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Worker Displacement by Artificial Intelligence in Interorganizational Systems: The Impact of Boundary-Spanning Employees on Supply Chain Agility

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ABSTRACT

Organizations are increasingly applying artificial intelligence (AI) in interorganizational systems (IOS) to mitigate demand and supply disruptions. This shift towards AI to enhance supply chain agility capabilities automates some tasks previously undertaken by boundary-spanning employees who serve as critical informational and influential links with supply chain partners. Given limited related research, we investigate the impact of AI not only on the potential displacement of boundary-spanning employee roles but also on subsequent supply chain agility. Leveraging dynamic capabilities and social network theories, we first conducted interviews with supply chain executives to develop a practitioner survey. Following a mixed-methods approach, we next applied structural equation modeling to this survey data and then probed further via follow-up interviews. The results reveal that despite displacing some employees, the use of AI in IOS enhances the remaining operational and strategic roles of the boundary-spanning employees to enrich supply chain agility. The ensuing theoretical and managerial contributions emphasize the essential role of boundary-spanning employees as part of a hybrid human-AI solution, providing insight into the need for an optimal human/AI balance in the supply chain to cope with dynamic marketplaces.

Keywords: *artificial intelligence, boundary-spanning employees, displacement, dynamic capabilities and social network theory, interorganizational systems, supply chain agility*

1. INTRODUCTION

Increasingly demanding global markets have heightened the importance of interorganizational systems (IOS) and management processes that strengthen agility across the entire supply chain to help recover from disruptions (Wiedmer *et al.*, 2021). In these interorganizational networks, boundary-spanning employees serve critical roles by linking and influencing actors both within the organization and with its supply chain partners (Korschun, 2015). More recently, some organizations have been applying artificial intelligence (AI) in interorganizational information systems, thereby increasingly automating key supply chain employee roles (Pournader *et al.*, 2021; Robert, 2022). This trend is corroborated by economists who have linked recent job cuts in tech and other key sectors to cost cutting by investing in AI (Picchi, 2024). From an agility perspective, AI can detect disruptions sooner than humans and formulate more rigorous and swifter responses while reducing detrimental human decision-making biases (Dubey *et al.*, 2022; Falcone *et al.*, 2021). AI is increasingly being applied in production optimization (Min *et al.*, 2019), supplier selection (Cavalcante *et al.*, 2019), vehicle routing and scheduling (Levy, 2018), and customer requirements management (Lyutov *et al.*, 2019). Recent operations and supply chain management journal publications have also touched on the benefits of AI-powered big data analytics to supply chain reliability (Es-satty *et al.*, 2025), as well as human factors that influence the use of AI-driven collaborative technologies at seaports (Lasse *et al.*, 2025).

Nevertheless, AI adoption in IOS leads to a conundrum regarding the role of boundary-spanning employees. On one hand, some boundary spanner roles may be automated by AI. On the other hand, effective personal relationships between supply chain partners historically play a critical role in agility (Sultan, 2022). Additionally, organizations also rely on inimitable boundary spanner supervisory and innovator roles to train AI to detect and cope with marketplace ambiguity (Winkelhaus *et al.*, 2022). Moreover, boundary spanners support AI adoption by other employees, thereby significantly impacting the organization's ability to recognize AI's vast potential (Klumpp and Zijm, 2019). With these latter points, the displacement of boundary spanners by AI may adversely impact supply chain agility capabilities.

Despite the growing body of literature on digitization and IOS adoption, research has yet to fully explore implications of the displacement of boundary-spanning roles within supply chain agility. Extant literature primarily focuses on the technological benefits of automation but offers limited insights into nuanced human-system interactions, particularly at the interorganizational boundary (Belanche *et al.*, 2020; Klumpp and Ruiner, 2022). Similarly, Millar *et al.* (2018) note how relatively little academic research has studied the impact of disruptive technology on macro-systems as well as on specific strategies and instruments to leverage, mitigate, or ameliorate systemic disruption like those experienced in supply chains.

To address this gap in the literature, we, therefore, analyze supply chain practitioner interviews and survey data to investigate the impact of AI in IOS on boundary-spanning employees, including their potential displacement. We focus specifically on boundary-spanner operational and strategic roles while also evaluating the ensuing impacts of the AI solution in IOS on agility. These points lead to the research questions, which were rooted in gaps identified in the literature and then enriched by an initial round of interviews.

- **RQ1:** How does the application of AI in IOS affect reliance on boundary-spanning employees' operational and strategic roles?
- **RQ2:** How do AI in IOS and the updated boundary spanner roles influence supply chain agility?

The rest of the paper is organized as follows. First, we introduce relevant literature and theory. We then detail the methodology of the three phases of this study, including 1, the initiating interviews, 2, the survey, and 3, the follow-up interviews. Finally, we present the study's implications and conclude with subsequent limitations and opportunities for further research.

2. LITERATURE REVIEW

2.1 Supply Chain Agility & Competitive Advantage

Stalk (1992) contends that an organization can derive competitive advantage via how well it quickly perceives and responds to changes in the environment. Over the last decade, a significant amount of literature has subsequently focused on the ability of organizations to respond to disruptions in the supply chain, interweaving related concepts such as agility, flexibility, resiliency, plasticity, and ambidexterity (Falcone *et al.*, 2022; Richey *et al.*, 2022). Some scholars, for instance, contend that flexibility reflects an organization's ability to manage known situations with a set of established business processes whereas agility in addition includes situations that involve an element of ambiguity (Bernardes & Hanna, 2009). Hughes *et al.* (2023) differentiate an agile response, which results in the supply chain returning to the previous (i.e., pre-disruption) state, from a plastic response, where the supply chain is permanently redesigned. Overall, the literature concurs that responsiveness capabilities like agility have become even more central to strategic organizational capabilities given increasingly problematic supply chain events like the 2011 earthquake/tsunami in Japan and, more recently, the COVID pandemic (Hughes *et al.*, 2023; Wiedmer *et al.*, 2021; McKinsey & Company, 2022).

We focus herein on agility given the inherent human ability to manage uncertainty and the potential for the displacement of some boundary spanners to impact businesses' ability to detect uncertainty. We follow its definition as "a firm's ability to quickly adjust tactics and operations within its supply chain to respond or adapt to changes, opportunities, or threats" (Gligor *et al.* 2013, p. 95). With roots in manufacturing, agility has evolved to the entire supply chain as an organizational capability for tackling uncertainty (Backhouse and Burns, 1999).

