exposure indices have demonstrated that O*NET provides a robust foundation for occupational task analysis, offering standardized descriptions, incumbent-reported importance weights, and hierarchical structure (Putka et al. 2026; Vasilauskas et al. 2026; Fenoaltea et al. 2026).

2.2. *AI and Supply Chain and Maritime Industry: Workforce Implications*

The supply chain industry represents a critical domain for examining AI's workforce implications. A critical skills gap emerges where existing employees lack technical expertise required for AI systems. Supply chain professionals traditionally trained in conventional logistics now need competencies in data analytics, machine learning interpretation, and AI system management, creating operational bottlenecks (Yusuf et al. 2025). AI requires supply chain professionals to develop new cognitive competencies in interpreting AI-generated insights, managing exceptions outside algorithmic parameters, and maintaining strategic oversight of automated systems (Yusuf et al., 2025). The maritime workforce requires competencies spanning traditional seafaring knowledge, digital literacy, data analytics, and AI system oversight - a combination rarely found in current training programs (Hussein et al. 2022). The maritime

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workforce requires substantial upskilling to handle new digital tools, necessitating significant investment in education and training (Margaretha et al. 2025).

2.3 The Research Gap

The topic of training has received little attention within the current AI exposure literature. Westover (2026) identified a paradox of AI enthusiasm and upskilling inaction: despite widespread recognition of AI's transformative potential, organizations struggle to implement systematic reskilling and upskilling of workforce capabilities. Effective reskilling must account for workers' existing competencies, learning capacities, and career aspirations, requiring personalized approaches (Westover 2025). While exposure indices have proliferated, translation of exposure metrics into training prioritization frameworks remains underdeveloped (Westover 2026). A critical gap exists between AI exposure measurement and actionable workforce upskilling strategies. Several frameworks attempt to bridge AI exposure measurement and training prioritization, though most remain conceptual or limited in empirical validation. Manning et al. (2026) demonstrated that occupations vary in both AI exposure and workers' capacity to navigate job transitions, suggesting training frameworks should account for both exposure levels and adaptive capacity, prioritizing interventions for occupations with high exposure and low adaptive capacity (Manning et al. 2026).

In this paper, we aim to develop a basic framework to analyze the training priorities when facing a disruptive technology in the workplace for specific industries - supply chain and maritime - using the O*NET occupational classification and LLM usage data. The supply chain and maritime sectors encompass diverse occupational roles with varying exposure profiles. Training needs differ fundamentally between work activities facing replacement risk versus the ones with augmentation potential. Current approaches do not provide systematic methods for identifying which work activities within the supply chain and maritime cluster should receive training priority and along which training axis - reskilling or upskilling.

3. Methods

3.1 Industry and occupation selection

For this paper, we selected a subset of 31 occupations which are relevant for the supply chain and maritime industry from the O*NET framework. The idea of focusing on one industry and not across all industries is to get a better analysis at the task level, as well as at detailed and intermediate work activity levels. As can be inferred from the provided literature review, most of the papers are focused on occupation level for all industries in the O*NET framework as the main goal was to analyze the overall impact of AI on jobs in the United States. By focusing on task and work activity level contributes to evaluating the training needs.

3.2 Task and work activity analysis

For the 31 occupations, we obtained from the O*NET framework the General Work Activities (GWA), Intermediate Work Activities (IWA) and the Detailed Work Activities (DWA) associated with these occupations. We also obtained the tasks associated with the Detailed Work Activities (DWA). The 31 occupations in the supply chain and maritime industry represent 151 IWA, 351 DWA and 689 Tasks. At task level, there is no task overlap between occupations, as they are specific to the occupation. As we go to the work activity level, as they are more general, we can start seeing the same work activities reflected in different occupations. For example, for the IWA level, the work activities can be found in a range from one to 22 occupations. On average, one IWA can be found in 3.5 occupations in this industry. For the DWA, with a more level of detail, on average one DWA can be found in 1.68 occupations.

3.3 Criticality

Starting with the lowest level, we need to define how important a task might be. For this determination, we used the elements of task *importance*, and task *relevance* in the Task Ratings file in O*NET. The task importance is a range from 1 to 5 and the task relevance is a range between 0 to 100. We define task *criticality* as the product of the importance of the task and the relevance of the task. This is shown in the following expression, where criticality is bounded in the range [0,1].

