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Osaro: Picking the Best Path

As the fog lifted from downtown San Francisco, Derik Pridmore, CEO of Osaro, Inc., gazed out of his office window overlooking Mission St. It was January 2019, and he was waiting to pitch the next venture capital firm during his latest funding round. Derik reflected on the winding path he had followed to this moment. In 2004, he received a master's degree from MIT in Computer Science and Electrical Engineering. Building on his background in physics and computer science, he then pursued a decade-long career in finance, working in derivative trading units at JP Morgan before moving to a hedge fund. Throughout his time on Wall Street, he continued to explore advances in fundamental technology. In 2009 while serving as Vice President at Peter Thiel's hedge fund Clarium Capital Management, Derik pulled Thiel aside to discuss advances happening in a new field called deep learning. Thiel offered Derik a job as a Principal at the venture firm Founders Fund to focus on the area. Derik would later lead the series A funding round for DeepMind, a UK-based startup that had no product but was exploring uses for deep learning and other machine learning methods. By the time DeepMind was acquired by Alphabet (then Google) for \$500 million in 2014, Derik had sensed opportunity.^{1a}

Machine learning was a technique by which machines found patterns in data. A type of machine learning, deep learning used a structure called deep neural networks, which was a mathematical method analogous to the human brain and particularly adept at finding complex relationships. Notably, deep learning allowed computers to perform many tasks that were impossible to hard code because of the complexity involved. These included tasks that humans consider relatively simple, like manipulating objects, localizing an object in an image, or visually understanding the environment, which were too complex to explain in simple terms or code explicitly, a phenomenon known as "Polyani's paradox." Deep learning reached an inflection point around 2012, as technology trends, including processing power, availability of data, and improvements in algorithms, combined to make deep learning a viable approach to solving many problems previously intractable.^b One notable

^a DeepMind was widely regarded at the forefront of deep learning. Notably, it created AlphaGo, the first program to reach better-than-human performance at Go, a Chinese board game with near-limitless combinations of moves.

^b For more background on deep learning, see Kerr, William R., and James Palano. "Modern Automation (A): Artificial Intelligence." Harvard Business School Case 819-084, December 2018.

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benchmark it passed was outperforming humans in image recognition on a stock dataset of photos, proving for the first time a viable path to vision for machines. For these types of applications, prior machine solutions were said to be “brittle,” as they lacked the ability to handle the wide range of possible configurations of input. Deep learning could overcome this challenge, opening up a vast array of potential applications.

Deep learning, like other types of machine learning, allowed a machine to recognize patterns associating an input with an output after being “trained” on considerable amounts of data. This data, in a technique called supervised learning, generally included an input (e.g., images to be recognized) labelled with the output variable (e.g., the word describing the image). Many applications do not have a natural “label” for output. Reinforcement learning gets around this by using positive and negative feedback to provide a signal to the machine when it has correctly or incorrectly performed the task. This technique was valuable in robotics applications by providing an “output” in the form of “successful” or “not successful” which could be used to train the model. The technique was first demonstrated by Gerry Tesauro’s “TD Gammon” and later popularized and scaled to much more complex problems by DeepMind which showed that deep reinforcement learning could be used to teach a computer to play Atari without hard-coding or demonstrating to the computer how to play.²

Derik realized that deep reinforcement learning could unlock a wide range of applications previously unavailable to machines. Derik believed the technology could revolutionize robotics usage in a wide range of industries. But, he was concerned about the many barriers to bringing the technology to a new use case, including: productizing a new technology, selling the product, retaining the best talent, and addressing risks from competitors on all sides. Derik also worried about scaling production and balancing advancement with a focus on selling a product. But when he started, Derik did not even know what his product would be.

History of Osaro

Derik cofounded Osaro in 2015 with Michael Kahane to commercialize deep learning technology in novel applications. Michael was previously a serial entrepreneur with a background in chip design. After a decade of positions in industry, Michael reconnected with an academic and former colleague from the IDF, Professor Itamar Arel, and began doing research at the University of Tennessee in cutting-edge techniques for deep reinforcement learning. After Itamar introduced the two, their first project was a proof of concept demonstrating that a combination of deep learning and “imitation learning” based on observations of a human playing Atari could increase the speed a machine could learn the game by 100 times.

Aided by this demo, Osaro raised a seed round of \$3.3 million from Peter Thiel, Jerry Yang, Sean Parker, and others in March 2015. In April of 2017, Osaro raised a \$10 million series A round from iRobot Ventures, ZhenFund, Fenox Venture Capital, Compound, Comcast Ventures, and Arab Angel Fund. The series A round valued Osaro at \$50 million. **Exhibit 1** show’s Osaro’s funding table.

Early projects

Beginning in late 2015 and continuing into 2016, Osaro completed a string of pilot projects. Their first was an advertising pilot with a prominent social media company. Shortly after, they began a pilot project with KUKA, an industrial robot manufacturer based in Germany. According to Derik, “Social media advertising and robotics sound insanely different, but the unbelievably true thing is that the core technology is the same.”

After investor leads connected him to KUKA's Chief of Innovation, Derik flew to Germany in November of 2015 to meet with him. KUKA's request was to see how efficiently – in terms of data, equipment, and time – Osaro could program a robot to handle objects based only on visual input. Through a program where KUKA shared robots with external partners to spur innovation, they sent a robot to Osaro to program. According to Derik, "We not only succeeded, but we did it with a very small amount of data, and we actually did it in a very robust way. We were able to pick the object up even if we moved it in adversarial positions. That impressed them." After the successful demo, Osaro made a substantial partnership proposal centered around the development of technology that would enable industrial robot arms to intelligently recognize and pick up various objects.

Realizing the potential in this area, Osaro pitched a project to ABB, a competing Switzerland-based industrial robotics manufacturer in the summer of 2016. Building on their demonstration with KUKA, Osaro proposed to make the program more robust and able to handle more complexity such as placing objects in smaller windows or more specific orientations. Osaro and ABB subsequently formed a joint development agreement in which Osaro would own the intellectual property relating to their software and ABB would own any improvement in their robots' software interface. In the fall, Osaro demonstrated to IHI, a Japanese integrator, the ability to pick up clear items – a significant technological challenge. This led to an Osaro deployment in an IHI test facility. These early demonstrations convinced Derik and the Osaro team to focus on robotics for the next steps with Osaro's core technology.

Robotics applications

Derik commented, "Although there are one billion cars in the world, there are only 5 million robots. In the case of cars, human operators (conveniently being transported) serve as the sensing and control algorithms. Although robots can theoretically perform many more tasks, while a car can perform only one, their use cases remained limited to simple rote actions because most robots are blind. They cannot react to changes in the environment. They cannot learn to handle a wide variety of different tasks. They take no sensory feedback from the environment, so they are only able to repeat the tasks they are programmed to do."

Osaro sought to change that, "bringing machine learning to robotics that allows the machines to perceive the environment and learn to handle varieties, react to changes, and perform tasks more autonomously." Machine vision, powered by deep learning, had recently reached better-than-human performance and could solve robot blindness.³ But Osaro sought a step further through the use of technology such as deep reinforcement learning, which added elements of control. Derik commented, "Most machine learning companies are still focused on using deep learning for pure vision applications, which addresses only part of the problem: enabling machines to perceive. That's important, but the next step is to use perceptual knowledge to achieve a goal of some sort. Osaro's deep reinforcement learning technology fills this gap. We enable products that move beyond merely processing images to automatically take informed, complex actions."⁴

Deep reinforcement learning could also allow robots to manipulate objects by learning patterns in best approaches to pick up products. And once a single robot learned to perform a task, that program could be used by other robots. Osaro saw their mission as using deep learning, deep reinforcement learning, and motion planning to enable robots to handle greater variability and be useful in a wider range of applications. At that point, as Derik put it, "Having committed to robotics, we had a decision to make about who our customers were going to be, and in exactly which market segment we would operate."

Industrial robotics

The word “robot” was commonly used for more than one type of machine. One common use was for small guided or autonomous vehicles. Industrial robots, sometimes called “robot arms,” were able to perform actions like lifting or using a tool. The International Organization for Standardization (ISO) defined an industrial robot as “an automatically controlled, reprogrammable, multipurpose manipulator programmable in three or more axes, which can be either fixed in place or mobile for use in industrial automation applications.”⁵ Industrial robots generally included an articulated arm, an “end effector,” which attached to the end of the arm to perform the required task, a computer, software that allows simple movement of each joint (for instance, back and forth between pre-programmed positions), and sometimes sensors like cameras which could provide input that would be used to guide the robot. Computing was almost exclusively done locally. **Exhibit 2a** shows an industrial robot and **Exhibit 2b** shows a variety of end effectors.

The industrial robotics industry consisted of original equipment manufacturers (OEMs) and robotics integrators who installed robotics systems. A few large OEMs dominated the international market. Integrators provided robotics solutions to end users and operated at a more local or regional scale. The largest customers of industrial robots were in automotive manufacturing and electronics assembly. **Exhibit 2c** shows industrial robot sales across industries. Industrial robots often performed dangerous tasks (e.g., handling heavy or hot objects and welding) or those requiring very high levels of precision. They also were generally deployed on manufacturing lines which repeated the same tasks huge numbers of times. For instance, U.S. auto plants produced hundreds of thousands of cars per year with each car requiring around 4,500 welds.^{6,7}

As of 2016, the major industrial robotics companies were making limited visible strides towards incorporating deep-learning capabilities in their products. Some produced lines of collaborative robots, or “cobots” which were widely seen as cutting-edge. These robots incorporated new technology such as “teach-in” to be easily repurposed and safe to operate around humans. The new functionality was marketed as a major change given that industrial robots were generally not reactive to their environments and operated behind fences exclusively on separate tasks from humans. However, Osaro executives were skeptical of this approach as the collaborative functionality was achieved by manually moving the robot to pre-set robot poses rather than granting the robot the ability to perceive and react flexibly to the environment. These products also often resulted in diminished functionality (such as slower movement or lower payloads). But by 2017, every major robot arm manufacturer was producing some form of collaborative robot arm.

Traditional consumers of industrial robots valued speed and precision, since robot errors were very costly in certain contexts (e.g., precision assembly, lifting heavy or complex components, applying paint or chemicals, welding). Despite the large value in these applications, state-of-the-art perception and robotic control systems powered by deep learning were not yet precise enough for manufacturing and assembly tasks. Moreover, traditional industrial customers operated at a scale that allowed for the deployment of very specialized robots, weakening the value of the flexibility offered by deep learning.

