

# A road map for digitizing source-to-pay

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Technologies available today could automate more than half of the source-to-pay process. The potential? Lower procurement costs, greater savings, and more opportunities to pursue new sources of value.

Summer 2021. The engineering department has finalized its concept design for a critical component in the next product generation. The procurement team enters the specifications into an analytics-based sourcing system, which interprets the document and—drawing on its database of suppliers and the outcomes of prior sourcing efforts—identifies three current suppliers, plus two newly added companies able to produce the part.

Next, the system automatically draws up an electronic request for quotation and sends it to the potential suppliers. When their quotes come back, it conducts an automated review, basing its analysis on internal clean-sheet cost models for the parts, together with data on each supplier's capabilities and structural costs. The report it generates highlights the top negotiating points for the procurement team—and the system continues to revise its models and guidance as the negotiations proceed.

Once supply commences, the sourcing system continually monitors the winning suppliers, covering not only their quality and delivery performance but also their progress on the ongoing cost reduction they agreed to during the sourcing process. Exceptions trigger a series of automated mitigating actions, with procurement staff alerted only if the actions fail to get supply back on track.

This scenario is closer to reality than you might expect—perhaps well before the summer of 2021. Much of consumer purchasing has already been digitized, and some is even automated: sensor-laden, Internet-connected printers can detect when

ink is low and order replacement cartridges, with no intervention from the user.

Large enterprises have not been so successful. Despite significant interest and investment, traditional approaches to automating source-to-pay (see sidebar, “Defining source-to-pay”) have yet to deliver on the promise of a fully digital process requiring minimal human involvement.

That may be about to change. Several emerging technologies, including robotic process automation (RPA), machine learning, and advanced artificial-intelligence programs or “cognitive agents,” have the potential to overcome hitherto stubborn barriers to automation in the enterprise environment. By applying a new form of analysis to the hundreds of individual tasks involved in the source-to-pay process, we have found that almost 60 percent of them have the potential to be fully or largely automated using currently available technologies. Crucially, we found significant automation potential not only in transactional activities, such as order and invoice processing, but also in sourcing's strategic elements, such as vendor selection and management.

The payback on a robust, automated end-to-end source-to-pay process could be high. Industry benchmarks suggest that most organizations waste 3 to 4 percent of their overall external spend on excessive transaction costs, inefficiency, and noncompliance (Exhibit 1). For an organization with an annual spend of \$2 billion, eliminating that leakage could send \$70 million a year straight to the bottom line.