$CR_k = I_k /5 * R_k/100$
Where k is the task defined in the O*NET framework
CR_k is the criticality of task k
I_k is the importance of task k
R_k is the relevance of task k

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In order to aggregate the criticality to IWA level, we use the core/supplemental definition in O*NET. The O*NET file Task Statements defines each task as either core or supplemental to an occupation. We assign a coefficient of 1 for core tasks and a coefficient of 0.5 for the supplemental, and we use these core points to weight the criticality of the tasks within an IWA. We assign double weight to a core task vs a supplemental one, following Eloudou et al (2025).

$$WCR_j = [\sum_{k=1}^{n} I_k /5 * R_k/100 * CP_k]/ \sum_{k=1}^{n} CP_k$$

Where k is the task defined in the O*NET framework
WCR_k is the weighted criticality of IWA_j
I_k is the importance of task k
R_k is the relevance of task k
CP_k are the core points of task k

Intermediate work activities with weighted criticality equal or more 0.8 are considered high criticality and those below 0.8 are low criticality.

3.4 Exposure

On the other hand, we need to define what is the LLM exposure of the tasks and work activities included in the 31 relevant occupations. For this, we follow Tomlinson et al. (2025) methodology. Tomlinson et al. (2025) employed a large dataset with the LLM conversations with Microsoft Copilot. The authors used the conversations to evaluate two elements: (1) how well LLM completed the task required by the user and (2) the impact of the LLM-completed task based on the scope - whether it was moderate or more. The exposure is measured by the applicability of Copilot for specific work activities, where the usage is significant. One of the drawbacks of this dataset is that the exposure is only available at IWA level and not a task level. Hence, the exposure is defined as:

$E_j = DS_j * C_j * S_j$
Where j is the number of IWA in the 31 selected occupations
E_j is the exposure of IWA_j
$DS_j =$ 1 when share of conversations for IWA_j >= threshold
0 when share of conversations for IWA_j < threshold.
C_j is the User evaluated completion of tasks for IWA_j. Bounded in [0,1].
S_j is the Impact on scope of tasks for IWA_j. Bounded in [0,1].

The threshold used in Tomlinson et al. (2025) is 0.0005 or 0.05%. The idea of introducing the threshold is to eliminate the tasks that generated a very small number of LLM conversations with Copilot. For our analysis, we used a threshold equal to the median of the distribution of user shares for all IWA for the 31 relevant occupations. IWAs that show exposure equal or higher than 0.5 are considered high exposure and the ones below 0.5 are deemed low exposure.

3.5 Complementarity

A key contribution to the analysis is the introduction of a measure of *complementarity*. We assess the complementary by estimating the share of the relevant occupations that include the same IWA. This measure aims at providing an additional weight to the work activities that are part of different occupations. This is relevant for workforce training designs - training at scale while focusing on reinforcing concepts that might be used across different occupations. The complimentary measure will be augmenting the other measures.

$CO_j = 1+ (PO_j)$
where
CO_j is the complementarity for the IWA_j
PO_j is the percentage of occupations that include the IWA_j

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3.6 Training Index

As an aggregate measure of the training priorities, we propose an index that reflects the criticality of the work activity, the exposure of this activity to AI and the complementarity of the work activities across occupations. We introduce the *AI Training Priority Index* (AITPI) which will be defined as following:

$AITPI_j = WCR_j * E_j * CO_j$
where
WCR_j is the weighted criticality of IWA_j
E_j is the exposure of IWA_j
CO_j is the complementarity for the IWA_j

The more critical is the work activity, the higher is the exposure to LLMs and the complementarity of the activity, the higher will be the *AI Training Priority Index* (AITPI).

3.7 Training Categories

We define the training categories based on the AITPI at IWA levels, as well as the weighted criticality and exposure at the IWA level. First, we define three categories for the AITPI level. We deemed AITPIs above 0.6 as high or priority, AITPIs between 0.4 and 0.6 medium level or plan now, and AITPI below 0.4 as low or IWAs that just require monitoring.