Warehousing

Warehousing was generally grouped with the supply chain and logistics industries. Warehouses, also called distribution centers, served as storage and distribution hubs for producers, suppliers, and retailers, and were used heavily for direct-to-consumer fulfillment. One estimate valued the industry’s 2018 U.S. revenue at \$42 billion.⁸

Explosive growth in ecommerce sales, among other factors, lead to a dramatic reorganization of the sector (see **Exhibit 3a** and **Exhibit 3b**). Companies competed over fast and inexpensive order fulfillment (see **Exhibit 4**) leading to intense pressure on supply chain operations. Ecommerce distribution was particularly intensive in handling a wide variability of items. Consumers bought a wide and growing range of products online (see **Exhibit 5**). To highlight the ascendance of ecommerce, in 2018 Amazon's revenue per employee was \$314,251 compared to \$211,249 for Walmart.⁹ Logistics companies reported intense competition for customers whose demands included short-term contracts, frequent shopping, demands for flexibility, and support of omnichannel shopping experiences. These posed additional challenges as locations were often developed to serve specific customers. Logistics companies competed primarily on speed and variety as well as price. Industry observers said these pressures could act as both incentives and disincentives to investing in automation.¹⁰

By the end of 2018, nearly 50% of U.S. e-commerce sales occurred on Amazon's platform.¹¹ New Amazon fulfillment centers in 2017 and 2018 were generally over 800,000 square feet and employed over 1,000 workers. By 2019, Amazon's operation was estimated to include nearly 170 facilities for fulfillment.¹² One analysis estimated that Amazon's logistics division would be the fifth-largest logistics company in the world, were it a separate company.¹³ Amazon notably had "warehouses within 20 miles of half of the U.S. population," as ecommerce fulfillment centers need to be widely dispersed to supply retail locations or fulfill customer orders.¹⁴ A 2018 industry survey found the top challenge for supply chain industries was "customer demands on the supply chain" followed closely by "hiring qualified workers."¹⁵ **Exhibit 6a** shows the other challenges reported by supply chain companies.

At the same time as this boom, warehousing jobs were becoming increasingly difficult to fill, as the jobs were often menial, low-paying, located in harder-to-reach areas, and offered little by way of career trajectory. There were about a million workers in the U.S. warehousing and storage industry in 2017, around 270,000 of whom were storage stock workers. The industry's average wage was about \$15 an hour.¹⁶ 55% of warehouse operations reported availability of labor as a major issue in 2018, an increase over previous years.¹⁷ **Exhibit 6b** shows the workforce challenges reported by supply chain companies. Labor generally made up over 50% of a warehouse's operating cost.¹⁸ Warehouses often struggled to keep up with seasonal retail demand as well. In 2017, they employed 30,000 more workers in December than in October, with payrolls reverting after the holidays.¹⁹

Warehouse automation landscape These pressures contributed to a rise of warehouse mechanization. **Exhibit 7** shows the increasing importance of automation and robotics in the supply chain industry. Warehouses were automated to a wide range of degrees (see **Exhibit 8** for one analyst's levels of automated warehouse). Some warehouses featured automated unloading docks where goods were unloaded, scanned, and later de-palletized. Warehouses could also employ "automated storage and retrieval systems" (ASRS) which moved inventory to be stored and later retrieved goods to be shipped. ASRS could use a variety of different technologies, including conveyor belts and autonomous guided vehicles (AGVs), to store or retrieve individual items or racks of items. These systems could enable storing objects much more closely than human retrieval would allow in so-called high-density storage systems. Conveyors often employed sorting technology which could automatically route new goods to the correct destinations. After items were retrieved, warehouses would sort and box items to fulfill individual orders, if shipping to consumers. Warehouses that made bulk shipments would generally operate with the unit of a box, rather than an item, and might feature machinery to palletize boxes autonomously before shipment. Computers, called programmable logic controllers (PLCs), controlled the equipment along with software. The software managing the flow of goods through the warehouse was called the warehouse management system (WMS). Industrial robots saw limited use in warehouses, and were generally only used for palletizing or de-palletizing goods.

Exhibit 9 shows the growth of robot sales in logistics applications, mostly in the form of AGVs. One estimate valued the ASRS market at \$12.4 billion in 2017, expecting it to grow to \$22.6 billion by 2023.²⁰ A survey run by Deloitte and MHI, the international material handling and logistics industry association, found that 34% of supply chain operations used robotics or automation in 2018 and an additional 39% planned to by 2023. 65% of respondents stated that robotics and automation had potential to disrupt or create competitive advantage, up from 39% in 2015.²¹ And by 2018, 93% of distribution centers used WMS to manage and optimize warehouse operations.²²

Warehouse automation solutions were generally provided by material handling companies (MHCs). The top ten MHCs made up roughly 70% of the global warehouse automation market and the top five accounting for nearly 50%.²³ MHCs supplied the equipment, and material handling integrators installed the solutions in a customer warehouse, customizing the system for the specific use case. Integrators were generally smaller, regionally focused service providers, but many of the large, global MHC equipment makers offered extensive integration services as well.

Amazon controlled about 50% of the U.S. ecommerce market in 2018.²⁴ In 2012, Amazon purchased Kiva Systems for \$775 million, making waves in the warehousing industry.²⁵ Kiva was perhaps the most influential innovator of materials handling technology; its warehouses featured a “swarm” of AGVs which navigated around the warehouse to lift and transport racks of goods and bring them to “picking” stations where individual orders were fulfilled. **Exhibit 10** shows photos of Amazon warehouses automated with AGVs. After being acquired, Kiva was renamed “Amazon Robotics” and ceased taking on new customers. Amazon employed 80,000 robots in their fulfillment centers by the end of 2017.²⁶ By the end of 2018, 14% of Amazon’s 185 fulfillment centers employed mobile-robot-based ASRS systems.²⁷ ^c In some warehouses, Amazon employed “CartonWrap” machines, which could box items at four to five times the rate of a human. They did this by scratch-building custom boxes around goods as they travelled down a conveyor after a person retrieved items from the AGV-transported racks for a given order. JD.com’s automated warehouses used similar technology. People working with the technology estimated it would remove 24 roles at each warehouse where it was installed.²⁸

Other companies raced to compete in this space. XPO Logistics, a leader in logistics and warehousing, named warehouse automation as a strategic priority at the beginning of 2017.²⁹ ^d In 2018, XPO entered into an agreement with GreyOrange to deploy 5,000 semi-autonomous robots in similar systems to Amazon’s.³⁰ That same year, GreyOrange raised a \$140 million Series C round led by Peter Thiel’s Mithril Capital and including Indian ecommerce giant Flipkart.³¹ DHL Supply Chain, another leader in U.S. warehousing, announced a \$300 million investment in new technologies in November 2018.³² British supermarket company Ocado, a leader in ASRS technology,^e began selling their technology as a solution to other grocers in 2015. By 2018, AGV-based ASRS’s were being offered more widely by incumbent MHCs as well. Business Insider Intelligence estimated that the logistics companies globally would use over 600,000 robots by 2023, up from about 100,000 in 2018.³³ **Exhibit 11** shows the warehouse automation value chain.

Large ASRS companies provided full-warehouse systems which required expensive warehouse retrofits. One estimate compared the cost of smart warehouse retrofits at \$150 per square foot with \$10

^c Amazon’s ASRS system: <https://www.youtube.com/watch?v=qRQwkJLRfWw>.

^d From XPO Logistics’ 2017 10-K: “Our warehouses are becoming high-tech hubs: we have robots working side-by-side with our people, and drones helping out with inventory management. We use smart glasses for order picking, and numerous other technologies, some of which are purpose-built for individual customers.”

^e Ocado’s warehousing solution: https://www.youtube.com/watch?v=4DKrcpa8Z_E.

per square foot for traditional warehouses.³⁴ Other robotics companies focused on robotics solutions that could increase warehouse efficiency without retrofits or large investments in capital. These companies, which included Locus Robotics and 6 River Systems, provided semi-autonomous robots to locate items and transport goods throughout warehouses and relied on human workers to load and unload them. InVia Robotics, which provided semi-autonomous robots as a service, relied on humans only for the final pick.³⁵ In May 2018, inVia announced that it would provide its robots-as-a-service solution to Rakuten Super Logistics, beginning with 20 robots at a 3,000 square-foot facility.^{36f}

State-of-the-art facilities like Amazon's used semi-autonomous robots to bring shelves to humans waiting in "picking" stations who then picked up individual items and placed them into bins or packages to be shipped (see **Exhibit 12**). "Pick and place" was widely considered to be the last repetitive task that could not be performed by machines. Picking individual items was a different physical task than moving bulk crates or cartons, which were more uniform. Existing technology could not handle the full range of possible pick and place tasks as there were near-infinite combinations of geometry, weight, appearance, and other physical properties. Brad Porter, VP at Amazon Robotics, noted in 2018: "When it comes to using robotic manipulation for item picking, while we're encouraged by the work in the research community, the simple fact is the current state of the art is not capable of handling the diversity of Amazon's product selection."³⁷

Many raced to find technology solutions for this final piece of warehouse fulfillment. Amazon, Ocado, GreyOrange, Alphabet, and others experimented with robotic picking. Amazon looked to bolster external development efforts as well. The company hosted annual "picking" challenge, where teams competed to pick and place a basket filled with a variety of goods, and funded an MIT class about robotic manipulation. In 2018, it replaced its picking challenge with a grant program to fund academic research called "Amazon Research Awards."³⁸

Warehouses did not have uniform picking demands due to the variability of the objects handled, and ecommerce fulfillment required as much as three times the staff of other warehouses.³⁹ Symbolic created a full warehouse automation system for grocery suppliers which required no human intervention for picking, as machines could stack the relatively uniform bulk packaging on pallets for shipment.⁴⁰ § Massive Chinese ecommerce company JD.com reportedly created a fully-automated warehouse in 2018.⁴¹ Though, in 2018, JD.com announced it would host a picking challenge of its own.⁴²

Derik saw picking as an opportunity to monetize deep reinforcement learning quickly because it involved handling more variability than the current state of the art could handle and it was adjacent to tasks that were becoming increasingly automated. Warehouse picking also involved less need for precision and speed than manufacturing applications. And, unlike manufacturing operations, warehouse picking allowed for a comfortable tolerance for error. This made it friendlier to early versions of the technology, with Derik noting: "For our first products we needed an application where, if the robot fails its first three efforts and succeeds on a fourth, we still have a useful product."

As the technology improved, Derik felt that deep learning could provide value in a variety of applications of industrial robots. "We are extremely optimistic about the power of AI to solve problems now, as opposed to in some distant future, and provide real value to people's lives. We wanted to start with markets that are huge today rather than markets which are still developing, like drones and household robotics. After we tackle those markets, we'll move on to other applications by leveraging

^f inVia's Rakuten deployment: <https://www.youtube.com/watch?v=1stl-UBtGO4>.

