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The Deinstitutionalization of Business Support Functions through Artificial Intelligence

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Abstract: Technological advances in the field of artificial intelligence offer enormous potential for organizations. In recent years, organizations have leveraged this potential by establishing new business models or adjusting their primary activities. In the meantime, however, the potential for greater efficiency and effectiveness in support functions such as human resource management (HRM), supply chain management (SCM), or financial management (FM) through these technological advances is also increasingly being recognized. We synthesize the current state of research on AI regarding the potentials and diffusion within these support functions. Building upon this, we assess the deinstitutionalization power of AI for altering organizational processes within business support functions and derive implications to harness the full potential of AI across organizations.

Keywords: artificial intelligence; business support functions; deinstitutionalization; business transformation

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1. Introduction

The diffusion of artificial intelligence (AI) across organizations is steadily increasing [1]. From 2020 to 2021, the share of organizations applying AI-based applications to their operations has increased by 12 percent [2]. However, the rise of these applications is not surprising, given their enormous potential [3]. AI-based applications (i.e., machine learning or natural language processing) can process significantly larger amounts of data quickly, enabling faster, more precise, and unbiased decision-making compared to humans [4]. Hence, AI-based applications are capable of assisting, augmenting, or even completely automating tasks that previously could only be solved by human intelligence [5]. These capabilities apply to the execution of existing processes as well as to the development of new processes [6]. Thus, AI-based applications can be utilized for the exploitation of efficiency gains but also for the exploration of new business processes that could alter the way organizations operate [7]. However, despite its vast potential, the academic literature rarely addresses the mechanism of how AI might lead to a paradigm shift in the management of organizations.

Therefore, in this paper, we attend this gap by investigating the potential and diffusion of AI-based applications related to the exploitation and exploration foci of managers. Prior studies mainly focus on AI-based applications in the context of primary business activities, such as product development or marketing, that provide rapid top-line growth opportunities [8–10]. However, as AI holds vast potential within various business functions, we shed light on the fragmented AI research within traditional resource provision functions that has historically focused on the bottom line: human resource management (HRM), supply chain management (SCM), and financial management (FM). Based on our synthesis, we assess the exploitation of efficiency gains as well as the exploration of new opportunities within these functions through AI. Besides the vast potential in all analyzed support functions, we observe different stages of diffusion regarding exploitation and exploration foci. We conclude that, currently, managerial attention predominantly focuses on the exploitation and barely considers the exploration of AI potential. Thus, to harness the full potential of AI, managerial attention needs to shift, and organizations need to address cross-functional homogenous challenges for which we derive implications.

2. Artificial Intelligence and Deinstitutionalization

Notwithstanding its current dominance in the practical and theoretical debate [5,11], the concept of AI is anything but new. Already in 1955, the Dartmouth Research Project defined AI as machines behaving in ways that would be considered intelligent if humans behaved alike [12]. AI can be understood as the ability to make a deductive statement or decision similar to what human intelligence would come up with based on certain inputs [13]. Thus, the generic expression AI represents an umbrella term for applications that intelligently perform tasks [14]. Among others, these include machine learning (ML), robotic process automation (RPA), and natural language processing (NLP) [15]. These applications can be used for assisting, augmenting, or automating tasks. Assistance refers to the support provided by machines to humans in the execution of certain subtasks. Augmentation refers to a close collaboration between machines and humans to perform a task. Automation, in turn, implies that tasks are completely performed by intelligent machines [5]. Based on extensive technological advances, the processing capabilities and speed of such intelligent machines far exceed human capacity. Thus, besides the possibility to exploit efficiency gains in tasks that previously could only be solved by humans, AI-based applications can even explore opportunities beyond the scope of human intelligence [16].