Gligor *et al.* (2019) propose several dimensions of agility, including scanning the environment, adjusting tactics, integrating intra and inter-organizational processes, and empowering the customer. Internally, companies manage such capabilities via the sales and operations planning (S&OP) process, which relies on organizational integration, information sharing, and top management support to coordinate supply and demand to minimize disruption risks and improve supply chain performance (Ekezie and Hong, 2024; Swaim *et al.*, 2016; Dittfeld *et al.*, 2021). Externally, S&OP requires effective relationships, including collaboration, across the chain (Sultan, 2022).

Finally, the appropriate theoretical lens to approach agility for this study is Teece's (1997) Dynamic Capabilities Theory, because the displacement of boundary-spanning employees (BSE) by SC AI can be viewed as being driven by the need to reconfigure organizational capabilities to meet the demands of highly dynamic business environments. The dynamic capabilities approach emphasizes improving efficiency to achieve competitive advantage (Teece *et al.*, 1997). A key benefit of incorporating AI in inter-organizational systems is that AI outperforms the left-hemisphere brain functions, making it more efficient than the average BSE in data mining tasks. This enables IOS to evaluate large and complex datasets in a fraction of the time that it would take humans to process (Cotter, 2022), thereby, speeding up decision-making with a direct positive impact on SC agility. Boundary spanning activities, along with resource orchestration have been identified as micro-foundations of dynamic capabilities (Ariwibowo *et al.*, 2024). Next, we examine the unique role of Boundary-spanners.

2.2. Boundary Spanners

Boundary-spanning employees play a critical role by sharing information and influencing the organization and its supply chain partners to drive the needed agile adjustments to disruptions (Korschun, 2015). Tushman and Scanlan (1981) describe boundary-spanning as communication links that facilitate critical information and resource coordination. One particular activity involves scanning the external environment for relevant trends, opportunities, and threats (Hargadon, 1998). Boundary-spanning employees can, thus, most effectively support the required inter-organizational collaboration for supply agility. Nevertheless, AI in IOS can enhance the rigor and speed in processing complex information needed for boundary-spanner-supported agile responses (Robert, 2022; Falcone *et al.*, 2021).

We adopt the classification of boundary-spanning activities as operational and strategic (Noble & Jones, 2006). Operational activities typically involve repetitive business processes performed by junior employees, which can often be automated by AI. For instance, organizations have applied

AI to automate portions of S&OP to incorporate significantly deeper customer, market, and supply intelligence, thereby enhancing agility (McKinsey & Company, 2022). Other interorganizational information system applications where machine learning and other forms of AI are increasingly finding applications include demand forecasting, order fulfillment, and procurement (Loeb, 2019; Cadden *et al.*, 2021; Loske and Klump, 2021; Mariappan *et al.*, 2023).

In contrast, strategic boundary-spanning activities, generally performed by senior managers, are typically too complex to fully automate (Jemison, 1984; Noble & Jones, 2006). For example, boundary spanners review irregular S&OP exceptions, such as demand spikes or supply interruptions, that currently cannot be managed by AI. With such delineation of operational boundary-spanning tasks that can be automated using interorganizational systems and AI from more tactical and strategic boundary-spanning tasks, which are inimitable and difficult to automate, AI may substantially transform the operational and strategic roles of boundary spanners, including displacing some supply chain employees. Yet, limited literature evaluates such impacts.

2.3 Social Networks

With roots in social network theory, Borgatti and Li (2009) describe network concepts in supply chain management (SCM) as being based on hard and soft ties. Hard ties facilitate the flow of money and materials, while soft ties involve social relations, such as friendships and information sharing. Borgatti and Li (2009) explain how the network perspective views systems as a set of interrelated actors or nodes, distinguishing between, ties among actors as collective entities (such as firms), and those that exist through the individual relationships of their employees. These types of ties have been the subject of research into knowledge exchange at the firm level (Powell *et al.*, 1996). Personal ties between employees of different organizations are considered significant in SCM literature because they stem from relationships developed through a history of interactions (Can Saglam *et al.*, 2022).

Borgatti and Li (2009) explain that a fundamental maxim in network analysis is understanding how actors influence each other. A key mechanism for this influence is the instigation of flow (of both tangible and intangible resources) between nodes. They suggest that if information is acquired through ties, the transmission mechanism indicates that having more ties should lead to receiving more information, a property they refer to as degree centrality. The centrality (or significance of actors/nodes) in social networks has four forms: degree centrality (number of ties), closeness centrality (degree of reachability and communication), betweenness centrality (controlling information flow), and eigenvector centrality (higher levels of social capital) (Hernández-García *et al.*, 2015). Borgatti and Li (2009) clarify that not all nodes in a network are equally connected; that is, not all have strong ties—well-connected nodes tend to have more ties than less-connected ones —eigenvector centrality. A layperson might interpret this to suggest that weak ties are undervalued in social networks, but according to Granovetter's (1973) strength of weak ties theory, this view is somewhat misleading. Weak ties are more likely to serve as sources of novel information than strong ties, as they often act as bridges connecting to sources outside a network (Granovetter, 1973; Borgatti and Li, 2009).

3. CONCEPTUAL DEVELOPMENT

3.1 AI-Driven Worker Displacement

Next, we build the research model and hypotheses to delineate the role of boundary-spanning employees in supporting supply chain AI. We are specifically interested in how AI use in IOS impacts supply chain agility as it takes on tasks traditionally performed by boundary spanners. We first consider the direct impacts of AI worker displacement on agility then introduce the effects of updated boundary spanner roles (Figure 1). Finally, we provide further empirical support for the model with practitioner interviews.

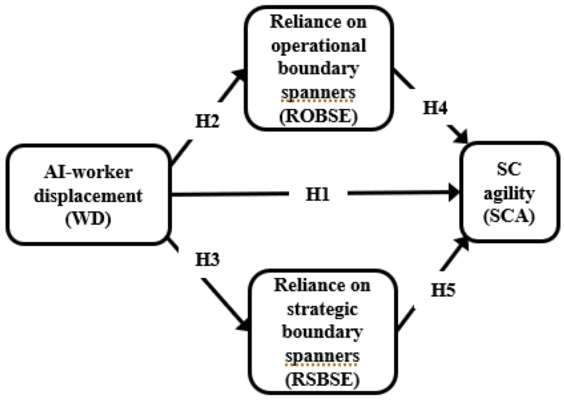

Figure 1 Full conceptual model

Specific to agility, AI can enhance demand planning, inventory management, and production planning by evaluating complex and rigorous data that humans cannot effectively process (Cotter, 2022; Gupta *et al.*, 2022). As evidence, Neary *et al.* (2018) report that 64% of retailers are investing in AI to drive inventory planning and supply chain automation. Wang *et al.* (2019) further theorize that AI's continuous analysis of traceable data and algorithm updates collectively influence organizational agility functions of sensing, decision-making, and responding to market stimuli. Thus, supply chain agility is strengthened by AI adoption and positively impacts related concepts like operational ambidexterity (Modgil *et al.*, 2021; Kartiko *et al.*, 2022).