^g Symbolic's full warehouse automation solution: <https://www.youtube.com/watch?v=XO7fvrdrTCgs>.

the generality and broad applicability of deep reinforcement learning as the technology improves over time.”⁴³ **Exhibit 13** lists some potential markets for deep-learning-enabled robotics.

Osaro’s product

Osaro recognized that it must provide an end-to-end product which included object recognition as well as robotic motion planning to provide value in warehouse picking. Therefore, its robotics software system had two major components. First, it allowed robots to perceive a wide range of items with generalizable machine learning models which, unlike traditional computer vision prior to deep-learning-based machine vision, did not require pre-registration of items. Second, it made use of motion planning, which used the interpreted visual input data and models of the robot and other environmental components to instruct the robot how to lift an object. The product used data from commodity cameras to visually identify an object and its structure. **Exhibit 14** shows a representation of what Osaro allowed a robot to “see.” Robot arms could be equipped with various grippers or suction devices as end effectors to lift objects. In early 2019, robots powered by Osaro could pick items at rates of 1.33 – 6.0 seconds per object depending upon application, rates that were constantly getting faster.

The training data and machine learning models were all uploaded to Osaro's cloud using Amazon Web Services and could be deployed locally on warehouse computers at client sites. Osaro used a “pipeline” deployment approach where all on-site sensory information (e.g. data from cameras and grippers) and robot performance data were packaged and uploaded to cloud servers for further operations while minimizing the amount of model training and customer supervision required at the client site. This approach offered several benefits: it required less computing resources at client sites and allowed Osaro to analyze, visualize, and process data for the best choice of machine learning algorithms to solve a particular robotic task. The modular approach also made system-level decisions more interpretable and provided transparency, down to the finest level of detail, into how the system translated inputs to actions, making it easier to debug and troubleshoot. In addition, the approach provided Osaro with valuable on-site robot performance feedbacks/metrics which would be used to further improve the product in other settings.

Osaro's software interfaced with existing robotics control systems. **Exhibit 15** shows Osaro’s position in the architecture of material handling technology. Osaro built the integrations necessary to work with robots from all major manufacturers. Robots made by different manufacturers were controlled with different Application Programming Interfaces (APIs). Osaro adapted their models to whichever robots and end effectors were chosen by the integrator for a particular use. Osaro’s product could run on basic GPU, unlike many competitors which required higher-end controllers, and required only commodity 3D cameras, as opposed to high-end manufacturing grade cameras (e.g. 3D structured light sensors), by using advanced machine learning to handle lower-quality data. Derik stated, “We are convincing people that machine learning has progressed to the point where you need to make almost no hardware. We can build models that fit between super cheap sensors.” Osaro saw compatibility as a key competitive advantage to disrupt from below.

Osaro also sought to operate in a wider range of circumstances than competitors. For instance, Osaro’s platform was unaffected by the orientation of objects it would pick and could locate objects that were moved or that it dropped during an attempted pick. It could also operate in various lighting conditions and pick items with traits that other systems found confusing. These functions could not be hard coded, as traditional coding was too “brittle” to allow robots to have the general understanding of lifting that allowed it to handle non-standard situations. **Exhibit 16** shows important lessons that Osaro’s product helped robots learn. Osaro’s models also required minimal training to add a new product. When adding new types of stock to the warehouse, warehouse managers could instruct the

Osaro-powered robot to move the object. If the robot failed, the system would teach itself how to lift the new object by collecting data from the failures, sending it to the cloud, and retraining. By contrast, one competitor required 3-D scans and CAD renderings of new objects before it could attempt to handle them.

Osaro focused on solving piece picking through vision and motion planning. Said Derik of this choice: “There is a deep moat around using deep learning models for both perception and control. Manufacturing robots is difficult and resource-intensive, but learning algorithms and computing are so powerful that the hardware does not matter.” In contrast, competitor Soft Robotics took the approach of employing pliable end effectors, allowing for more flexibility in robotic control. CEO Carl Vause stated, “We do no training. We don’t do the offline learning, we don’t create the 3D models, because all of the things that are driving you to create those models, we can solve with the material science.”⁴⁴ Another competitor, RightHand Robotics, also created a perception and control system which could handle a wide range of objects, but sold its solution as a robot enabled with the software using a lightweight cobot from Universal Robotics after starting as a manufacturer of a particular specialized “end effector.” RightHand Robotics received substantial investment⁴⁵, including from Vanderlande, a large MHC, and Playground Ventures, a top Silicon Valley VC run by Andy Rubin.^{46,47,h} Kindred was another well-funded competitor which provided a product combining a perception and control system with a robot.^{48,49} Kindred used a fixed hardware configuration called an Orb that could be deployed free standing such that a human dumped products in one side and received sorted products on the other side. Kindred sold this solution directly to retailers, such as Target, by guaranteeing functionality which was backstopped by human teleoperation.⁵⁰ **Exhibit 17a** shows Osaro’s positioning relative to direct competitors. There were also many startups working to add intelligence to robotics without focusing on a particular industry. Veo, for example, focused on safety modules that allowed industrial robots to perceive and avoid humans.⁵¹ **Exhibit 17b** shows the broader landscape. Due to their approach to focus on perception and control, Derik felt Osaro’s true competitors were the manufacturers of advanced industrial cameras.

Engineering and product development

Engineering talent was Derik’s top priority and a major strategic concern. “We have a very complex product. Getting the right people and not just creating a team, but retaining them and having them work together well is difficult. This is especially challenging in a market with a few near-monopolies like Facebook and Google, who are so eager for deep learning talent that they will pay people to work on pure research and publication as opposed to the hard challenges of actually productizing.”

Derik believed that Osaro’s engineers, with their strong academic backgrounds and impressive industry experience, gave the company a competitive advantage. He believed experience mattered a great deal in what he described as “a tightly integrated system that leveraged the latest machine learning innovations but in an MVP fashion.” Osaro sought to minimize hierarchy, provide meaningful work with observable results, and develop cachet within deep-learning circles. Derik often encouraged his team with the mantra “speak truth into chaos.” One challenge with recruiting machine learning engineers is that many wanted their code to be free to the public, or “open source” which ran contrary to the general practice of keeping product development proprietary. While one senior engineer published while working at Osaro, this was not common a practice at the company.

^h Smart Robotics’ solution: <https://www.youtube.com/watch?v=NeYjq5gYTNA>.

Osaro prioritized staying at the forefront of research given the rapid pace of development in the field of machine learning. Each week, engineers proposed research papers, and the winning two were presented each Wednesday. Engineers read the papers in advance and came prepared to discuss how the new technology may be valuable to Osaro. Osaro's senior engineers focused on new research that was not immediately applicable to the core product but that would be valuable for product enhancements and new applications (e.g., enabling the system to use a wider range of sensory input than visual input alone).

Because it was based on deep learning, Osaro's product required both model architecture design as well as data collection and training. In Osaro's case, data collection meant instructing a robot to randomly attempt to lift a variety of items. The robot would then update its model based on success or failure until it was able to successfully lift them consistently. Osaro's strategy emphasized making deep-learning-based grasping methods both more robust and more scalable. Osaro was constantly working to improve its model and require less training. Initially using imitation learning and behavioral cloning, a technique by which the machine learned from a human performing a task, Osaro continually tried new methods. In 2018, Osaro's perception team experimented with several new deep learning architectures, with groups of machine learning engineers working together on each approach. Although the company initially built its own model training infrastructure in CUDA, Osaro made it a practice to leverage platform advances as rapidly as possible. Osaro switched to Alphabet's TensorFlow machine learning platform in 2015 and made a practice of exploring alpha releases of undocumented model architectures within TensorFlow.

Osaro tailored products to the needs of clients. MHCs sent Osaro a list of products that would be stored in client warehouses, and Osaro would then train its system to identify and lift those products. Osaro's perception team requested photos or samples of the types of stock that would be kept in the warehouse and ensured that the system could handle them. Training the system took a matter of hours, and the planning and simulation team adjusted the software for new contexts or non-standard picking setups. The team sought to make progress on better simulation technology that reduced or removed the need for training in the physical world. Osaro's resources were thus split between developing scalability-enhancing technologies and deploying systems for customers. Osaro also worked with a few of the top manufacturers, including KUKA, to develop the technology in other industrial applications.

Despite these emerging capabilities, Osaro remained guarded. Development of many applications of deep learning was dominated by a few large players, including Microsoft, Alphabet, and Facebook, who had access to huge amounts of data, organizational expertise with AI, and top-notch machine learning engineers. Osaro's hypothesis was that publishing would hamper focus at large companies by removing teams' incentives to work together, as well as the desire to focus on the hard integration and scaling problems needed to go from prototype to product.

Business development

Osaro sold licenses to its system per robot on which it was installed. For example, a warehouse with five picking robots would purchase five licenses. Osaro opted to sell their solution to material handling integrators since their product was only part of the overall technology architecture of the warehouse automation system. Osaro's head of business development, Sid Henderson, noted: "Our sales process was building a relationship with the MHCs, as we first had to convince them that our solution was the right one, and we then had to convince them to ultimately stand behind and sell our product to their customers." Osaro ultimately relied on MHCs to sell its product to end users.

MHCs provided Osaro with sample products from a client facility, which Osaro used to train their picking model. Once Osaro created a product that could handle the necessary range of objects, Osaro demonstrated that their solution's performance could meet the desired specifications (e.g., compatibility with selected equipment, pick speed, and accuracy). Osaro defined accuracy as the percent of times where the machine registered that it had made the correct pick when it actually had. Osaro used internal benchmarks and reporting tools originally developed to monitor progress as sales tools. MHCs also included instruction of Osaro's system in its safety training of warehouse employees after installations and assumed liability.

The payback period for Osaro's system was anticipated to be two to three years, and Osaro planned to save customers at least 50 percent on labor costs over the first five years. As the economic case was strongest in high-wage settings, Osaro targeted Japan for business development efforts due to the country's aging demographics and rising wages. Osaro hired employees with proficiency in the Japanese language and set up an office in Tokyo in 2017. Other advanced countries were also forecast to have an increasingly older and limited workforce, following after Japan (see **Exhibit 18a**). Labor force trends and advances in technology led to many efforts to project the path of automation across countries and types of occupations. **Exhibit 18b** shows one such set of estimates.

By the end of 2018, Osaro had deployed its product for demos with MHCs across multiple locations. See **Exhibit 19** for the standard demo setup. Two companies were in the United States and three were in Japan. Several German companies were also slotted for deployment. Osaro mostly worked with international equipment manufacturers, but they also worked with a Japanese regional integrator. Osaro was unsure of the degree to which they would need to engage downstream with regional integrators in the future.