However, even if these intelligent applications might enhance the value of business operations, their diffusion across organizations is difficult, as institutions suffer from organizational inertia [17,18]. As such, over time, various processes and institutional routines emerge and define how organizations operate [19]. These processes and routines are difficult to supersede as they are viewed as legitimate business practices [20]. In this vein, institution theory addresses how organizations introduce patterns and artifacts that are ultimately established as organizational procedures [21]. These procedures become stable, repetitive, and enduring business practices that produce value beyond the mere technical requirements of the task [22]. Although institutional theory mostly addresses the mechanism of achieving legitimacy for processes and routines, deinstitutionalization refers to the mechanism by which these erode or cease to exist [23]. Thus, new innovative methods have the potential to foster changes in organizational processes and institutional routines, altering how organizations operate [24]. To harness this deinstitutionalization power, the management of organizations must not only recognize the theoretical capabilities of new innovative methods but also corresponding practical use cases within business functions. The managerial horizon model describes different managerial foci with regard to the implementation of innovative methods across the organization [25]. Figure 1 illustrates the framework with two horizons.

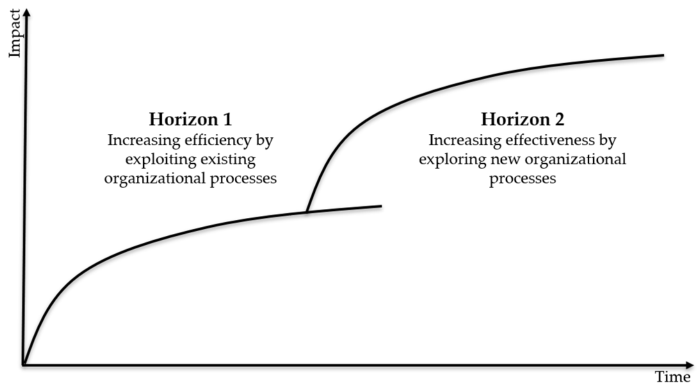

Figure 1. Managerial horizon model.

Chronologically, the diffusion of innovations starts at the first horizon. The first horizon refers to the exploitation of efficiency gains. Thereby, organizations apply new methods to their processes which can be carried out more efficiently as a result, but which are not subject to any fundamental change. These methods quickly yield high-impact results, although their increase starts to weaken as soon as "low hanging fruits" have been exploited. The development of this first horizon is necessary to level the ground for the second horizon. In turn, the second horizon refers to the exploration of effective opportunities. Innovations are leveraged to amend organizational processes, thereby fundamentally changing how organizations operate. These changes in organizations' operations potentially exceed the value contribution of existing processes [5]. From a deinstitutionalization lens, we conjecture that only under the second horizon do opportunities emerge to achieve the erosion of organizational processes.

3. Artificial Intelligence within Business Support Functions

As new innovative methods, AI-based applications could foster the ongoing transformation of business support functions from service providers to internal business partners [26]. We synthesize the current state of research on the applications of AI within traditional support functions that are responsible for the resources of labor (HRM), material (SCM), and capital (FM). Within each function, we highlight key activities and tasks to discuss the extent to which AI-based applications hold exploitation (horizon 1) and exploration (horizon 2) potential to assess their deinstitutionalization power.

3.1. Human Resource Management

HRM combines all aspects related to supplying the resource of labor to the organization. Thus, HRM is responsible for attracting new talent for the organization and for retaining and developing existing talent. Relevant tasks for HRM are the recruitment and selection of appropriate candidates, training and development of current employees, and compensation and benefits [27].

Within recruitment and selection, HR professionals assess the number of new employees, as well as the skills and qualifications needed. In so doing, AI-based applications combine large amounts of data from internal and external sources at tremendous speed to determine future staffing needs. Thus, besides increasing the efficiency of current recruiting processes, AI-based applications can increase the effectiveness of HR professionals in proactively addressing new challenges, whereas they might otherwise only reactively address staffing shortages [27]. Once open vacancies are identified, AI-based applications help to increase the success rate of job postings. Hence, intelligent applications can identify the most appealing designs and the most promising channels to promote vacancies [28]. In addition, AI-based applications also help identify suitable candidates by reviewing applicant profiles and matching them with the requirements of the respective job. These applications are similar to the matching algorithms of dating platforms that determine a specific match for two parties based on predefined metrics [29]. Compared to human assessment, AI-based applications can be trained to avoid susceptibility to cognitive bias based on gender, race, or other factors that might impair judgment [30]. AI-based applications are also well suited to improving the efficiency and effectiveness of job interviews. For example, simulations and asynchronous video interviews preselect promising candidates without recruiters having to invest a lot of time [31]. Again, intelligent applications provide an objective assessment of candidates without being biased by human factors.