Second, we define categories for the combination of exposure and weighted criticality. Work activities with high exposure and high criticality are the primary targets for AI Collaboration Training. Work activities with high exposure and low criticality will be subject to Transition Training, which will focus more on reorganization of the task, especially with the AI agents. Work activities with low exposure and high criticality will remain the core of the business and require Core Competency Training. The work activities that are low on exposure and criticality will be subject of Regular Training as needed.

4. Data Collection

The main sources of data:

a. The source for the occupations, GWA, IWA, DWA and tasks is the O*NET by the US Department of Labor. From these files, we obtained the importance, relevance and core status at task level.
b. The source for the user share of LLM conversations, user evaluated completion of tasks, and the impact on the scope of tasks is coming from the dataset from Tomlinson et al. (2025).
c. The US employment levels by occupation were obtained from Richmond (2026).

5. Results and Discussion

Applying the methods and methodology described in section 3 of this paper, we were able to define a priority for the training needs for the supply chain and maritime industry. The results are as follows:

5.1 Numerical results

In Table 1, we show the 31 selected occupations within the supply chain and maritime industry based on the O*NET job classification, along with 2024 employment levels. These occupations represent typical industry-specific jobs, ranging from manual jobs like packers and packagers to administrative jobs like transportation, storage and distribution managers.

The 31 occupations in the supply chain and maritime industry represent 151 IWAs, 351 DWAs and 689 Tasks. Eight tasks were eliminated because they did not have relevance and importance scores. For each of the 689 tasks, we collected the importance, the relevance and the type (core or supplemental). Based on those values, we computed the weighted average criticality at the level of Intermediate Work Activity. This was combined with IWA-level exposure based on the Tomlinson et al. (2025) dataset. In Table 2, we show the top four IWAs for the combination of criticality (high and low) and exposure (high and low).

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Table 1. Selected 31 occupations in the supply chain and maritime industry

O*NET code	Position	Employment ('000)
11-3061.00	Purchasing Managers	81
11-3071.00	Transportation, Storage, and Distribution Managers	107
11-3071.04	Supply Chain Managers	107
13-1022.00	Wholesale and Retail Buyers, Except Farm Products	162
13-1023.00	Purchasing Agents, Except Wholesale, Retail, Farm	162
13-1041.08	Customs Brokers	57
13-1081.00	Logisticians	79
13-1081.01	Logistics Engineers	79
13-1081.02	Logistics Analysts	79
17-2051.01	Transportation Engineers	118
17-2121.00	Marine Engineers and Naval Architects	8
19-3099.01	Transportation Planners	37
43-4011.00	Brokerage Clerks	40
43-5011.00	Cargo and Freight Agents	49
43-5011.01	Freight Forwarders	49
53-1041.00	Aircraft Cargo Handling Supervisors	10
53-1042.00	First-Line Supervisors- Helpers, Material Movers,	227
53-2012.00	Commercial Pilots	52
53-2022.00	Airfield Operations Specialists	17
53-3032.00	Heavy and Tractor-Trailer Truck Drivers	2,070
53-4011.00	Locomotive Engineers	32
53-4013.00	Rail Yard Engineers, Dinkey Operators, and Hostlers	3
53-4022.00	Railroad Brake, Signal, and Switch Operators	12
53-4031.00	Railroad Conductors and Yardmasters	43
53-5011.00	Sailors and Marine Oilers	31
53-5021.00	Captains, Mates, and Pilots of Water Vessels	35
53-5031.00	Ship Engineers	9
53-7031.00	Dredge Operators	1
53-7062.00	Laborers Freight, Stock, Material Movers, Hand	1,491
53-7064.00	Packers and Packagers, Hand	601
53-7065.00	Stockers and Order Fillers	2,780

Work activities such as “responding to customer problems or inquiries” fall within the high exposure and criticality, whereas other activities such as “schedule operational activities” fall in the low exposure and criticality. Activities with high exposure and criticality are more likely to be expanded or augmented, whereas activities with high exposure and low criticality are more likely targets for reorganization. Workers in high-replacement activities may need reskilling for alternative roles, while those in high-augmentation activities require upskilling to leverage AI tools. In Table 3, we show the distribution of the 151 IWAs by the four training categories and three AITPI categories.