Osaro had deployed their product with one end-user by early 2019 and expected deployments with at least five more end users by the end of the year. End users could be ecommerce fulfillment centers, retail distribution centers, and any other warehouses along the supply chain. Early expected users included distribution for grocery and convenience stores, restaurant suppliers, and cosmetics manufacturers. After Osaro's picking solution had been implemented, humans continued to pick alongside the robots before being slowly phased out over the course of months.

Osaro learned a great deal from their early deployments. Their engineers needed to communicate significantly with engineers working for system integrators and make many site visits to resolve complications during installation. Osaro had to be sure that their technology operated with the warehouse management software and the broader ASRS automation system. In addition, some integrators lacked experience with industrial robots and so did not have expertise deploying robot arms and did not know the amount of engineering resources to dedicate to the portion of the project involving the picking robot. Others were better prepared, having more experience with the technology and delivering clear specifications up-front to preempt issues.

Osaro also demonstrated its technology at various trade shows. In June 2018, Osaro's capabilities were put to the test on a large stage. Two weeks before a major food robotics exhibition in Japan called the International Food Machinery and Technology Exhibition (FOOMA) robotics maker Denso asked Osaro if their software could assemble bento boxes at their booth – a task which required distinguishing between individual chicken nuggets, which had proven too challenging for other platforms. Osaro was able to program the robot in one week to successfully perform the task.ⁱ

ⁱ Watch the FOOMA demo here: <https://www.youtube.com/watch?v=tZEaCpcjk8A>.

Sid reflected, “In 2018, Osaro’s focus was on building an industrial-grade machine which could meet the expectations of material handling companies. By 2019, it had become deploying our solution with integrators and manufacturers to showcase Osaro to their customers. After that, we will be able to ‘flip the switch’ and include our product as a standard offering in our clients’ warehouse automation solutions.”

The path forward

Derik envisioned creating software that could power robots to manipulate objects across the full spectrum of possible applications. “Imagine a robot that can pick and place anything, anywhere. That’s a really, really big market given that about a billion people in the world are doing that.” Derik hoped Osaro would stay an independent company, likely with a future initial public offering for investors.

Despite Osaro’s progress, the path forward included significant obstacles. First, Osaro’s market was very complex. While there was opportunity to be a part of the growing warehouse automation market, most warehouses were still highly manual and many opted for cheaper solutions reliant on human labor. Osaro’s position upstream of MHCs had advantages but also insulated them from the end-user and made the selling process extremely long. Partnering with the MHCs was also risky, as MHCs could work to develop the technology in-house or purchase another startup working on the technology. One had already invested in a small competitor called Smart Robotics.

There were also questions about market selection. Derik had turned away from potentially easier software-only applications, but he also turned down repeated requests by manufacturing companies, holding that the technology was not yet advanced enough for those applications. Derik wondered whether he was making the right choice to perfect the warehouse picking product before expanding into the manufacturing market. Derik remarked: “In retrospect, I would never advocate for starting a technology company without a firm target customer set. Essentially, you shouldn’t start a company until you have a paying customer already.” Was warehouse picking really that attractive? Osaro had also made a strong bet on taking a universally-compatible, modular approach which ended with instructing a robot rather than selling an off-the-shelf robot solution. This made the product more complex to engineer and maintain, which slowed the company’s velocity. At the same time, the approach opened wider market opportunities, and Derik remained convinced that the approach was a bet on continued progress in machine learning. Osaro executives felt that, in a sense, their approach allowed Osaro to harness the free research produced by the giant technology companies such as the FANGs (i.e., Facebook, Amazon, Netflix and Google).

Derik also worried about the challenges inherent to being a deep learning company. Osaro was consistently working to be on the cutting-edge of technology, lest their approach become out-of-date while another company brought a technology with more commercial value to market. They had to strike a delicate balance between being up-to-date with the research and experimenting with the latest approaches while focusing on Osaro product delivery. Derik noted Osaro would need to invent more technology in the future and build scalability, but those resources came at a cost from proving their product to paying customers and earning revenue. Osaro also had a nuanced relationship with the big tech companies, using Amazon’s cloud services and Alphabet’s machine learning platform while simultaneously competing with Alphabet on machine vision and facing a potential threat from Amazon on picking.

The deep learning space also required Osaro navigate potential future concerns regarding worker displacement versus augmentation due to advanced technology. To date, Osaro’s products had been most sought out in settings challenged by labor scarcity and shortfalls, not job loss, but would Osaro’s

experience in Japan reliably predict what would happen in other countries as technology improved? Derik believed in the positive potential of the emerging technology and wanted to ensure a productive conversation and policy environment existed. These big thoughts, however, would have to wait for a while as Derik got back to fine tuning the investor pitch deck.

Exhibit 1 Osaro Funding, 2015 - 2018

Date	Round	Amount
13-Apr-17	Series A	\$10M
30-Mar-15	Seed Round	\$3.3M

Source: Osaro company records.

Exhibit 2a Industrial robot



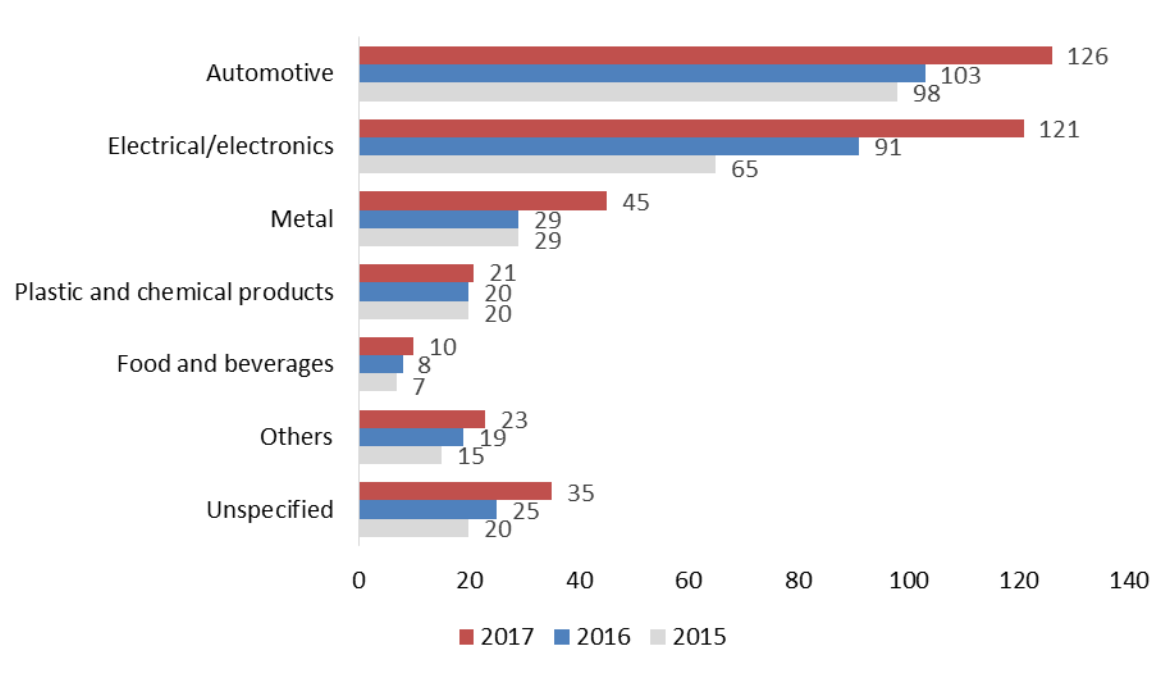
Source: "KUKA Robot Arms | Available Now at MRO Electric and Supply," *MRO Electric and Supply*, March 1, 2018, <https://www.mroelectric.com/blog/kuka-robot-arm/>, accessed July 2019.

Exhibit 2b Example end effectors for gripping objects



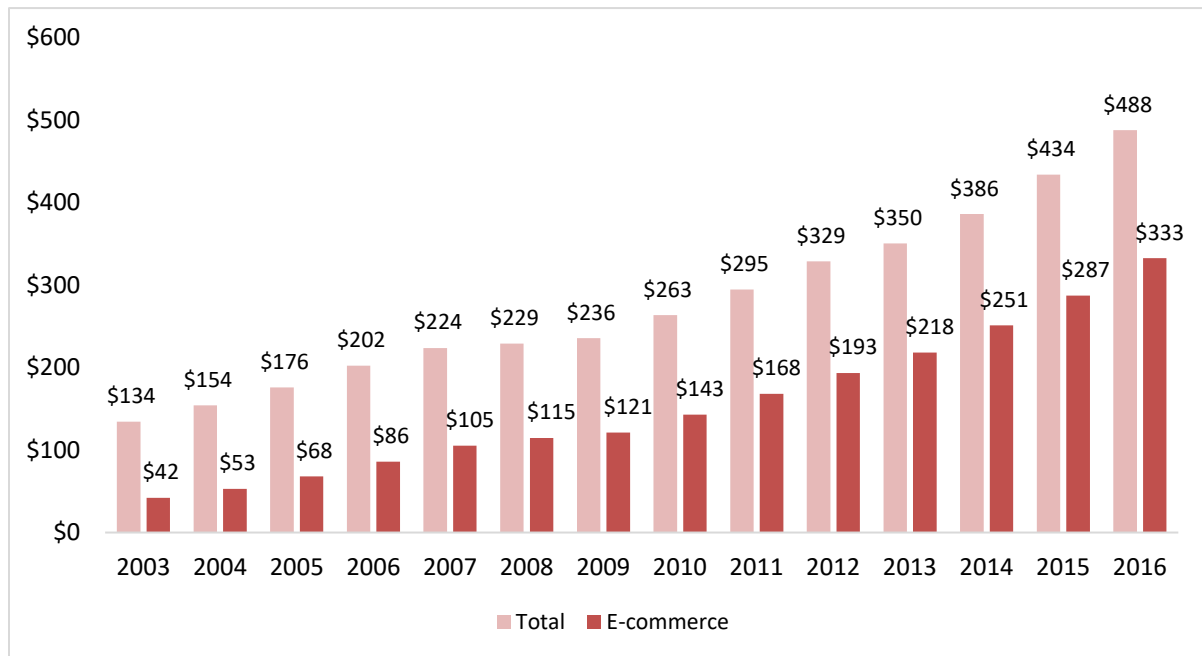
Source: Osaro company documents.