For training and development, AI-based applications enable HR professionals to quickly assess each employee's individual information, including current qualifications and personal development goals. Derived from the gap between the current and desired state, the lack of skills and qualifications can be assessed, and the most relevant training opportunities can be identified more swiftly and efficiently [27]. This customization allows employees to interact with the personal development HR systems themselves. Instead of time-consuming research of various training programs or the necessity to involve an

HR professional, these systems quickly provide an initial overview of the most relevant training for each employee. One way of interacting with these HR systems is to apply intelligent (chat) bots that are always accessible and provide efficient first-level support for user requests. AI-based applications can also enable the training to be more efficient and effective because smart simulations that are customized to individual employees' needs can address a lack of skills or qualifications. Furthermore, for internal talent development, AI might help assign the right employees with the appropriate skills and motivations to optimal positions [32]. In this sense, AI might enable a more rigorous process for developing new ways to address promotion opportunities. Assuming that an employee is interested in taking on a new role, the system could trigger development opportunities for another person to fill the upcoming vacant role. In this way, the right employee is selected early on, smooth transitions and overlaps for onboarding can be ensured, and ultimately, employee turnover can be reduced, as future development prospects are an important motivational factor [33].

For compensation and benefits, HRM needs to ensure that employees receive fair and appropriate pay to motivate and retrain talent within the organization. Therefore, AI systems can capture and match data on employee compensation to minimize ungrounded dispersion within the same hierarchical levels [34]. Doing so potentially increases employee satisfaction and attachment to the organization, as unwarranted pay disparities are a substantial cause of employee dissatisfaction [35]. By transferring the idea to the organization's environment, AI-based systems can be used to compare the company's salary structures with those of competitors. By providing an appropriate level of payment in relation to their respective roles, organizations can gain a competitive advantage in the "war for talent" [30]. Besides monetary compensation, which is historically the most important motivational factor [36], intangible perks and benefits are becoming increasingly important to attract and retain employees [37]. As such, organizations increasingly provide corporate benefits for employees, such as grants for sports activities, mobility budgets, and other private activities. On the one hand, these benefits increase employee satisfaction; on the other hand, corporate benefits that increase employee health (e.g., sports club memberships) also reduce absenteeism due to illness. Since these benefits can encompass a multitude of different activities, AI-based applications can help address employee desires more efficiently. Assuming that employees have different preferences based on their current life circumstances (e.g., childless single individuals versus married parents), customized corporate benefit programs could be granted to each employee or group of employees individually [38].

3.2. Supply Chain Management

SCM refers to various intra- and interorganizational relations. These include all aspects, starting from the initial supplier to the final customer, intending to add value at each stage to maximize customer satisfaction [39]. Depending on the definition, SCM can also include aspects of an organization's primary activities. However, the focus herein is on support-oriented activities that aim to provide the resource of material to the organization: purchasing, supplier relationship management, and logistics.