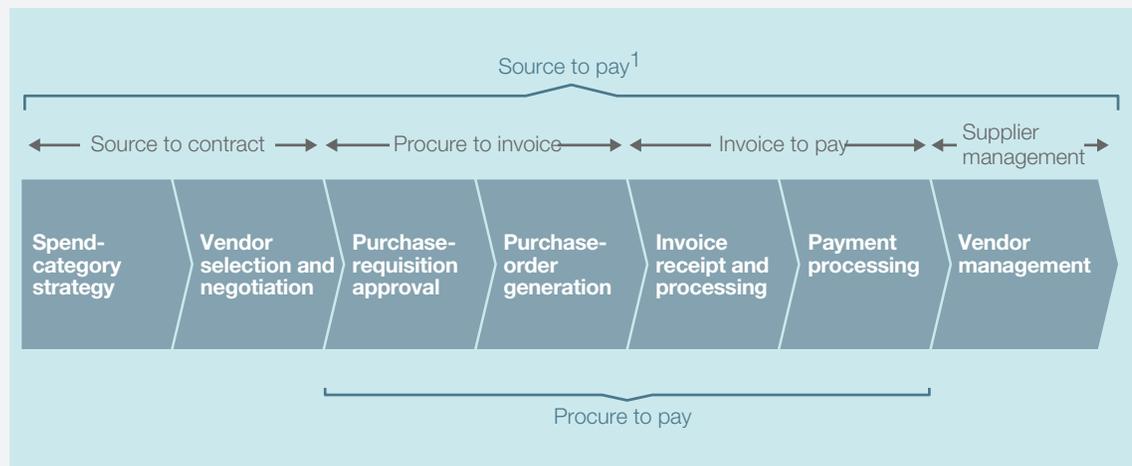
## Defining source-to-pay

We define source-to-pay as the end-to-end value stream that encompasses all the activities required for an organization to obtain and pay for goods and services from other entities. These activities start with the development of specific sourcing strategies to best obtain the goods and services an organization needs. They continue with the selection of specific suppliers, contracting with those suppliers, the

placement of orders, the verification that appropriate goods and services have been delivered, and finally the authorization and release of payment. In addition to these core tasks, the overall value stream also includes the activities necessary to support the end-to-end process, such as vendor and master-data management (exhibit).

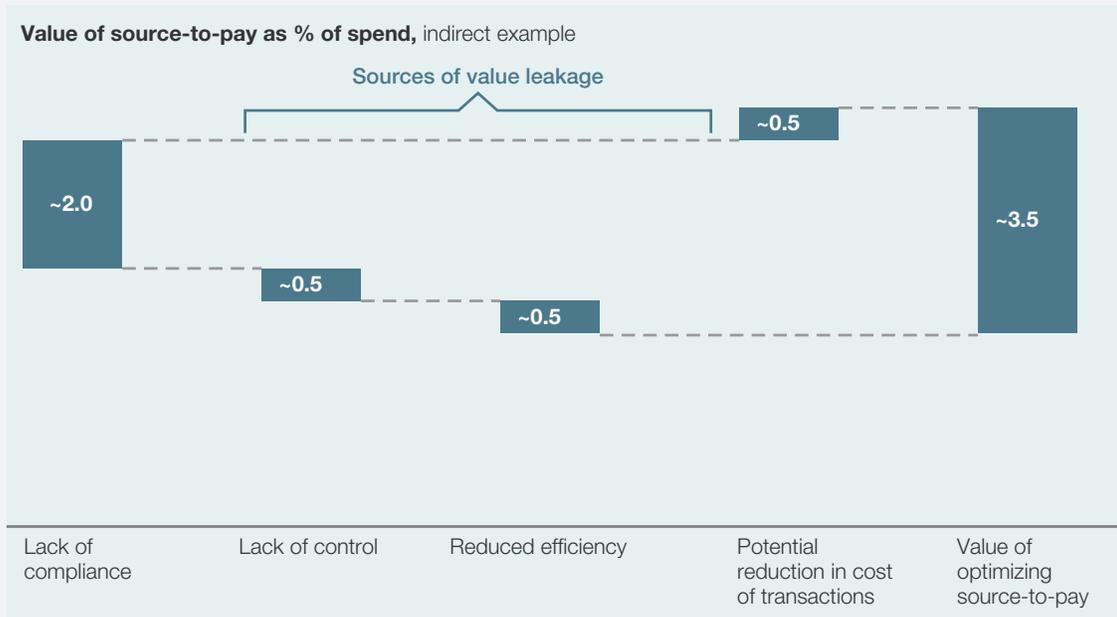
### Exhibit

#### **A well-designed source-to-pay process aligns all activities from strategic sourcing through to vendor management.**



<sup>1</sup>Most end-to-end source-to-pay processes must accommodate multiple buying channels that deviate from a single set of steps.

**Exhibit 1 Automating source-to-pay processes can reduce spend by up to 3.5 percent.**



Source: Expert interviews; McKinsey analysis

**The role of emerging technologies in source-to-pay automation**

Advances in software and artificial intelligence have vastly expanded both the number of activities that can be automated and the degree of automation that is possible. For example, the McKinsey Global Institute has found that across occupations, activities accounting for 46 percent of US workers’ time could be automated using already-demonstrated technologies.<sup>1</sup>

We believe that five emerging technologies are particularly pertinent to source-to-pay:

- **Robotic process automation** uses simple rules to emulate repeatable tasks that

would otherwise be performed by human users of software. One large advantage of RPA is that, unlike traditional system-integration approaches requiring access to each relevant software program’s underlying code, the bots that perform specific tasks only need to access other software in the same way a human user would. A consequence is that bots can only perform tasks in situations where there is no room for interpretation—but many tasks in source-to-pay (such as invoice upload and approval) are sufficiently unambiguous to make deployment worthwhile.