Table 3 shows that 13 IWAs (8.6%) are in the high AITPI in the areas of AI Collaboration Training and Transition Training. These activities are a priority for firms. There are 32 IWAs (21.2%) that are in the medium AITPI range. These activities should be part of future training programs. The majority (70%) of the IWAs are in the low AITPI area, which implies monitoring to determiner ongoing needs. Training programs aiming to reskill and/or upskill for the new technology should focus on the high AITPI group. In Table 4, we provide the list of High AITPI and AI Collaborative Training and Transition training.

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Table 2. Four top IWA for selected occupations based on AITPI, criticality and exposure

	Low Criticality	High criticality
High Exposure	● Communicate with others about operational plans or activities. ● Advise others on business or operational matters. ● Obtain information about goods or services. ● Present research or technical information.	● Explain technical details of products or services. ● Respond to customer problems or inquiries. ● Determine operational methods or procedures. ● Assist individuals with paperwork.
Low Exposure	● Schedule operational activities. ● Estimate project development or operational costs. ● Evaluate the quality or accuracy of data. ● Coordinate with others to resolve problems.	● Explain regulations, policies, or procedures. ● Develop professional relationships or networks. ● Interview people to obtain information. ● Measure physical characteristics of materials, products, or equipment.

Table 3. IWA classification by AITPI categories and training categories (in number of IWAs)

Training categories	**High AITPI**	**Medium AITPI**	**Low AITPI**	**Total**
AI Collaboration Training	8	7		15
Transition Training	5	22	10	37
Core competency training		2	19	21
Regular training		1	77	78
Grand Total	13	32	106	151

Table 4. IWAs in the high AITPI area

AI Collaboration Training / High AITPI	Transition Training / High AITPI
1. Advise others on legal or regulatory matters. 2. Assist individuals with paperwork. 3. Assist others to access additional services or resources. 4. Determine operational methods or procedures. 5. Explain technical details of products or services. 6. Maintain facilities or equipment. 7. Provide information or assistance to the public. 8. Respond to customer problems or inquiries.	1. Advise others on business or operational matters. 2. Communicate with others about operational plans or activities. 3. Explain regulations, policies, or procedures. 4. Obtain information about goods or services. 5. Present research or technical information.

The activities in the high AITPI and AI Collaboration Training area need upskilling training targeted to help workers to expand and augment the IWAs by adding capabilities by the usage of LLMs within the scope of the tasks. The activities in the high AITPI and Transition training area need a combination of upskilling and reskilling training as those activities are more likely to be reorganized. Further determination for reskilling and upskilling should be done based on the role of the firm in the supply chain and the specifics of the commodities and supply chain structure.

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5.2 Graphical Results

Figure 1 shows the scatterplot of the 151 Intermediate Work Activities (IWAs) for the 31 occupations in the supply chain and maritime industry. Based on the weighted criticality and exposure to LLMs/AI, we divided the scatterplot in four regions that correspond to the different training categories. We show on the X-axis the IWA which were assessed an exposure of zero due to the low user share of conversations with LLMs in the data set. The IWAs activities with zero exposure were 78 (52% of all IWAs). Additionally, we found a weak positive correlation between exposure and weighted criticality, which is only significant at 10%.