In doing so, AI will disproportionately reduce the need for human involvement in supply chain processes by as much as 50% (Gruetzemacher *et al.*, 2020). AI is already beginning to impact labor markets, including blue and white-collar jobs (Kotler, 2020). Many AI applications center on repetitive tasks, thereby reducing the workload of supply chain professionals in both internal and external roles. For instance, the use of machine learning in forecasting enables the analysis of more complex demand patterns and the generation of more reliable forecasts (Jeong and Lim, 2019; Watanabe *et al.*, 2019). Additionally, Zhang *et al.* (2021) use a resource orchestration perspective to infer that AI and human capabilities combined enable more efficient order fulfillment. Similarly, AI in procurement has been shown to enable buyers to identify suitable suppliers as well as accelerate agreeable material pricing and lead times with suppliers (Chopra, 2019; Cui *et al.*, 2022). Adopting AI technology in IOS will, thus, displace some knowledge workers while improving supply chain agility competencies.

H1: *AI worker displacement will have a positive relationship with supply chain agility.*

3.2. Boundary Spanner Impacts

We, next, add the impacts of operational and strategic boundary-spanning employees to supply chain AI adoption in IOS to complete the research model. It is important to clarify the difference between operational and strategic boundary spanners. Operational boundary spanners tend to be more and exchange mostly explicit information with supply chain partners. Specifically, their interactions with other firms are more function-spanning, such buyer quality control interfacing with supplier quality control or buyer planning interfacing with supplier order management for instance. On the other hand, strategic boundary spanners, such as a purchasing director or account manager, exchange more tactical and strategic information like market intelligence. These strategic boundary-spanner roles also impact relationships, including trust, with supply chain partners (Zhang, 2018). While both types of boundary-spanner roles have implications on agility, operational boundary-spanner roles are easier to automate compared to strategic boundary-spanner roles (Noble and Jones, 2006).

Although AI will displace some employees, human support roles in AI are critical to the organizations' ability to boost agility competencies. Specifically, advanced AI algorithms are currently limited to recognizing and responding to patterns within large datasets mainly via deep or reinforcement learning (Lee *et al.*, 2018). Yet, ambiguity involves insufficient information with subjective probability distributions that cannot be precisely coded by AI (Takemura, 2014). With the right hemisphere of the human brain specialized in detecting and responding to ambiguous circumstances, boundary spanners, thus, critically evaluate and train AI decision-making (Ransbotham *et al.*, 2020). That is, non-displaced boundary spanners take on supervisory roles that improve the reliability of AI, particularly in coping with ambiguity. Furthermore, boundary spanners support collaboration with supply chain partners, critical to AI implementation (Falcone *et al.*, 2021).

Social network theory provides support for the enhanced responsibilities of boundary spanners even as AI displaces other employees. Specifically, eigenvector centrality highlights the importance of "well-connected nodes" with strong ties in a network (Li *et al.*, 2016). In situations of eigenvector centrality, the organization relies more heavily on boundary-spanning employees (Figure 2), who must continue to perform as well as, if not better, than when the organization had more boundary spanners. Eigenvector centrality is corroborated by Burt's (1992) theory of structural holes wherein organizations embedded in sparsely linked networks realize efficiency and brokering advantages from non-redundant information exchanges. As such, the organization will rely more heavily on its remaining boundary-spanning employees to ensure adoption success.

With these points, human-computer interaction sets a foundation for technical innovation in supply chain, increasing the organization's dependency on boundary spanners to enable the full potential of AI (Klumpp and Ruiner, 2022). From an operational perspective, the boundary spanners will share critical information, including forecasts and demand, within the organization and with supply chain partners. From a strategic perspective, boundary spanners maintain relationships and exert influence with those partners.

H2: *AI worker displacement will have a positive relationship with reliance on operational boundary-spanning employees.*

H3: *AI worker displacement will have a positive relationship with reliance on strategic boundary-spanning employees.*

As a core operational responsibility, boundary spanners must identify anomalies in the business environment that the organization may circumvent or exploit (Hargadon, 1998). For instance, unforeseen events (such as COVID-19) and the increased location diversification they engender imply a greater need for the boundary spanning function (Schotter, 2021). Relatedly, the duo of boundary spanning and knowledge brokering have been shown to support organizational agility (Rosenkranz and Kautz, 2014). Operational boundary-spanning tasks include communicating forecasts, actual demand, and marketing initiatives to enhance flexibility as a core dimension of agility (Gligor *et al.*, 2013). Further, Gligor and Holcomb (2012b) note that logistics capabilities, a core operational function, are essential in achieving supply chain agility, while Blome *et al.* (2013) show how employee compliance enables supply chain agility competencies.

H4: *Reliance on operational boundary-spanning employees will have a positive relationship with supply chain agility.*

Boundary-spanning employees also provide strategic roles, particularly by exchanging selected information with supply chain partners as well as influencing how these partners navigate unpredictable markets (Chatterjee *et al.*, 2022). Specifically, Piercy (2009) notes how strategic relationships between boundary spanners enhance agility, while Reuss (2018) highlights how the ensuing trust from inter-firm relationships plays a key role in achieving agility. Similarly, as the literature also presents strong supply chain relationships as antecedents to agility (Tse *et al.*, 2016), Gölgeci and Kuivalainen (2020) suggest that the social capital derived from inter-organizational relationships between boundary spanners can lead to supply chain resilience. Additionally, Fan and Stevenson (2019) found that the strength and diversity of inter-firm ties among boundary spanners positively moderate the link between relational capital and supply-side resilience.