RPA can therefore help companies stitch together their existing systems, eliminating

low-value manual interventions at the interfaces between systems and process steps. A large basic-materials company found that by deploying bots to scan and code invoices directly into its core enterprise-resource-planning (ERP) system, it could reduce invoice-processing costs by 80 percent.

- *Machine-learning* algorithms, unlike RPA, can handle tasks that involve complex rules and require some form of pattern recognition to be executed correctly. Machine learning is therefore suitable for tasks that traditionally require some level of human judgment, such as the assignment of transactions to formal spend categories and subcategories—a crucial first step in uncovering sourcing opportunities. A financial institution that is currently deploying machine learning for these judgments has greatly increased the accuracy and speed of essential analyses, such as the concentration of spend by supplier for a given category. As a result, the institution is finding procurement savings much more quickly than was previously possible.

At a global technology-services company, machine learning now guides its negotiation approach, tracking and evaluating the success of different negotiation tactics in different settings. The resulting patterns lead to specific recommendations on which type of negotiation is likely to be most successful in a particular situation.

- *Smart work-flow* technologies can link tasks conducted by different people and machines into a coherent process with well-defined handoffs—even if the combination of tasks differs markedly from case to case, as in risk-management processes for supplier qualification. A business-services company is piloting a smart work-flow solution that dynamically routes work between

procurement and financial systems according to whichever risk-management logic applies to a given supply contract. The system then governs the assignment of tasks across all participants in onboarding, risk-assessment, and supplier-certification activities, and may eventually cover supplier performance management as well.

- *Natural-language-processing (NLP)* technologies process textual data and provide a convenient way for purchasers to document requirements without resorting to drop-down menus or structured lists. The technologies are already in use in consumer environments, guiding customers to appropriate technical-support resources or extracting insights about product performance from social-media streams. In procurement, they may assist in organizing many types of unstructured information.

The example that opened this article may sound like science fiction, but a European multinational is already piloting such technologies (in combination with RPA) to digitize its sourcing approach for its long-tail spend—the long list of small purchases that together may account for only a few percentage points of the budget. Robots in each major external-spend category process incoming orders from the business, using NLP to interpret free-form text and match order requirements to particular groups of suppliers. The procurement system then automatically sends out requests for bids, which the robot can compare. An internal buyer is notified once the bids have been received, so that he or she can decide which bid to accept based on the information provided by the robot.

- *Cognitive agents* can be deployed whenever a deep knowledge base must be quickly searched to determine the right course of action. The

chatbots that several financial-service institutions now use in assisting contact-center staff can answer a wide range of customer queries by selecting appropriate responses from a previously documented set of answers. In the source-to-pay process, vendor and business-procurement help desks often involve similar types of interactions, pointing toward a similar solution.

As the capabilities of cognitive agents improve, they may also become useful for even more complex tasks, such as estimating an item's global-sourcing potential by comparing its cost, quality, and technology requirements with databases of similar products and sourcing decisions. By analyzing supplier capabilities, cognitive agents may even be able to make recommendations on the selection of specific suppliers.

### **The automation potential of source-to-pay**

Because source-to-pay is such a complex, diverse set of activities, it has not until now been clear exactly how much of the entire end-to-end process is suitable for automation or where the primary sources of value lie.

We therefore undertook a new type of analysis that decomposed source-to-pay into a large number of discrete tasks. That let us assess how easily each task can be automated using currently available technologies, and which types of those technologies are most appropriate to achieve that level of automation.