In an increasingly globalized world, all organizations need to act globally in their purchasing processes. Although this opens up plenty of opportunities, it also increases the complexity of selecting the right suppliers from a wide range of possible options [40]. Organizations must handle the increased complexity of purchasing to capitalize on these opportunities. Therefore, organizations need to select the most promising suppliers based on certain criteria [41]. However, suppliers who do not meet these criteria also frequently represent fruitful business partners, as they might offer advantages in ambiguous ways. Previous studies have shown that these suppliers, in particular, help organizations gain new perspectives on existing problems, and thus, help reach solutions more quickly [42]. Besides increasing the efficiency of the supplier selection process, AI-based applications can also help to increase their effectiveness by utilizing a multitude of different parameters and weightings and learning from those to identify the most suitable business partners [43]. AI-based applications are capable of investigating potential business relationships that seem ill-suited or inappropriate on the surface, but might, nevertheless, exhibit great potential [44]. These systems can also help ensure that suppliers are not evaluated individually, but rather as part of the whole supplier network. As such, organizations can reduce their exposure to macroeconomic risks or diversify their purchasing dependencies [29]. Once a supplier is selected, purchasing processes can be managed more efficiently using AI-based applications for aspects such as group purchasing of items, determining the optimal route, and batch sizing in real time [45]. Potential bottlenecks in the supply chain can be identified at an early stage and actively addressed [46].

After a supplier is selected as a business partner, the task of supplier relationship management is to control, maintain, and manage this relationship [47]. On the one hand, AI-based systems can analyze large amounts of data to measure the performance of various suppliers and, if necessary, initiate appropriate measures to improve performance. Because the systems can objectively incorporate quantitative as well as qualitative data, the performance of suppliers is no longer limited to costs and meeting deadlines. Important aspects, such as sustainable development, the quality of the business relationship, and the ability to innovate resulting from the business relationship, can be determined and evaluated effectively [29]. As part of supplier relationship management, organizations benefit from the permanent opportunity to exchange information, which can help increase the value of the business relationship on both sides. For this purpose, intelligent bots can be used on the basis of AI-based applications. These bots can interact with human counterparts or even other bots to provide first-hand support regarding aspects such as technical specifications, quality features, or delivery modalities [48]. In so doing, purchasing professionals' time can be spared, as they only need to step in for cross-checking or in more complex situations to provide second-level support. In addition, identifying risks throughout the supply chain by applying AI-based applications can help address issues more effectively in collaboration with suppliers at an early stage [49].

The broader field of logistics can be roughly divided into inbound, internal, and outbound logistics. Inbound logistics refers to the transport of items into the focal organization, whereas outbound logistics deals with the processes of transporting items from the focal organization to its customers [50]. Internal logistics, on the other hand, addresses processes that take place within an organization; for example, in the organization's warehouse [51]. AI-based applications can help support transportation-related logistics aspects by using algorithms to calculate optimal routing. Instead of focusing on minimizing costs through transportation, routes can thus be determined from a multilayered set of target criteria, allowing for increased effectiveness. Thus, the economic factor cost can be supplemented by aspects of sustainability and social factors. In warehouses, fully automated systems can support the efficient handling of items, with intelligent systems taking over the unloading and loading of transport vehicles [52]. However, these systems can also support operations activities by providing the necessary input resources [53]. In a thin vein, intelligent machines can provide relevant items just in time and sequence based on the information gathered from operations activities [54]. These intelligent and autonomous systems can serve as bottlenecks for performing logistics activities adequately without requiring multiple employees [55]. In addition to increasing efficiency in handling items, AI-based systems can also trigger automated ordering processes. By linking the organization's information sources, these systems can identify delivery times and potential supply bottlenecks in real time, which allows proactive countermeasures to be taken at an early stage to ensure security in the organization's supply chain.

3.3. Financial Management

FM describes the activities related to providing the resource of capital to an organization. This includes the input and output of capital streams and, based on these, their planning, management, and control from an internal and external perspective. Among others, relevant tasks of FM include financial accounting, management accounting, and risk management.