Exhibit 2c Industrial robot sales by industry (thousands of units)



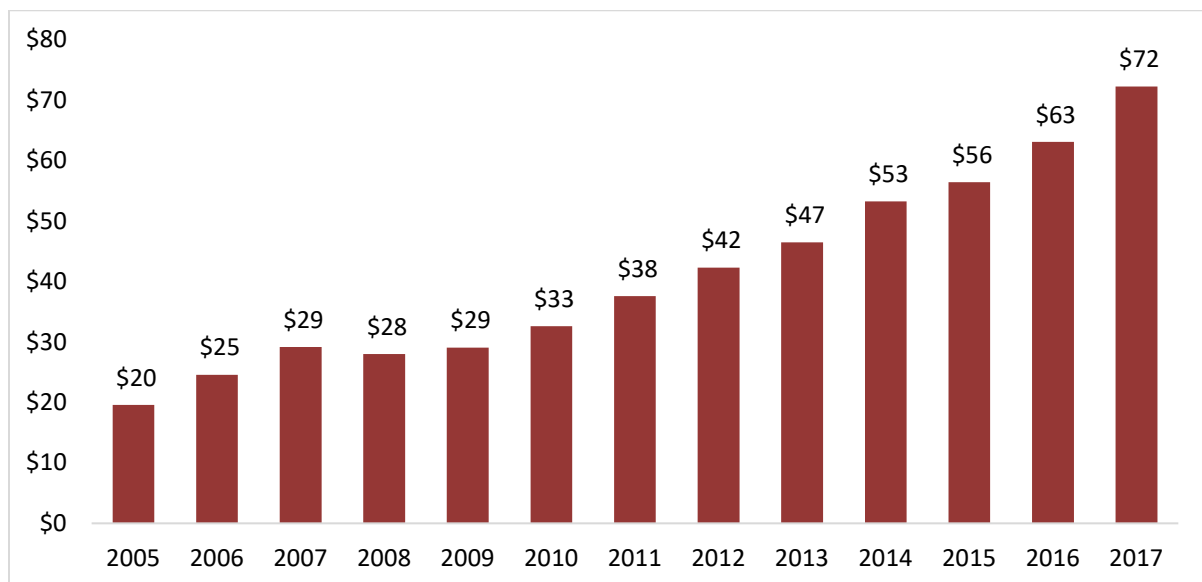
Source: "World Robotics 2018," *International Federation of Robotics*, October 2018, https://ifr.org/downloads/press2018/WR_Presentation_Industry_and_Service_Robots_rev_5_12_18.pdf, accessed July 2019.

Exhibit 3a U.S. ecommerce and mail-order home sales (\$ in billions)



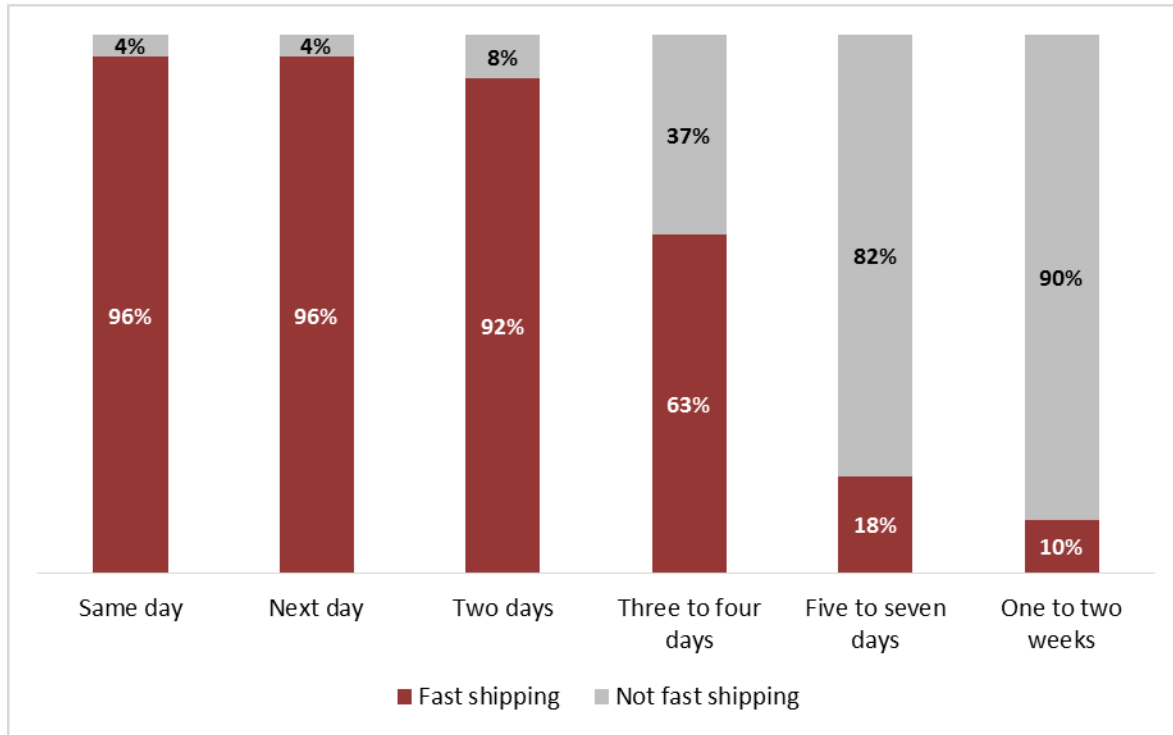
Source: "2017 Annual Retail Trade Survey (ARTS)," U.S. Census Bureau, March 21, 2018, <https://www.census.gov/data/tables/2016/econ/arts/annual-report.html>, accessed July 05, 2019.

Exhibit 3b U.S. holiday season desktop retail e-commerce sales (\$ in billions)



Source: "Holiday season desktop retail e-commerce sales value in the United States from 2005 to 2017," March 16, 2018, comScore via Statista, <https://www.statista.com/statistics/191173/us-holiday-season-retail-e-commerce-sales-since-2005/>, accessed July 05, 2019.

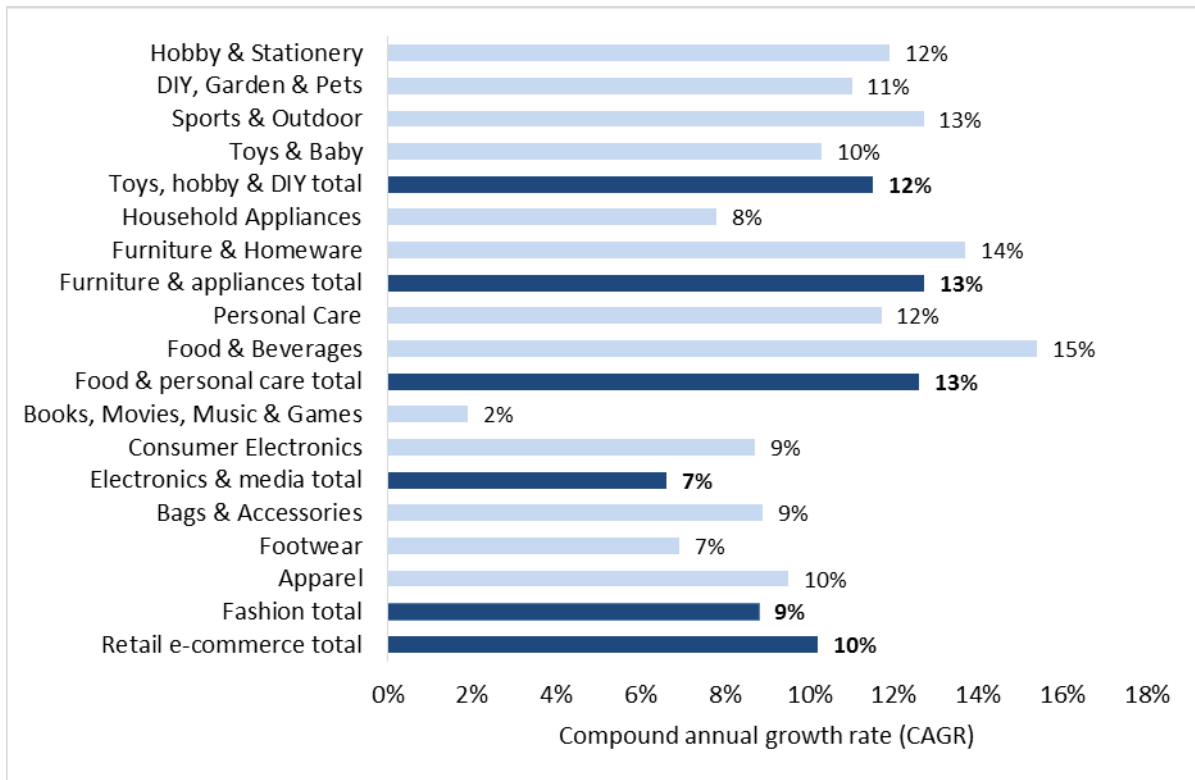
Exhibit 4 Consumer ideas about shipping speed (2015)



Source: "E-commerce drives growth in logistics industry jobs," *Business Insider Intelligence & Deloitte*, August 10, 2016, <https://www.businessinsider.com/e-commerce-drives-growth-in-logistics-industry-jobs-2016-8>, accessed July 2019.

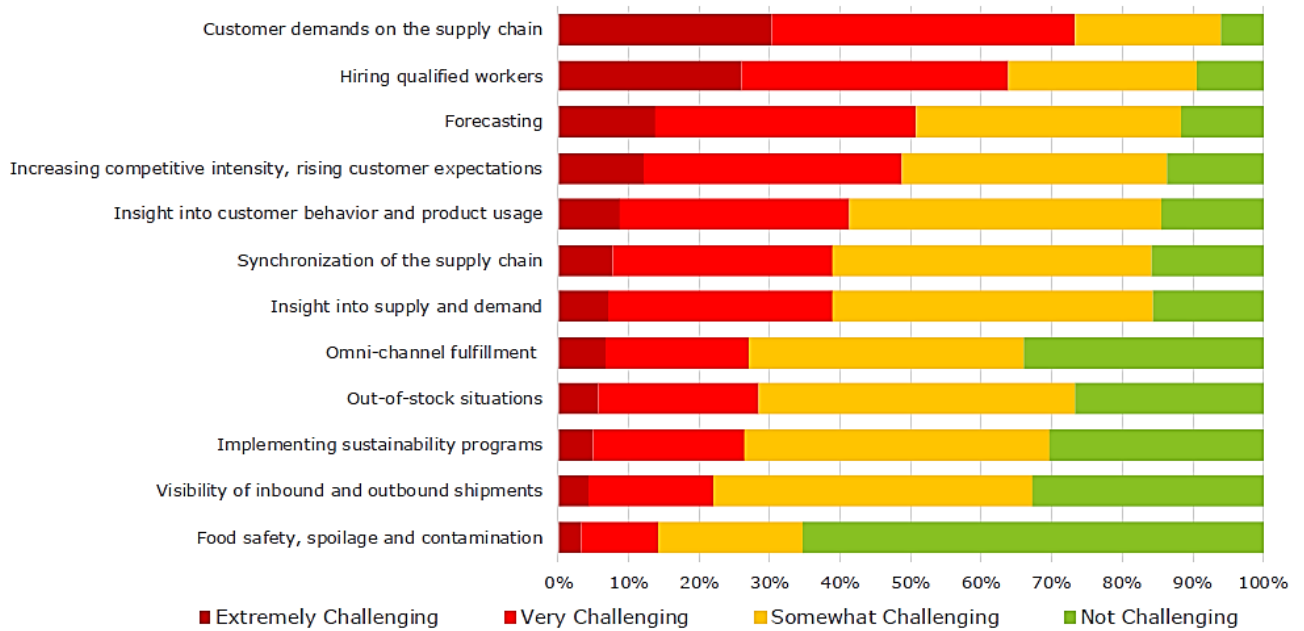
Note: n=4,009.