To do this, we employed a “framework of capabilities,” developed by our colleagues at the McKinsey Global Institute.<sup>2</sup> This framework classifies the capacities used by humans to perform different tasks into 18 specific capabilities (Exhibit 2).

The automation requirements of any task will depend on the specific combination of capabilities required, together with the complexity associated with the relevant capabilities. For example, some tasks might require a modest amount of pattern recognition (for example, the data-lookup functions used in spreadsheets), while others may require the ability to recognize highly complex patterns (for instance, assessing which suppliers are most likely to cease being a sustainable source of supply).

### [Seeing the potential across the entire source-to-pay process](#)

We mapped the complexity requirements across each of the 18 capabilities, using a highly granular 240-item taxonomy covering every task in the end-to-end source-to-pay process. While a majority of the 18 capabilities are required at many stages of the process, the level of complexity associated with these capabilities is fairly low. In most cases, existing technologies can meet those requirements.

Our analysis shows that, overall, 56 percent of the tasks associated with the source-to-pay process are fully or largely automatable using existing technologies. That's a significant finding, suggesting that source-to-pay activities as a whole are more suitable for automation than is a typical US-based job.

Unsurprisingly, the automation opportunity is highest in the more transactional parts of the process: in placing and receiving orders, 88 percent of tasks can be automated, and the figure rises to 93 percent in payment processing. Moreover, even the strategic elements of source-to-pay show considerable automation potential. Our analysis shows that 47 percent of vendor-selection and negotiation activities can be automated (Exhibit 3).

**Exhibit 2 A framework of 18 capabilities helps explain the performance requirements of different work activities.**

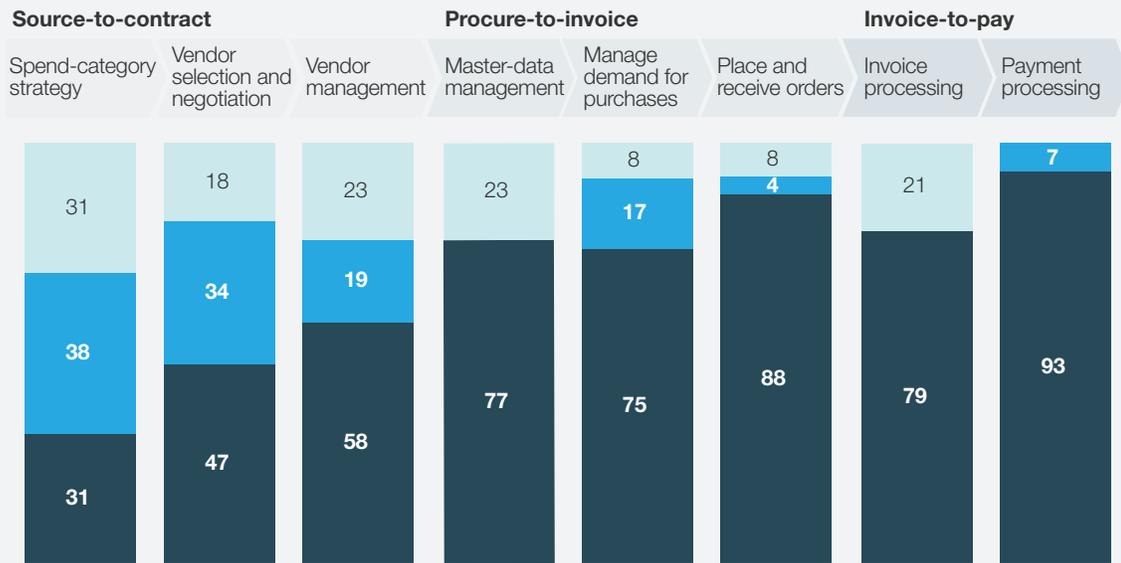
	Capability	Description
Sensory perception	Sensory perception	<ul style="list-style-type: none"> <li>Autonomously infer and integrate complex external perception using sensors</li> </ul>