H5: *Reliance on strategic boundary-spanning employees will have a positive relationship with supply chain agility.*

3.3 Empirical Support – Initiating Interviews

To both further validate the above research hypotheses and inform the development of a subsequent practitioner survey, we conducted semi-structured interviews with supply chain executives to explore the impacts of AI on IOS (Creswell & Plano-Clark, 2007). Specifically, we interviewed 11 mid-to-senior-level supply chain executives from 10 companies across several product-based industries (Table 1), exploring AI's potential to displace boundary-spanning employees and the subsequent effects on organizational capabilities (Appendix A). Several rounds of coding iterations of the interview transcripts in MaxQDA yielded a set of causally related core themes. Within each theme, we isolated constructs that capture the essence of the research questions about the possible impacts of AI in IOS. These emerging constructs thereby form the basis for theoretical sensitivity for the research hypotheses.

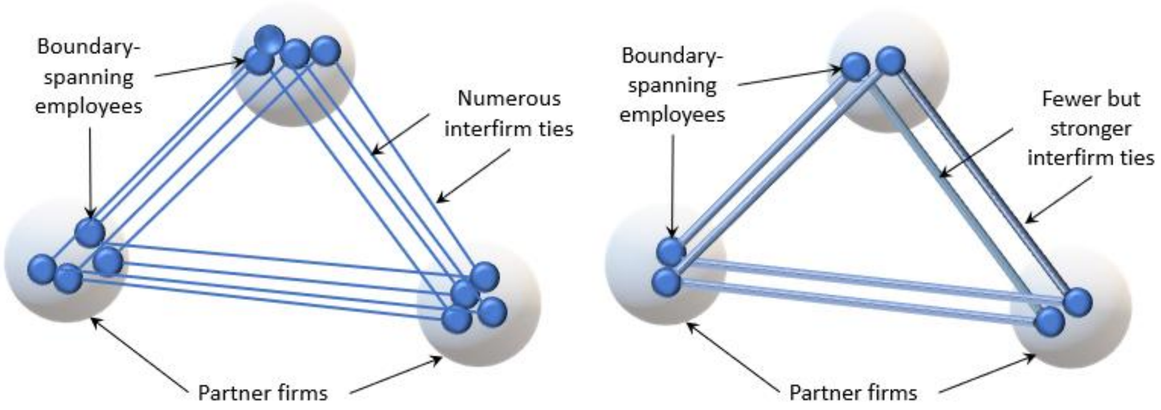

Figure 2 Illustration of eigenvector centrality social network among actors (nodes).

First, the interviews validated the importance of boundary-spanning employees. For instance, participant I talks about their reliance on strategic boundary spanners with, "Employees are involved when it involves managing relationships and exchanging market intelligence, which leads to strategic decisions in our firm." Another respondent, participant IV, further describes such reliance with, "Now, the good thing about the partner-customer is that they don't just let you work with the peripherals or the boundary-spanning employees, they let you come into the heart of the project. So, usually, it is sales, procurement, and logistics; these are usually your boundary-spanning employees, but with a partner like … they would allow interaction with their quality, with their R&D, with their engineering, and their upstream R&D team … These things make a hell of a difference in differentiating a partner from a regular customer."

Second, the interviews delineated operational and strategic boundary-spanner roles as constructs, including organizational reliance on each. An example of this was provided by Participant I who described an IOS in his company, which utilizes AI to analyze batch production records for the release of production batches still at the supplier's warehouses. He said, "We use machine learning in tracking batch defects, our systems can talk to their data depository to identify defects in advance." Another respondent, participant X, describes the use of AI in IOS at his firm, "Again if there is a specific visual attribute, how a good part should look, AI can be trained, in fact we do use AI right now, where the algorithm is trained on what a good part looks like and so AI can tell what the difference is between a good part and the bad part and based on whatever difference it's noted determine what the potential causes of that particular defect is."

Third, the interviews highlight the importance of supply chain agility. For example, participant VI emphasizes "In an ever-fluctuating market where commodity prices and … things like foreign exchange rates are changing on a daily/weekly basis, we need to be able to react fast." Participant III expresses concern about a partner's agility, "Asking them to improve their system to basically scale up supply to building them up, and you discover they're not able to scale up supply, because when you want something like more volume they can't deliver."

These constructs that emerged from this initial round of interviews formed the basis for refocusing the research questions, theoretical sensitivity, and the development of hypotheses shared in the quantitative part of this study.

4. STUDY 1 - SURVEY

With the above initial interviews strengthening the hypotheses, we applied a further mixed-methods approach to evaluate the research model (Figure 1) (Creswell & Plano-Clark, 2007). First, we evaluate the model with structural equation modeling (SEM) on practitioner survey data. We procured an email list of practitioner members of the Council of Supply Chain Management Professionals (CSCMP). The electronic surveys were deployed via Qualtrics—an online data collection software. After an initial pilot test which was used to confirm factors would load as hypothesized in a trial EFA, a main deployment of electronic surveys followed in two waves, the first wave from February to May 2022 and the second wave from June to August 2022. We received 210 responses from the 2,235 valid emails in the list, 158 of which were deemed usable for an effective response of 7%. Although the response rate is low, it is comparable to existing SC research (Gimenez and Sierra, 2013; Melnyk *et al.*, 2012; Hristov *et al.*, 2024; Iftikhar *et al.*, 2023). We also confirmed, using G Power software, that this number of responses provided enough power for our threshold effect size.

4.1 Measurement

The survey (Table 2) was constructed with existing scales where possible. Specifically, supply chain agility was applied from Gligor and Holcomb (2012a, 2012b). Measures for reliance on strategic and operational boundary-spanning employees were adapted from Faraj and Yan (2009). Finally, the AI-driven worker displacement measures were adapted from Gruetzemacher *et al.* (2020). In the survey, participants were asked to consider one specific supply chain partner when responding.

4.2 Demographics

The majority of responding firms were based in North America (53.8%). Also, most firms operated in the manufacturing industry (59%) and had less than $500 million in revenue. Other details are provided in Table 3.

Table 1 Initiating interview participants**.**

Participant	Role	Organization Type	Firm HQ & Size	Interview Location	Interview Date	Duration (mins)
I	Technology Manager	Technology manufacturing	US Corporation	Zoom	10/2/2021	45
II	Transportation Manager	E-commerce	US Corporation	Zoom	10/2/2021	48
III	Engineering Quality Manager	Technology manufacturing	US Corporation	Zoom	10/11/2021	36
IV	Managing Director	Manufacturing	South Africa SME	Zoom	10/13/2021	32
V	Marketing Director	Manufacturing	Nigeria SME	Zoom	10/24/2021	35
VI	Project Manager	Fast-moving consumer goods	UK Corporation	Zoom	03/31/2022	30
VII	Project Manager	Defense contractor	US SME	Zoom	10/23/2021	42
VIII	Materials Manager	Energy	US Corporation	Zoom	10/9/2021	46
IX	Software Engineering Director	Medical device	US Corporation	Zoom	03/16/2022	31
X	Engineering Manager	Manufacturing	Canadian Corporation	Zoom	11/06/2021	30
XI	Product Manager	Technology manufacturing	US SME	Zoom	03/31/2022	30

Table 2 Survey and descriptive statistics.