Exhibit 5 Projected retail e-commerce sales growth in the U.S. by product category (2016 – 2022)



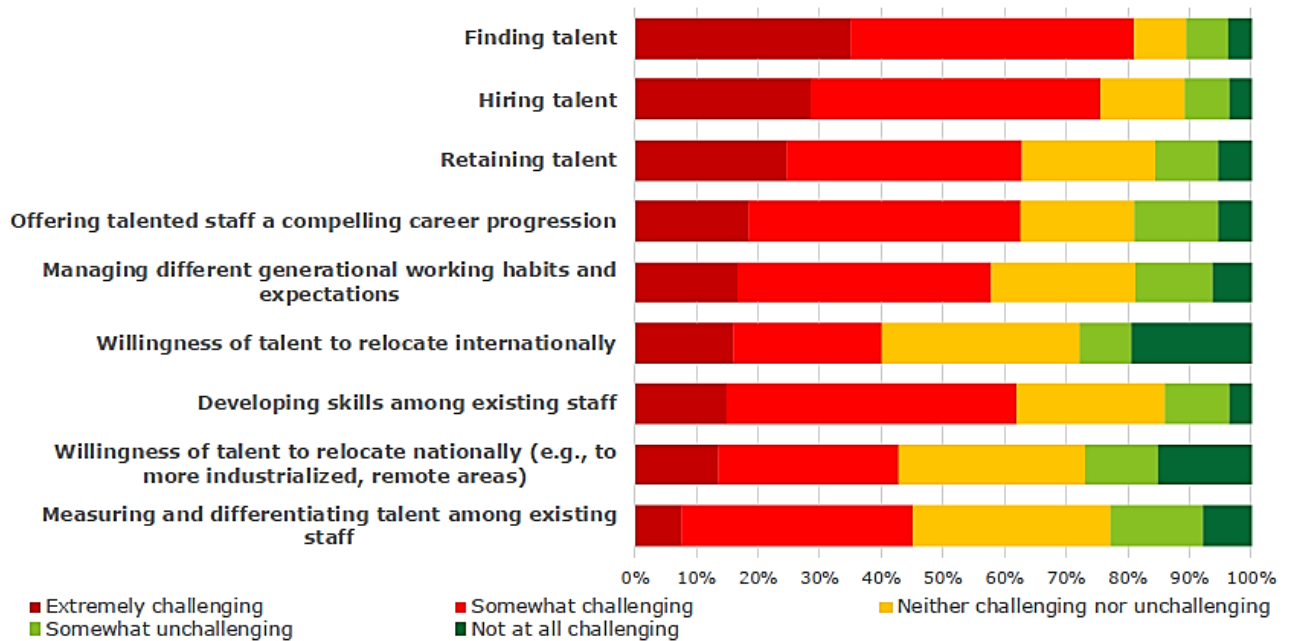
Source: Statista Digital Market Outlook, November 2018, <https://www.statista.com/statistics/257516/us-retail-e-commerce-sales-cagr-by-product-category/>, accessed February 3, 2019.

Exhibit 6a Top supply chain challenges (2018)



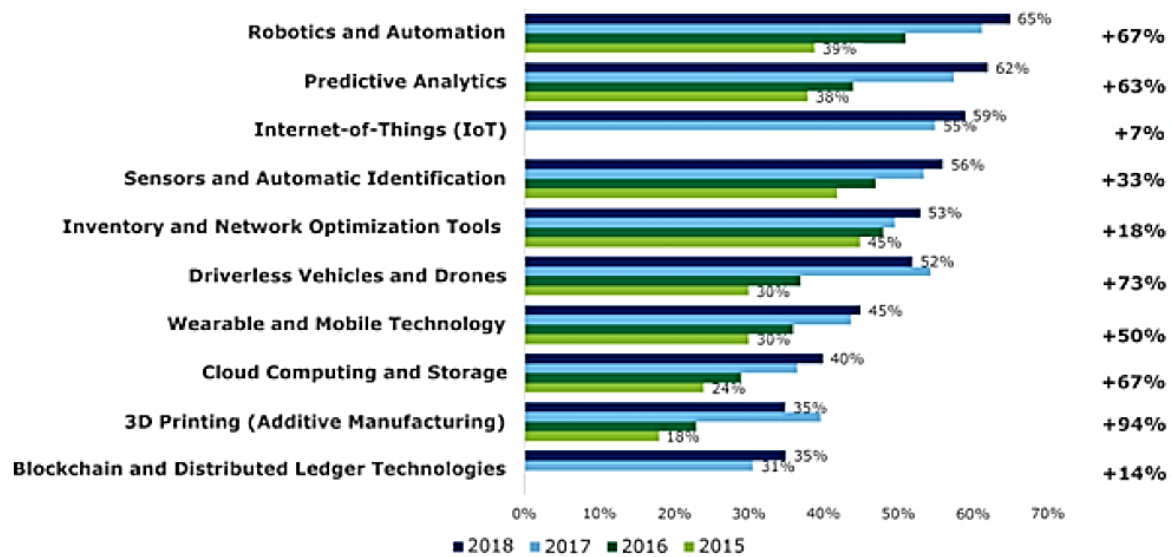
Source: "The 2018 MHA Annual Industry Report: Overcoming Barriers to NextGen Supply Chain innovation." MHI & Deloitte. <https://www.mhi.org/publications/report>, accessed July 2019.

Exhibit 6b Top workforce challenges in supply chain and manufacturing (2018)



Source: "The 2018 MHA Annual Industry Report: Overcoming Barriers to NextGen Supply Chain innovation." MHI & Deloitte. <https://www.mhi.org/publications/report>, accessed July 2019.





Exhibit 7 Top disruptive trends in supply-chain and manufacturing (2015-2018)



Source: "The 2018 MHA Annual Industry Report: Overcoming Barriers to NextGen Supply Chain innovation." MHI & Deloitte. <https://www.mhi.org/publications/report>, accessed July 2019.

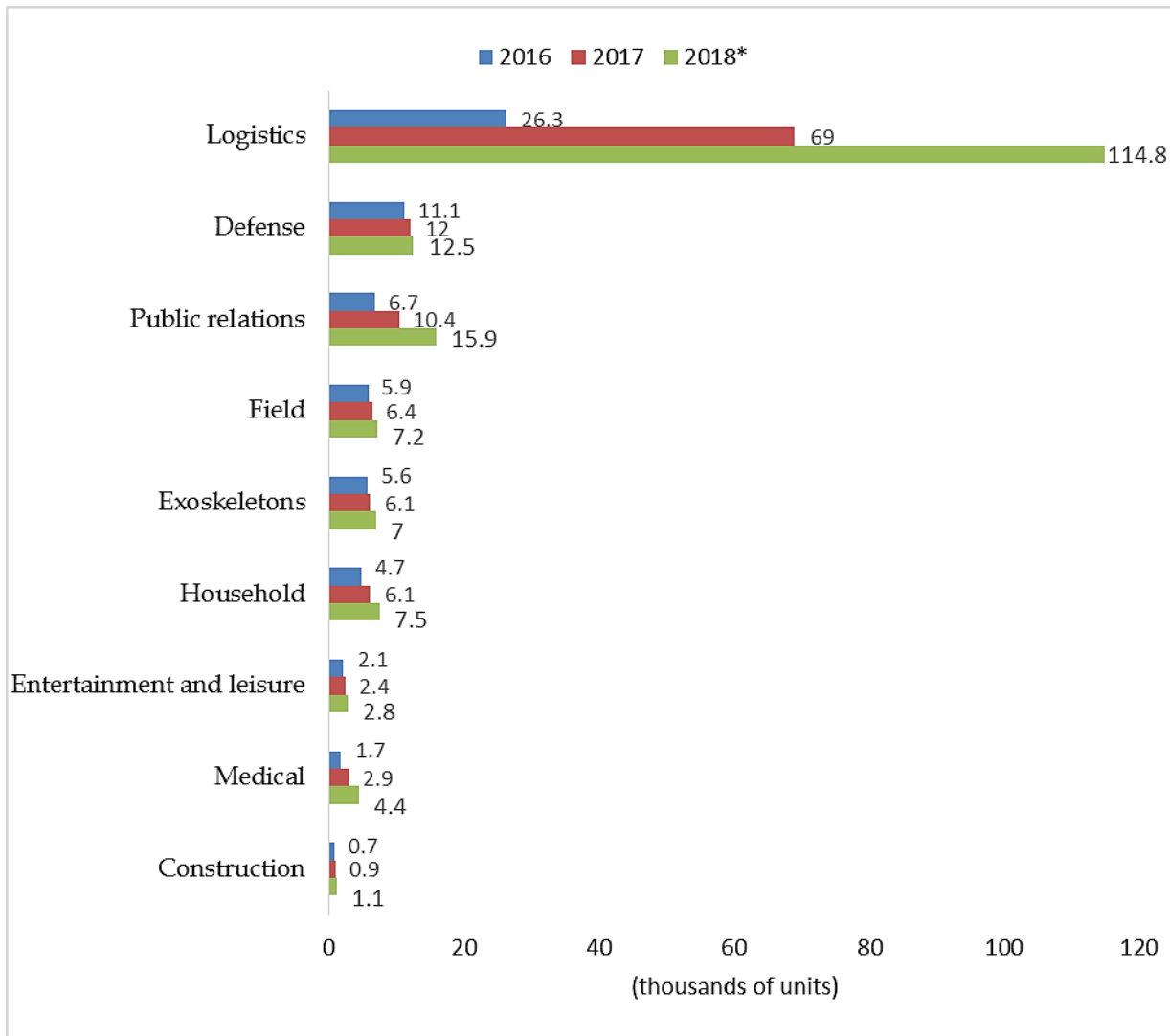
Note: Chart shows the percent of manufacturing or supply-chain professionals who selected a force had the potential to be disruptive or create competitive advantage (2015-2018); N = 1,100.