Financial accounting addresses organizations' legal obligation to disclose their financial situation to their various external stakeholders. This disclosure is regulated by applicable accounting standards and follows a periodic schedule (e.g., IFRS or US-GAAP). These standards stipulate how to present the organization's transactions and provide guidance on the outlook of the organization's future operations. To support these tasks, a range of AI-powered software exists that can, for example, process account payables and receivables more swiftly and efficiently than accounting professionals [56]. Payments and invoices can be sent to suppliers and customers in real time, which can help increase the company's credit reputation [57]. In addition to higher efficiency in the execution of tasks, AI-based systems are less error-prone than manual processing of entries by humans. Based on accounting standards, unambiguous rules can be specified, and thus, a large part of the manual work can be taken over by computer-aided processing without being error-prone [58]. This allows professionals to execute more strategically compelling tasks and focus on communicating their implications to internal and external stakeholders [59]. The standardized execution of predefined processes also increases the comparability of organizational reporting to external stakeholders as opportunities for opportunistic behavior (e.g., window dressing) diminish. Furthermore, the preparation of financial statements consumes a large amount of time, whereas required tasks are often repetitive and tedious. By linking AI-based systems with the organization's central data systems (possibly on a cloud basis), the necessary data for annual or quarterly reports can be generated swiftly and easily [60]. Intelligent algorithms can also support qualitative assessments of the outlook on an organization's future operations. Based on the quantitative inputs, these algorithms can generate preliminary written statements, including normative assessments of the business situation, which can be used as a blueprint for developing the final statements [61].

Management accounting refers to the internal perspective regarding investment and liquidity planning, management, and control. In so doing, internal and external information is gathered and organized to derive sound recommendations for management. Although some experts already predict the extinction of the management accountant profession due to AI-based applications, the field should be viewed in a more nuanced way [62,63]. First, operational management accounting covers short-term activities, such as budgeting, contribution margin accounting, and variance analyses. These analyses can be automated and carried out more efficiently, to a large extent, through the application of AI-based applications. These applications also have great potential for increasing the effectiveness of operational management accounting. By linking internal and external data sources from a central data storage system with applications of the reporting dashboard, managers or their staff should be able to access automated custom reports and analyses in real time [64]. Second, strategic management accounting addresses the long-term strategic focus of the organization, which is derived from the overall strategy. Strategic issues, such as the organization's portfolio or expansion opportunities in terms of markets and customers, are valid use cases in which the performance of AI-based applications can offer a huge value add for the management accounting domain [65]. Thus, there is also potential for AI-based applications in terms of efficiency and effectiveness gains to address these strategic issues.

An organization's risk management refers to the identification, analysis, assessment, and management of potential risks [66]. In doing so, risk management is primarily directed toward the future to identify potential risk factors at an early stage. Risk factors can be both external and internal. From an external perspective, material shortages, capital market fluctuations, and geopolitical conflicts might affect an organization's operations. From an internal perspective, issues such as liquidity shortages, employee turnover, and loss of competitive knowledge represent risk factors. In this sense, the value contribution of risk management traditionally depends on the experience or intuition of employees regarding changes in the business context [67]. Despite the extensive experience of employees, assessments are ultimately subjective and error-prone. In comparison, models relying on AI-based applications are significantly more effective at predicting potential risk factors as they are able to create links among available information and incorporate interdependencies [68]. As such, AI-based systems have access to both inside information and all other types of information gathered from outside the organization from which to draw conclusions [69,70]. Therefore, various financial and nonfinancial quantitative and qualitative information can be evaluated as a whole, and in the event of an imminent risk, a variety of scenario analyses can be carried out at an early stage to derive countermeasures. Consequently, the use of AI-based applications in predictive risk management opens up new possibilities for how organizations can proactively perceive potential threats and respond accordingly.