Factors	Variable	Constructs	Mean	SD
AI worker displacement (WD)	WD-1	Increasing portions of our SC are relying on AI vs. humans	4.56	1.94
	WD-2	AI innovation is reducing the need for additional boundary-spanning headcount at our company	4.42	1.96
	WD-3	There is a trend of boundary-spanning white-collar work increasingly done by AI in my company	4.20	2.08
	WD-4	Increasingly, tasks are done by AI versus humans in my company	4.43	1.96
	WD-5	Increasingly, tasks are done by AI versus supply chain professionals in my company	4.34	1.96
Reliance on strategic boundary-spanning employees (RoSBSE)	RoSBSE-1	We depend on BSE to regularly exchange information or resources with partners	5.66	1.20
	RoSBSE-2	We depend on BSE to regularly influence important actors at our partners	5.57	1.24
	RoSBSE-3	We depend on BSE to make use of their relationships with our partners on the company's behalf	5.79	1.27
	RoSBSE-4	We depend on BSE to deflect or absorb outside pressures from our partners on the company's behalf	5.44	1.43
	RoSBSE-5	We depend on BSE to actively exchange information with partners beyond what comes via official channels	5.19	1.62
Reliance on operational boundary-spanning employees (RoOBSE)	RoOBSE-1	We depend on BSE for communication on forecasts	5.62	1.44
	RoOBSE-2	We depend on BSE for communication on orders	5.71	1.34
	RoOBSE-3	We depend on BSE for communication on product and service specifications	5.72	1.25
	RoOBSE-4	We depend on BSE for communication on marketing initiatives	5.28	1.56
	RoOBSE-5	We depend on BSE for communication on process improvement ideas	5.61	1.36
Supply chain agility (SCA)	SCA-1	We can reconfigure SC resources to respond to strategic opportunities	5.65	1.40
	SCA-2	We can detect strategic opportunities in a timely manner	5.59	1.47
	SCA-3	We can detect changes in supply in a timely manner	5.58	1.47
	SCA-5	We can reconfigure SC resources to respond to supply changes	5.61	1.31
	SCA-6	We can reconfigure SC resources to respond to demand changes	5.66	1.32
	SCA-7	We can reconfigure SC resources quickly to respond to changes in supply	5.62	1.34

Table 3 Demographics

Industry			**Company Size**		
Manufacturing	59	37.3%	Under $500 million	72	45.6%
Transportation and warehousing	17	10.8%	$500 mill to $1 billion	15	9.5%
Utilities and technical services	9	5.7%	Over $1 billion	37	23.4%
Wholesale and Retail trade	10	6.3%	Did not indicate	34	21.5%
Real estate & accommodation services	3	1.9%	**Business Volume % with Partner**		
Healthcare, admin, and support	10	6.3%	0 to 28%	59	37.3%
IT, finance & educational services	9	5.7%	29 to 56%	35	22.2%
Unclassified establishments	7	4.4%	57 to 100%	30	19.0%
Did not indicate	34	21.5%	Did not indicate	34	21.5%
Age of Company			**Length of Business Partnership**		
Under 20 years	35	22.2%	Between 0 to 20 years	78	49.4%
21 to 60 years	44	27.8%	21 to 40 years	30	19.0%
61 to 100 years	17	10.8%	41 to 60 years	10	6.3%
Over 100 years	28	17.7%	Over 60 years	6	3.8%
Did not indicate	34	21.5%	Did not indicate	34	21.5%

4.3 Normality, Heteroscedasticity, and Non-Response Bias Test

The multivariate kurtosis (peakedness), which is a more critical measure of multivariate normality than skewness because kurtosis impacts tests of variances and covariances (Byrne, 2010), was used to confirm that the data did not depart from normality. We tested heteroscedasticity with Levene's test. Most of the variables are heteroscedastic. We also tested for multicollinearity, and recorded two VIFs of 6, otherwise VIFs results were 3 or below. Finally, evaluating non-response bias, bootstrapping results (5,000 samples) show no significant differences between early and late respondents (Armstrong and Overton, 1977), hence no non-response bias was detected.

4.4 Common Method Bias

Since the surveys were completed by single respondents, we took a multi-step approach to minimize common method bias (Conway and Lance, 2010). First, all respondents were assured of anonymity. Second, the survey included a psychological separation between the endogenous and exogenous construct scales. Third, the instructions reminded respondents about the importance of the study and how their accurate responses would benefit the field (Podsakoff *et al.*, 2003). Finally, accessibility was used as a marker variable, which is theoretically unrelated to reliance on boundary-spanners. The unadjusted R2 for the marker variable ranged from 0.081 to 0.150 (Liu *et al.*, 2010), a good indication that CMB is not an issue.

Given the adaptation of some of the scales from the literature, we first conducted an exploratory factor analysis (EFA) using the maximum likelihood method and Promax rotation. After removing two agility items (SCA-4 and SCA-8) due to poor factor loadings and detriment to scale reliability, the six extracted factors explain 75.51% of the total variance. Additionally, the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy, Bartlett's test of sphericity (0.92), and Chi-square ($\chi 2$: 4954.32) are statistically significant.

5. RESULTS

5.1 Measurement Model Evaluation

Three exogenous constructs and one endogenous construct emerge from the EFA, reliability, and AVE results. We next applied a confirmatory factor analysis (CFA) to further verify scale reliability and validity (Table 4). Following Hu and Bentler's (1999) criteria, the measurement model is validated based on parsimony ($\chi 2$/df = 1.08), absolute fit (RMSEA = 0.02), close fit (PClose = 0.93), and incremental fit (TLI = 0.99 and CFI = 0.99). Factor loadings, except for one, are all above 0.70, and the one exception is above the 0.50 minimum (Fornell and Larcker, 1981). Cronbach's alpha (α) and composite reliability (CR) metrics are strong. Further, average variance extracted (AVE) values exceed 0.50, confirming convergent validity. Additionally, all AVEs exceed the squared inter-item correlations, thereby verifying discriminant validity.