Cognitive capabilities	Recognizing known patterns/categories (supervised learning)	<ul style="list-style-type: none"> <li>Recognize simple/complex known patterns and categories other than sensory perception</li> </ul>
	Generating novel patterns/categories	<ul style="list-style-type: none"> <li>Create and recognize new patterns/categories (eg, hypothesized categories)</li> </ul>
	Logical reasoning/problem solving	<ul style="list-style-type: none"> <li>Solve problems in an organized way, using contextual information and increasingly complex input variables other than optimization and planning</li> </ul>
	Optimization and planning	<ul style="list-style-type: none"> <li>Optimize and plan for objective outcomes across various constraints</li> </ul>
	Creativity	<ul style="list-style-type: none"> <li>Create diverse and novel ideas, or novel combinations of ideas</li> </ul>
	Information retrieval	<ul style="list-style-type: none"> <li>Search and retrieve information from a large scale of sources (breadth, depth, and degree of integration)</li> </ul>
Natural-language processing	Natural-language generation	<ul style="list-style-type: none"> <li>Deliver messages in natural language, including nuanced human interaction and some quasi language (eg, gestures)</li> </ul>
	Natural-language understanding	<ul style="list-style-type: none"> <li>Comprehend language, including nuanced human interaction</li> </ul>
Social and emotional capabilities	Social and emotional sensing	<ul style="list-style-type: none"> <li>Identify social and emotional state</li> </ul>
	Social and emotional reasoning	<ul style="list-style-type: none"> <li>Accurately draw conclusions about social and emotional state, and determine appropriate response/action</li> </ul>
	Emotional and social output	<ul style="list-style-type: none"> <li>Produce emotionally appropriate output (eg, speech, body language)</li> </ul>
Physical capabilities	Fine motor skills/dexterity	<ul style="list-style-type: none"> <li>Manipulate objects with dexterity and sensitivity</li> </ul>
	Gross motor skills	<ul style="list-style-type: none"> <li>Move objects with multidimensional motor skills</li> </ul>
	Navigation	<ul style="list-style-type: none"> <li>Autonomously navigate in various environments</li> </ul>
	Mobility	<ul style="list-style-type: none"> <li>Move within and across various environments and terrain</li> </ul>