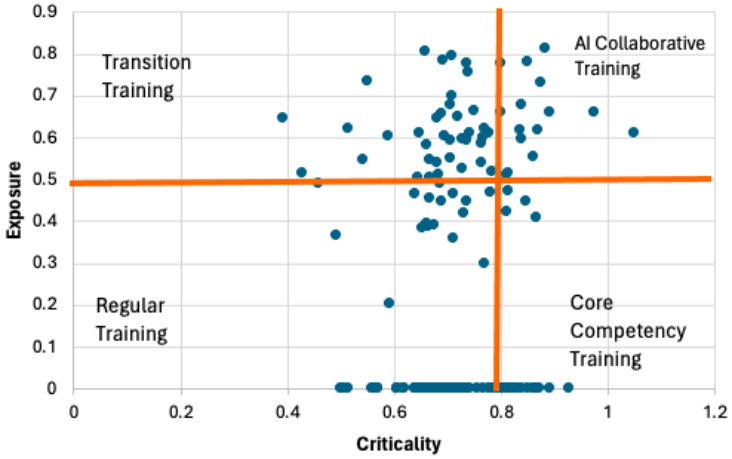


Figure 1. Scatterplot of weighted criticality and exposure

5.3 Proposed Improvements

This research can be expanded in the future in different directions. In this paper, for the exposure measure, we used the usage of Copilot conversations from Tomlinson et al. (2025). This can be improved using a set of conversations from different LLMs instead of only relying on one. The other way is to exploit the industry specific context to obtain the exposure measures from a detailed survey to human resource managers in the supply chain and maritime industry. In this paper, we did not use the frequency dimension of the task, and this can add valuable insights related to the strength of the complementarity across occupations in the industry. In terms of the training categorization, we can expand the categories to add the key taxonomic dimensions of AI-related worker training.

5.4 Validation

By combining the use of the O*NET framework plus the exposure usage from LLMs, we assessed the feasibility of a framework for training prioritization for companies in a particular industry. This framework is applicable to different industries, with industry expert input to tailor the needs for reskilling and upskilling. We also verify a positive correlation between exposure and weighted criticality.

6. Conclusion

This paper contributes to closing the gap in the literature by presenting a framework to translate exposure metrics into training prioritization and workforce upskilling strategies. This framework helps to analyze the training priorities when facing a disruptive technology in the workplace such as LLMs. The approach bridges AI exposure measurement and training prioritization, using weighted criticality, exposure and complementarity grounded in O*NET Intermediate Work Activities for the supply chain and maritime industry to define training strategies through an *AI Training Priority Index*. The index enables the identification of specific work activities requiring particular training intervention, while ensuring training priorities reflect actual task criticality and complementarity.

We applied this index to a set of 151 key work activities in the supply chain and maritime industry. We classified the IWAs by criticality and exposure. We found that activities with high exposure and criticality are more likely to be expanded or augmented, whereas activities with high exposure and low criticality are more likely targets for reorganization. We also introduce four training categories and three AITPI categories, which help to group the

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activities by the training intervention needed. We found that 8.6% of the activities need a high priority in the training strategy. These IWA require specific AI Collaborative training for upskilling and Transition Training for reskilling. This study provides a roadmap for supply chain and maritime firms to proactively set their training priorities for AI-driven workforce transition while strategically mitigating training-related investments. The proposed framework provides organizations with an actionable link between AI exposure measurement and strategic workforce development, enabling more targeted, data-informed, and cost-effective training investments in AI readiness.

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Biographies

Ricardo Ungo is a clinical assistant professor and the Director of the Maritime, Ports and Logistics Management Institute and Undergraduate Program director in the School of Supply Chain, Logistics and Maritime Operations at Old Dominion University. He served as the President of the Transportation Research Forum (TRF) for the 2024-2025 term. His research on maritime economics and market mechanisms has been referenced by Harvard research bodies, including the Harvard Institute for Economic Research. Additionally, his commentary on industry innovation and port automation has been featured in national outlets like The New York Times, Virginia Business, and others. During his 30+ years of professional experience in the manufacturing and maritime industry, he worked at the Panama Canal, participating in the Panama Canal Expansion project studies, and leading the development of studies for maritime related projects as its Business Development Manager. Prior to this, Dr. Ungo worked with Melo Industrial Group (Panama) managing industrial capacity expansion projects as Production and Sales Manager. Dr. Ungo specializes in the topics related to the maritime industry and global supply chains, AI-based supply chain management, and workforce development. He holds a Ph.D. in Economics from Vanderbilt University.

Nadiya Ungo is an experienced university administrator and, currently, a doctoral student in the Higher Education program at Darden College of Education and Professional Studies at Old Dominion University. She holds a master's degree in Higher Education Administration from Vanderbilt University. For more than 25 years, Nadiya Ungo has worked in various teaching and administrative capacities in both public and private educational sectors in Ukraine, Panama, and the United States. In her research, she is focusing on college-to-work transition, professional networks, and workforce development in supply chain and maritime industries.

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