We next evaluated the structural model, including control variables that could influence the hypothesized relationships. First, the maturity of respondent organizations could affect agility. We accounted for this with demographic questions, including the firm age and size (annual turnover) of the company. Second, the strategicness of the business relationship with the partner could also influence supply chain agility. We, hence, included two controls in the length of the business relationship and the strength of this relationship (% of category business volume). Only firm size proved to have a significant and positive relationship with RoSBSE. These controls also served as a check for endogeneity.

5.2 Measurement Model Evaluation

Overall, the model fit indices remain strong ($\chi 2$/df = 1.51, RMSEA = 0.057, PClose = 0.252, TLI = 0.960, and CFI = 0.974). Per Figure 3, all hypotheses, except H5 (strategic boundary spanner impacts on agility), are significant at $p < 0.0001$. Table 5 shows the detailed SEM results, including regression coefficients for controls.

Table 4 CFA results

Factors	Variable	Factor Loading	Cronbach α	Composite reliability	AVE
AI worker displacement (WD)	WD-1	0.91	0.97	0.97	0.87
	WD-2	0.93			
	WD-3	0.94			
	WD-4	0.92			
	WD-5	0.95			
Reliance on strategic boundary-spanning employees (RoSBSE)	RoSBSE-1	0.82	0.89	0.90	0.65
	RoSBSE-2	0.90			
	RoSBSE-3	0.86			
	RoSBSE-4	0.73			
	RoSBSE-5	0.66			
Reliance on operational boundary-spanning employees (RoOBSE)	RoOBSE-1	0.82	0.93	0.93	0.72
	RoOBSE-2	0.86			
	RoOBSE-3	0.91			
	RoOBSE-4	0.83			
	RoOBSE-5	0.83			
Supply chain agility (SCA)	SCA-1	0.81	0.96	0.96	0.80
	SCA-2	0.86			
	SCA-3	0.87			
	SCA-5	0.94			
	SCA-6	0.94			
	SCA-7	0.93			

Table 5 Structural equation model results.

Research Path		Coefficients	Results
H_1: AI worker displacement → SCA		0.275***	Supported
H_2: AI worker displacement → RoOBSE		0.205***	Supported
H_3: AI worker displacement → RoSBSE		0.200***	Supported
H_4: RoOBSE → Supply chain agility		0.369***	Supported
H_5: RoSBSE → Supply chain agility		-0.033	Not supported
Control Variables Coefficients			
Control	**RoOBSE**	**RoSBSE**	**SCA**
Age	-0.023	-0.066	0.076
Size	0.159	0.193*	-0.004
Length of Relationship	-0.060	-0.043	-0.021
Strength of Relationship	0.087	0.020	-0.017
Goodness of Fit Measures		**Estimate**	**Interpretation (1)**
Parsimonious fit	χ^2/df	1.510	Excellent
Absolute fit	RMSEA	0.057	Excellent
	PClose	0.252	Excellent
Incremental fit	TLI	0.960	Excellent
	CFI	0.974	Excellent

6. STUDY 2 – FOLLOW UP INTERVIEWS

The SEM results generally support the hypotheses that AI, while displacing some employees, enhances the roles of other operational and relational boundary spanners in enabling supply chain agility. Still, the application of supply chain AI remains in its initial stages for most organizations (Klumpp and Ruiner 2022). We therefore sought deeper insight into the perceived social network roles of boundary-spanning employees via interviews at one organization. The structured questionnaire (Appendix B) specifically explored how the reduction of knowledge workers affects the net efficacy of boundary spanners, including the unique set of capabilities that they bring to their organizations.

We collaborated with one U.S. pharmaceutical manufacturer that is currently applying AI to assist with supply chain processes. The interviews were conducted with eight supply chain practitioners at different levels of seniority. To ensure unbiased quality first-order data, interviewees were promised anonymity. Table 6 highlights key feedback from the respondents, which can be categorized into three groups. The first group, which included half of the respondents, agree that the added capabilities of AI strengthen organizational capabilities. Aligning with the survey SEM results, this group insists on the indispensability of boundary-spanner operational and strategic tasks. They position AI as a boundary-spanner-led decision-support function for business-to-business interactions.

In a second group, one respondent took a more extreme approach with the opinion that AI is completely outmatched by boundary-spanner human abilities to troubleshoot, deep-dive, and answer questions. This speaks to our ability to handle ambiguity and connect the dots. The final group, which included three respondents, believes that AI outperforms boundary-spanning employees on assigned tasks, which more than compensates for any benefits that boundary spanners provide. In fact, this group believes that boundary spanners tend to unnecessarily filter information and harbor biases, possibly as part of an agenda (Doz and Shuen, 1988).

As a final step, respondents were asked which social network centrality type was more important for the effectiveness of boundary-spanning functions for supply chain agility: eigenvector centrality (the strength of boundary spanner relationships) or degree centrality (the number of boundary spanners) (Borgatti & Li, 2009). Six respondents selected eigenvector centrality (four from group 1, one from group 2, and one from group 3), which aligns with the survey results depicting the enhanced value as boundary spanners maintain agility in supply chains. The remaining two interviewees who selected degree centrality were both from group 3.

7. DISCUSSION

Boundary-spanning employees support strong relationships with supply chain partners to navigate supply and demand uncertainties (Korschun, 2015). Nevertheless, the role of boundary spanners with supply chain AI remains unclear. Our results reveal how supply chain AI implementation, including the associated displacement of employees, supports enhanced supply chain agility (H1). However, the results also show that AI increases reliance on both operational (H2) and strategic (H3) boundary-spanner roles. Finally, operational boundary spanners enhance supply chain agility (H4), while strategic boundary spanners have no significant impact on agility (H5).

Overall, these findings highlight how organizational agility competencies are driven by a hybrid of human and artificial intelligence (Klumpp and Ruiner, 2022; Winkelhaus *et al.*, 2022). Some knowledge worker jobs are lost as AI automates tasks. However, the importance of the remaining knowledge workers is elevated to help the organization extract maximum value from AI (Klumpp and Zijm, 2019). Malone (2018) considers the intertwining "collective" intelligence of humans and machines, and our findings emphasize that organizations should retain some boundary spanners to have the best of both worlds. In contrast, employee resistance over concerns of job loss and personal intrusions will limit, if not negate, the success of supply chain AI adoption (Klumpp and Zijm, 2019; Hasija and Esper, 2022). Our findings concur with the human factor as a make-or-break factor for supply chain AI implementation.