Exhibit 8 Range of warehouse automation

Level 1 Conventional Picking with Process Improvements	Level 2 Mechanised Solutions	Level 3 Semi-Automated Solutions	Level 4 Fully-Automated Solutions
			
<ul style="list-style-type: none"> • Implement new WMS • RF Picking • Voice Picking • Labour Management 	<ul style="list-style-type: none"> • Conveyor/Pick Modules • Auto Stretch wrap & label • Layer Picking 	<ul style="list-style-type: none"> • AS/RS high density Storage • Conveyor • WCS/WMS Software 	<ul style="list-style-type: none"> • AS/RS • Conveyor • Automated Layer picking and case palletising • WCS/WMS Software
\$ 500k - \$1M	\$ 2M - \$ 5M	\$ 10M - \$ 15M	\$ 40+ Million
LOW		HIGH	

Source: Kuknin, Andre. "Warehouse Automation." *Credit Suisse*, April 10, 2017, <https://plus.credit-suisse.com/rpc4/ravDocView?docid=V60Zdc2AF-WEIY95>, accessed July 2019.

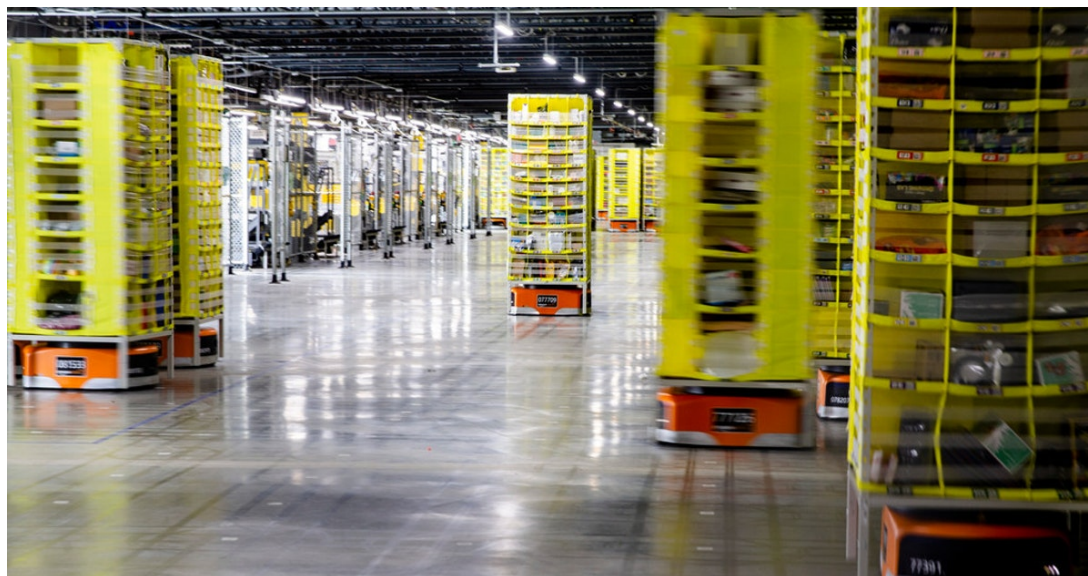
Exhibit 9 Robot sales in “service” (non-industrial) applications (thousands of units)



Source: “World Robotics 2018,” *International Federation of Robotics*, October 2018, https://ifr.org/downloads/press2018/WR_Presentation_Industry_and_Service_Robots_rev_5_12_18.pdf, accessed July 2019.

Note: “Service” robots were defined as those not used in industrial applications. Logistics robots were most often autonomous guided vehicles (AGVs).

Exhibit 10 Photos of automated Amazon fulfillment centers



Source: Halkias, Maria, and Repko, Melissa, "How Amazon delivers holiday gifts from the buy button to your door: Go inside a fulfillment center," *Dallas News*, December 12, 2018, www.dallasnews.com/business/retail/2018/12/12/amazon-delivers-holiday-gifts-buy-button-door-go-inside-fulfillment-center, accessed July 2019.



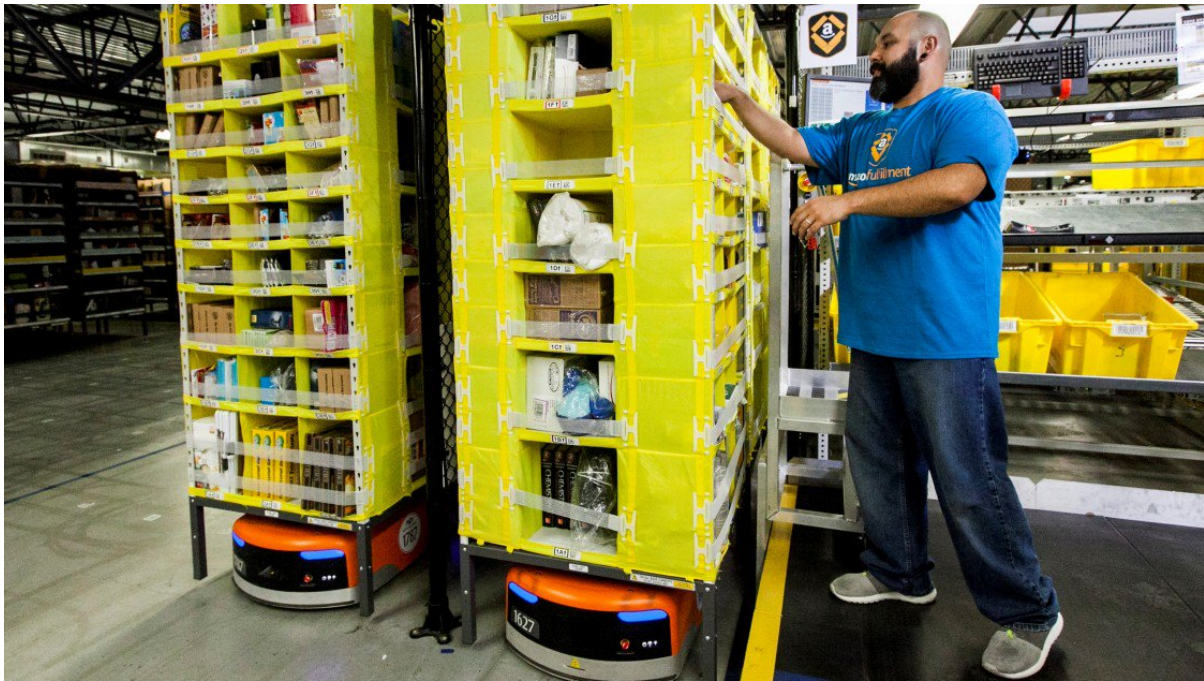
Source: Ian MacLellan Special to *The Seattle Times*, from González, Ángel, "Amazon's robots: job destroyers or dance partners?" *The Seattle Times*, August 11, 2017, <https://www.seattletimes.com/business/amazon/amazons-army-of-robots-job-destroyers-or-dance-partners/>, accessed July 2019.

Exhibit 11 Warehouse automation value chain



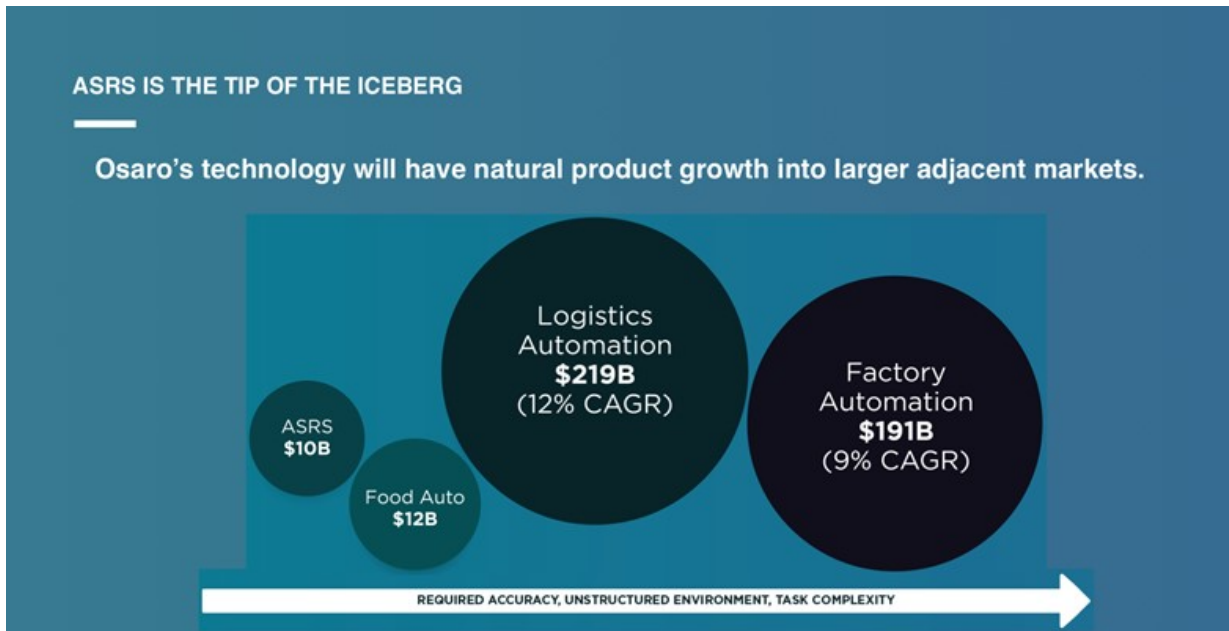
Source: Osaro documents.

Exhibit 12 Picking stations at Amazon



Source: Photo © 2014 Eric Slomanson. All Rights Reserved. From Winick, Erin, "Amazon's Investment in Robots is Eliminating Human Jobs," *MIT Technology Review*, December 4, 2017, <https://www.technologyreview.com/the-download/609672/amazons-investment-in-robots-is-eliminating-human-jobs/>, accessed July 2019.