Source: *Harnessing automation for a future that works*, McKinsey Global Institute, January 2017

**Exhibit 3 While downstream source-to-pay subprocesses show the highest potential, more-complex tasks are at least somewhat automatable.**

Potential for automation using currently demonstrated technologies by process stage, % of tasks within process stage

■ Difficult to automate ■ Somewhat automatable ■ Mostly or fully automatable<sup>1</sup>



<sup>1</sup>Tasks that can be digitized with minimal process changes using currently demonstrated technologies (“fully automatable” or “mostly automatable”).

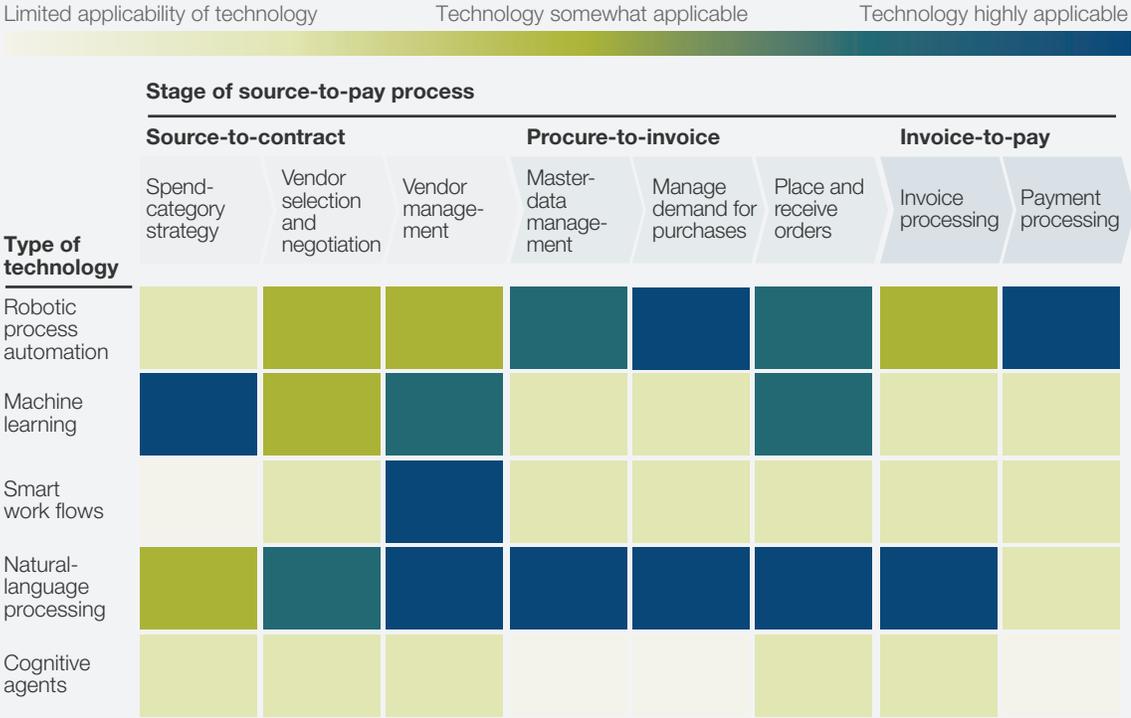
**Choosing the right automation technologies**

Although each task within the end-to-end source-to-pay process needs to be evaluated individually, some generalizations can be drawn by comparing the requirements of different parts of the process with the capabilities offered by different automation approaches (Exhibit 4):

- NLP technologies are applicable across many tasks in the process, as a bridge between human inputs and the most structured data used by machines.

- RPA is most applicable to the more transactional activities associated with procure-to-invoice and invoice-to-pay activities.
- Smart work flows apply to more-complex transactional activities, and especially in vendor management with its high degree of contextual information and its need to coordinate among multiple parties.
- Machine-learning and cognitive-agent capabilities are most applicable to the more

**Exhibit 4 New technologies show varying levels of applicability to source-to-pay activities.**



complex activities associated with the initial parts of the source-to-pay process, such as the development of spend-category strategies and the identification and selection of potential suppliers.

**The starting point in source-to-pay automation**

For companies, the next step is to identify the best targets for automation within their own processes. Organizations can do this by first evaluating the current level of automation they have implemented, compared with what is technically achievable for

each task in the source-to-pay process. They can then estimate the value of closing each gap.

This value will come both from the amount of work that can be automated and from likely improvements in compliance, cycle times, and payment terms associated with each step. Any gains must be set against the cost and complexity of implementing suitable technologies. Robotic process automation and smart work-flow solutions are likely to be quicker and cheaper to implement than sophisticated machine-learning technologies and cognitive agents, for example.

The emerging picture of the end-to-end process will provide a comparison of the relative benefits of addressing each step within it, set against the relative cost and difficulty of automating those steps.



The digital landscape is moving quickly. Companies that are prepared to experiment while taking a thoughtful, focused approach to the application of these technologies are likely to reap savings worth as much as 3.5 percent of all external spend. Even more important, by freeing sourcing

personnel from routine tasks, automation allows them to spend time pursuing innovative sources of additional value. ■

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<sup>1</sup> For more, see *Harnessing automation for a future that works*, McKinsey Global Institute, January 2017, on McKinsey.com.

<sup>2</sup> Ibid.

**Kalit Jain** is a senior expert in McKinsey's London office, and **Ed Woodcock** is a senior expert in the Stamford office.

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Contact for distribution: Allison Watson  
Phone: +1 424 249 1211  
Email: [Allison\\_Watson\\_Pugh@McKinsey.com](mailto:Allison_Watson_Pugh@McKinsey.com)

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