The follow-up interviews show that not all practitioners agree with the joint human-AI perspective, holding significantly varying levels of appreciation and acceptance of the role of AI in the supply chain. Some respondents concur with the joint role of AI and boundary-spanning humans in improving supply chain agility. Others believe AI alone can be more effective by avoiding human decision-

Table 6 Interview participant key responses (follow-up interviews).

Participant	Title	Response highlights
Ae	Associate Director Supply Chain	"AI has a greater amount of touchpoints vs human connections, greater reach by automation (i.e., geography and industry), machines show no bias in gathering data by not filtering information like humans do. There's less misinterpretation of facts, as would be coded in AI setup and simply a larger data pool would offset the benefits of a more detailed conversation by a human with a smaller sample size. Also, Humans are creatures of habit, and resistant to change, therefore looking for marketplace changes will be difficult, not to mention personnel costs vs higher upfront investment in AI, but economies of scale later on." *Doesn't the fact that one of the capabilities humans have over AI is the ability to cope with ambiguity better than AI which can only deal with scenarios its programmers have captured in its algorithm, play any part?* "Not really. I think that would be compensated by the higher volume of data gathered."
Be	Associate Director Supply Chain	"I'd imagine that machine-learning/AI would be better at drawing conclusions from data on trends and marketplace changes than your average employee in one of these roles. On average, you are unlikely to negatively impact firm's agility."
Ce	Senior Director	"AI or other machine learning technologies could be capable of analyzing a huge data set in a very short amount of time to inform on marketplace changes, which is potentially a reason why there is no negative impact on agility. However, the technology will have to be set up in a meaningful and accurate way which will take the expertise of boundary-spanning employees making their presence still a critical asset."
Dd	Supply Chain Specialist IV	"This could be due to the ability to train AI to detect and respond to market-place changes, using the same methodology and principles as boundary-spanning personnel."
Ed	Supply Chain Specialist III	"As much as AI can be very effective and trained on many different aspects, I'm indifferent. Comparing humans vs AI, I feel you'll get a more efficient and robust understanding in all aspects of the process with human-to-human interaction. You're able to trouble-shoot, deep-dive, and answer questions that AI can't answer."
Fe	Senior Supply Chain Specialist	"With advances in technology such as AI, there is analysis and information provided that firms did not have access to before. This information/data can help with a firm's vision and focus on KPIs to drive their agility, and this might explain why you're not seeing any negative impact with the reduction of employees in these boundary-spanning roles. Another reason could be the firm's shift in priority. With information and data coming from technology/AI, it may be more beneficial to shift the resources in boundary-spanning roles to focus on different priorities to help with the firms' strategy."
Ge	Director Supply Chain	"Over the course of the pandemic we have seen that virtual interactions allowed us to carry on with business effectively in many ways that we only thought possible via face-to-face interactions previously. It then stands to reason that the next step away from human interactions totally (towards AI) could still result in effective completion of many activities. I believe that there are still many activities that will always be more effective with face-to-face interactions, but it may be that boundary-spanning roles fall into the other category of activities that can more effectively be done via AI. The pandemic has likely shifted public perception in this direction. Further, it may not be factual that face-to-face (or even virtual) interactions are similar in effectiveness to AI interactions, but the pandemic has seemed to create a culture of undercutting the importance of human interaction. So, while it may be current popular opinion that human interaction is not as important as once thought (because we were able to still get so much done virtually during the pandemic), it is still very early days in this understanding, and we may be reading the situation incorrectly."
He	Associate Director Supply Chain	"There needs to be a balance between the capabilities of humans and AI, AI output might exceed human capability in terms of volume, but AI is not quite there in terms of decision-making. There has to be a hybrid – a balance of both. AI implementation can help reduce costs but can't completely replace human capability. Both have to work in unison, human intervention is needed. Machines can't handle ambiguous situations, and that's where humans are still needed. Both capabilities have pros and cons, AI enhances our ability to respond but it can't fully replace the workforce. Especially in pharmaceuticals. Maybe in other industries, it can play more of a role."

making biases. In contrast, one respondent completely discounted AI in handling the ambiguity of demand and supply market variability. This divide challenges the path of AI in the supply chain by limiting the required shift in "organizational structures, work design, and goal setting alter in the course of digitalization" (Klumpp and Ruiner, 2022:297).

7.1 Implications for Theory

From a theoretical perspective, this study contributes to dynamic capabilities theory, in particular by taking a Schumpeterian-like evolutionary approach to capabilities which firms must evolve (in this case the human-AI hybrid), in order to achieve and sustain competitive advantage in today's business environment. Specifically, some advocate evolutionary approaches as a better theoretical lens to understand technological and organizational change, such as the wave of AI adoption disrupting interfirm boundary-spanning functions (Hodgson, 1998). Our results, however, more so validate the dynamic capabilities theory in how organizations can safeguard competitiveness and ensure the right balance of human and AI competencies for highly dynamic markets (Freiling *et al.*, 2008).

In this study, we resolve this conundrum by viewing supply chain agility as a strategic objective of supply chain collaboration that is dependent on the roles of the human right-hemisphere brain functions versus AI, which performs left-hemisphere brain functions more efficiently. Both capabilities remain indispensable in the achievement of strategic objectives, at least until supply chain AI evolves to fully replicate human right-hemisphere brain functions. Until such a time, supply chain AI alone must be innovatively applied, as Breu *et al.* (2001) suggest, in decision support for business scenarios where outcomes are limited and predictable. Otherwise, supply chain agility may be compromised.

As a related contribution, this study addresses the dearth of research into the unique role of people in achieving organizational agility as well as the impacts of AI on the human side of supply chain (Klumpp and Ruiner, 2022). Social network theory, for instance, underscores how business network centrality plays an important role in enabling agility even with the dwindling number of interfirm ties via boundary-spanning employees. Earlier we identified four forms of social networks: degree centrality (number of ties), closeness centrality (degree of reachability and communication), betweenness centrality (controlling information flow), and eigenvector centrality (higher levels of social capital) (Hernández-García *et al.*, 2015). The suitability of closeness in disconnected groups and betweenness in connected groups are indicators of successful collaboration that rely on the reachability or distance between nodes and the mediation of interactions between other nodes (Saqr and López-Pernas, 2022). Modern technology reduces the significance of distances between nodes in B2B collaboration. Social capital theory suggests that organizations are better able to tap knowledge more effectively from other companies when sufficient social capital exists between those organizations (Krause *et al.*, 2007). Our study shows how high levels of social capital associated with business ties exhibiting eigenvector centrality increase the chances that boundary spanners will exploit their business relationships to exploit critical market intelligence of disruptions.