Exhibit 13 Osaro's projected industry order of AI-enabled robotics diffusion



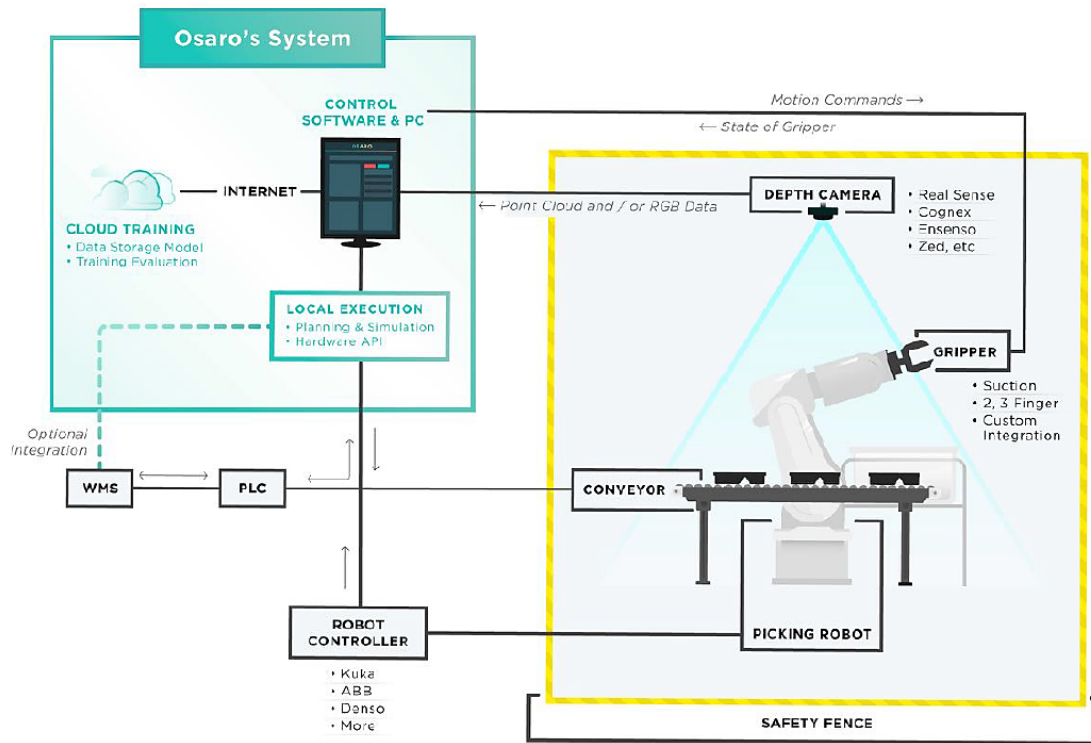
Source: Osaro documents.

Exhibit 14 Osaro's user interface



Source: Osaro documents.

Exhibit 15 Osaro's place in the robotics technology architecture



Source: Osaro documents.

Exhibit 16 Examples of obstacles to robot picking that Osaro's product overcame



Pick **clear box**, not what's inside



Avoid contour, pick flat parts



Avoid pump, aim for body



Target label, not gloves



Suction brush, not thin handle



Don't get fooled by **reflections**

Source: Osaro documents.

Exhibit 17a Osaro's positioning vs direct competitors



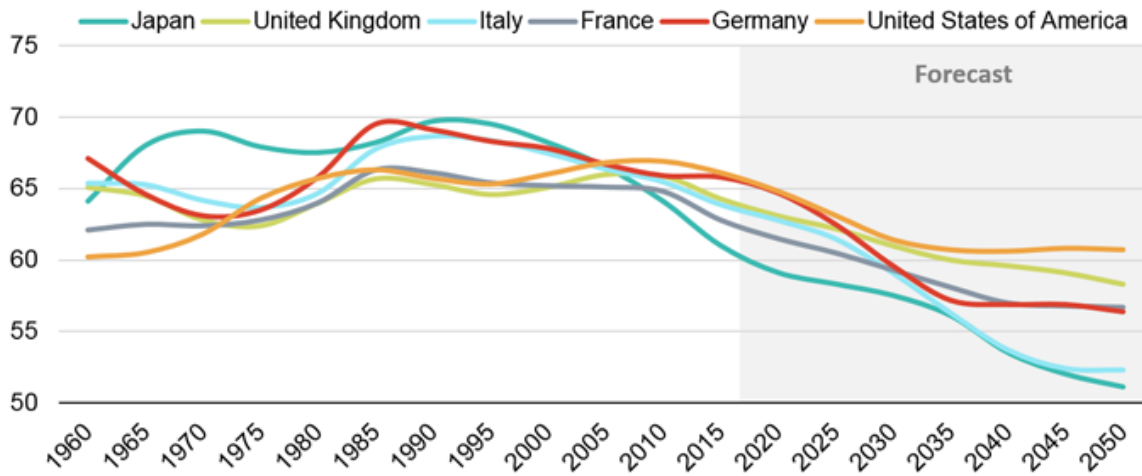
Source: Osaro documents.

Exhibit 17b AI-enabled robotics



Source: Osaro documents.

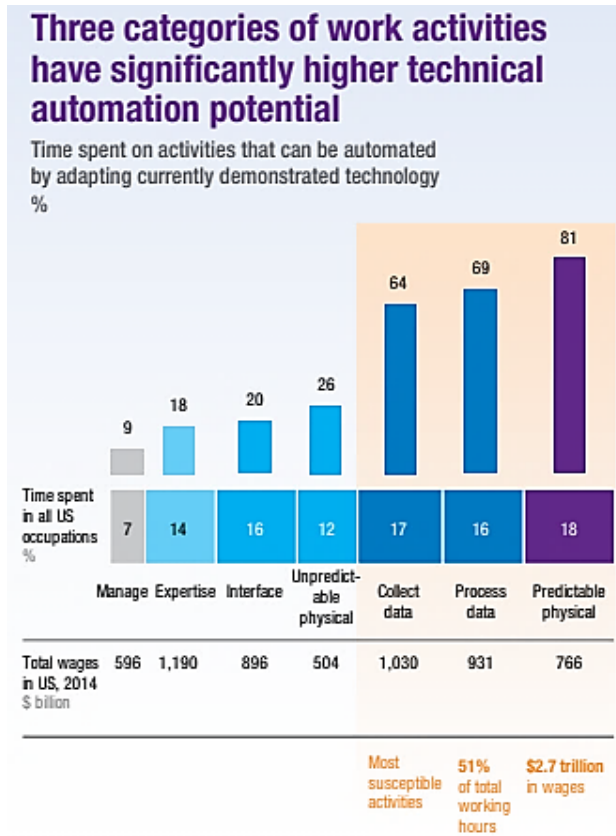
Exhibit 18a Working-age* population as a percentage of total population



Sources: United Nations, Department of Economic and Social Affairs, Population Division (2017); World Population Prospects: The 2017 Revision, custom data acquired via website. © 2019 by United Nations, made available under a Creative Commons license CC BY 3.0 IGO: <http://creativecommons.org/licenses/by/3.0/igo/>.

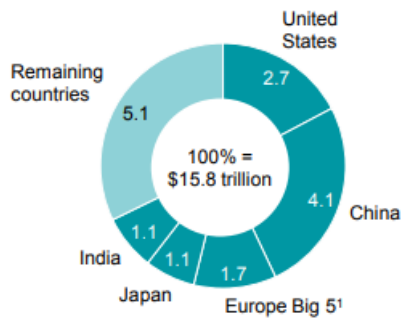
Note: *Working-age population is defined as anyone aged 15 to 64.

Exhibit 18b Automation potential across work activity type and geography

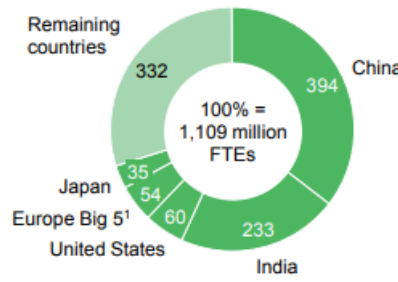


Technical automation potential is concentrated in countries with the largest populations and/or high wages
Potential impact due to automation, adapting currently demonstrated technology (46 countries)

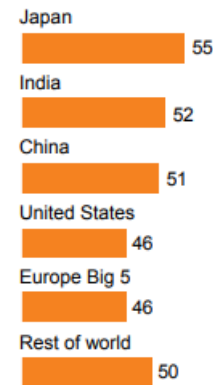
Wages associated with technically automatable activities
\$ trillion



Labor associated with technically automatable activities
Million FTE



Automation potential %

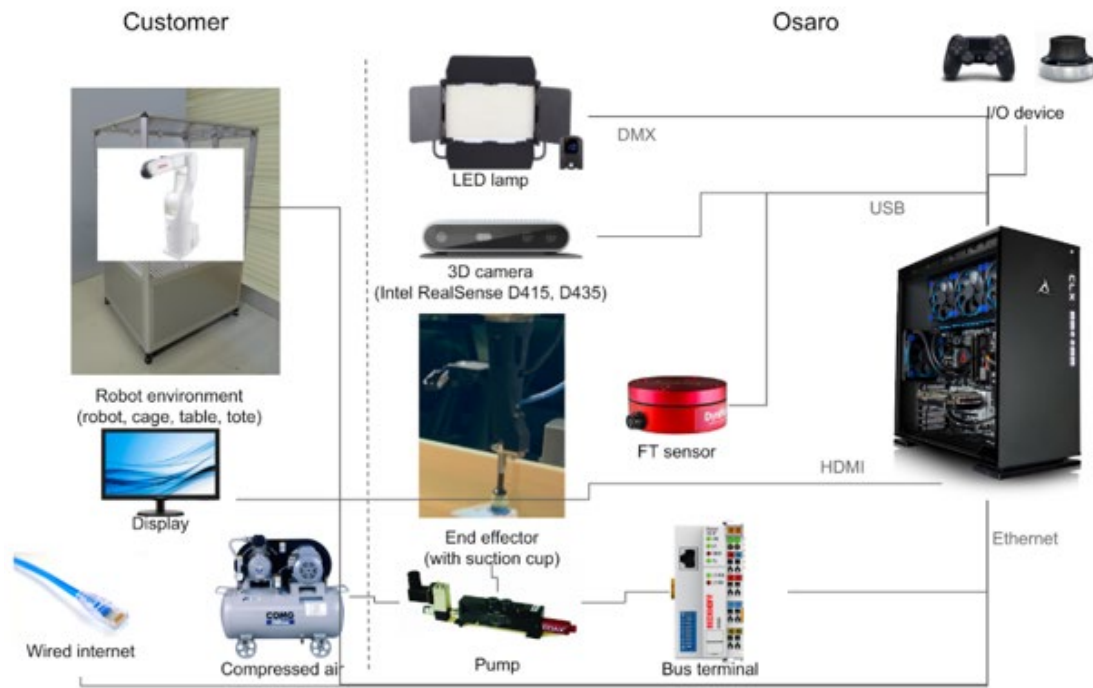


1 Pakistan, Bangladesh, Vietnam, and Iran are largest countries by population not included.
2 France, Germany, Italy, Spain, and the United Kingdom.
NOTE: Numbers may not sum due to rounding.

SOURCE: Oxford Economic Forecasts; Emsi database; US Bureau of Labor Statistics; McKinsey Global Institute analysis

Source: "Jobs lost, jobs gained: What the future of work will mean for jobs, skills, and wages", November 2017, McKinsey Global Institute, www.mckinsey.com. Copyright © 2019 McKinsey & Company. All rights reserved. Reprinted by permission.

Exhibit 19 Demo unit setup



Source: Osaro documents.

Endnotes

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