7.2 Implications for Practice

The COVID pandemic has permanently changed supply chain with its unprecedented breadth and magnitude of demand and supply disruptions (Falcone, *et al.* 2022). During the pandemic, companies responded with significant changes to S&OP processes via human-based manual workarounds (Sultan, 2022). Our study reiterates the importance of a holistic evaluation of organizational capabilities for supply chain agility, especially when making technology adoption decisions. Caldeira and Ward (2003) advise that IT related organizational competence is derived from a combination of technical, managerial, and general managerial skills. Bughin *et al.* (2018) suggest that adopters of AI need to understand that they not only still need employees but also must advance employee skills and work design. This is particularly important to minimize disruptions by proactively dealing with market shocks. As much as AI is adept at business process transformation for organizations embracing a data-centric culture, the human right brain hemisphere's ability to "take in the whole scene" and recognize overall patterns, remains difficult to replicate (Ransbotham *et al.*, 2020).

The research results also stress the importance of boundary-spanning employees to maintain relationships with supply chain partners to fully recognize the potential of AI for enhancing agility. The continuing evolution of AI technology in business is part of a new normal to be embraced by industry practitioners where business relationships are intertwined with the technologies that enable them. This point is well articulated by one practitioner interviewee, who describes inter-firm trust that is dependent on systems. That is, machine learning can boost inter-organizational trust between supply chain partners.

Relatedly, the skills and design shift needed for AI adoption creates an opportunity to address the supply chain workforce shortage that persisted before the pandemic (Maloni *et al.* 2017). COVID-19 disruptions simultaneously increased the need for supply chain professionals and fueled the unexpected "great resignation" of many employees, many of whom have not returned (Robert, 2022). Companies can position AI as an approach to backfill at least a portion of this workforce gap. In turn, the role of the remaining employees can be elevated from mundane tasks to more complex, interactive boundary-spanning roles, thereby enhancing employee satisfaction and retention. Given the perceived division of opinions of AI between humans, managers must carefully socialize AI within the organization to maximize acceptance among both eager and skeptical employees.

8. LIMITATIONS AND FUTURE RESEARCH

This study's findings and limitations yield promising opportunities for future research. First, longitudinal analyses could evaluate how boundary-spanner roles transform as AI becomes more adept at ambiguity. Future research could also better capture individual perspectives, such as the propensity to engage in a job-changing technology like supply chain AI, to provide deeper insight into how to support employee acceptance (Falcone *et al.*, 2021).

Expanding our understanding of how displaced and retained boundary spanners behave in particular business contexts and industries is also essential. For instance, Fine (1999) notes how business cycles are dynamic with mechanisms forcing change at different rates. Hence, a future research direction could focus on industries with shorter versus longer clock speeds. Our study could also be conducted in other markets or cultures, particularly where business relationships depend more on interpersonal strategies (Zhu *et al.*, 2006). Though a relativist ontology may be implied, evaluating our model on more global samples would be compelling.

Finally, social networks driven by interpersonal influence are essential to any business (Li *et al.*, 2016). AI adopters must consider their unique business models and associated social structures when deciding what business processes to automate. With complex networks being heterogeneous in structure, research could quantify network centrality to identify the most influential nodes (Kitsak *et al.*, 2010).

9. CONCLUSION

Technologies like AI, blockchain, and the Internet of Things provide tools to reduce the complexity of supply chains (Gupta *et al.*, 2023; Klumpp & Ruiner, 2022). Applications include but are by no means limited to shipment tracking, last-mile delivery, warehouse automation, autonomous vehicles, predictive maintenance, and even talent management (Cotter, 2022). While industry is taking a lead role in AI implementation, the future of supply chain jobs remains uncertain. We urge more scholarly research to help practitioners design and implement the technology-human interface that will continue to transform supply chain.

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APPENDIX A: SEMI-STRUCTURED INITIATING INTERVIEW PROTOCOL

Opening

- Interviewer and participant introductions
- Study purpose overview
- Confidentiality assurance
- Permission to record
- Title and responsibility of participant

Interview questions

- Think of one of the strategic partners that your company does business with (e.g., a customer or a supplier). Placing your interactions with that strategic partner in your mind; what is it like working with this strategic partner?
- Besides usual business volumes and transactions, does your firm provide or receive help to/from them? For instance, help in building in-house capability.
- What means does your firm use in exchanging important information with these strategic partners?
  - Please elaborate on one of these exchange relationships.
  - Does this exchange relationship have any unique benefits?
- Can you think of an instance where these means of know-how transfer were replaced by technological innovation (e.g., AI). How was your firm able to ensure this information continued to reach your partners?
  - When your firm eventually replaces these means of know-how transfer with AI, how else do you think your organization will ensure this information continues to reach these partners?
- What business practices or results, in your opinion, either were affected or do you think would be affected by the replacement of boundary-spanning employees with technology?

Floating prompts

- Can you tell me more about that?
- Will you explain that in more detail?
- Can you give me examples or tell a story of an experience about that?
- How does that work?
- Tell me about a time when that did not happen

Wrap-up

- Thank you for taking time to meet. If you are interested, you will receive a copy of our findings. If you have any questions or think of anything else, please don't hesitate to contact me.

APPENDIX B: STRUCTURED FOLLOW-UP INTERVIEW PROTOCOL (STUDY 2)

Opening

- Interviewer and participant introductions
- Study purpose overview
- Confidentiality assurance
- Permission to record
- Title and responsibility of participant
- *Description:* Boundary-spanning employees have external facing roles in a company, interacting with both strategic and non-strategic partners (either customers or suppliers).

Interview Questions

- In a recent study of surveyed practitioners, we assessed if the displacement of employees in boundary-spanning roles by AI was having any impact on their company's ability to detect and respond to marketplace changes. The results seem to suggest that this displacement was not having any negative effect on their agility. What in your opinion could be responsible for this?
- Besides the reason you just provided, can you think of any other reasons for this?
- Which of the following do you consider more important for boundary-spanning functions to be effective at detecting and responding to changes in the marketplace?
  - The number of boundary-spanning employees in an organization with business ties with their counterparts in other firms.
  - The connectedness or strength of business relationships boundary-spanning employees in an organization have with their counterparts in other firms.

Wrap-up

- Thank you for taking time to meet. If you are interested, you will receive a copy of our findings. If you have any questions or think of anything else, please don't hesitate to contact me.

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