4. Discussion

4.1. Diffusion of AI in Business Support Functions

Based on the analysis of the different business support functions, we observed vast potentials for AI within horizon 1 and horizon 2, but we saw a gap in the current state of diffusion [2,11]. According to Figure 2, we gauged that the overall AI diffusion within the support function is at a moderate stage, but with some differences between the functions. We attributed these differences to the nature of the respective activities within the support functions. FM has always been concerned with evaluating circumstances objectively based on quantitative factors (e.g., budgets, profit margins, sales growth, etc.). Therefore, the leap to assigning tasks to intelligent machines is relatively modest compared to other functions, which is reflected in the relatively advanced diffusion of AI-based applications [71]. In comparison, since HRM is particularly about attracting, retaining, and developing talent, its core tasks include a more subjective evaluation of qualitative factors (e.g., job-related qualifications, personal values, organizational fit, etc.). Although AI could also significantly impact HRM tasks, it implies a larger leap toward putting sensitive issues in the hands of intelligent applications [72]. As a result, ethical issues are more dominant, and acceptance of AI decision-making might be lower in HRM, leading to greater resistance regarding its diffusion [73]. Lastly, SCM involves many tasks that are objectively assessable, but also require some sensitive interpersonal intuition. In line with this, we considered the diffusion of AI-based applications in SCM between the other support functions [74].

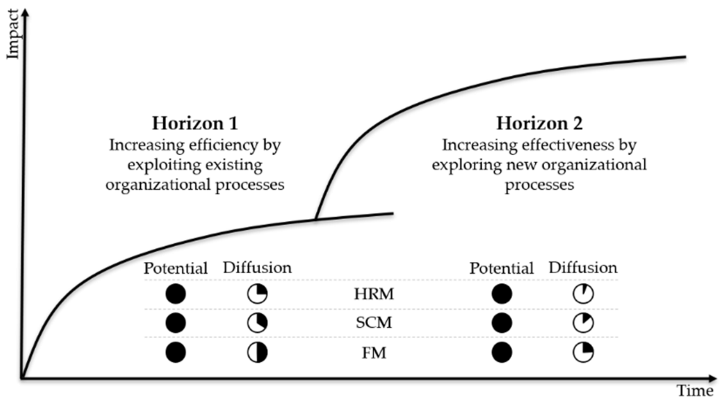

Figure 2. Potential and diffusion of AI-based applications in business support functions.

Since the integration of intelligent applications into existing organizational processes initially generates substantial efficiency gains, there is no immediate pressure to adjust these processes. Therefore, the diffusion of AI-based applications passes through horizon 1 until efficiency gains are mostly exploited and trust has been aroused [75]. Accordingly, the state of diffusion with regard to the exploration of new opportunities (horizon 2) shows a similar pattern among the support functions as for exploitation, but is far less advanced. Although management is currently focused on utilizing AI-based applications for the exploitation of existing organizational processes (horizon 1), the focus on the exploration of new opportunities (horizon 2) is barely existent. We contend that although AI has the potential to usher in a paradigm shift, it will first need to overcome the inertia of organizations. This, however, cannot be achieved under the management's current focus on the exploitation of existing organizational processes. Nevertheless, once the managerial focus shifts to the second horizon, triggering the exploration of new opportunities, AI can unfold its deinstitutionalization power and alter how business support functions operate. To enable this shift and accelerate the diffusion of AI-based applications in support functions, we identified some core challenges for organizations. Although the pertinence of these challenges varies, the challenges themselves are homogeneous across the business support functions, as discussed below.

4.2. Implications

To bridge the gap between AI potential and its current state of diffusion, we identified three cross-functional issues that organizations need to address. First, organizations must build and maintain trust in AI [14]. As with any novel technological innovation, people are suspicious of how AI might affect their daily working life [75]. It is these very human elements that organizations must consider to capitalize on the potential of AI-based applications. In this vein, employees might be concerned by the common belief that AI-based applications put people's jobs at risk [1]. Although organizations might automate basic routine tasks, utilizing AI can make employees' tasks more compelling and enhance their personal impact. As such, AI may serve as an enabler for realizing the transformation of support functions from service provision to business partnering [76]. Henceforth, organizations should raise awareness, particularly about the opportunities created through AI. In addition, managers might fear a loss of positional power due to the implementation of AI. Although the distribution of power relations is stable under existing processes, the question of power has to be redefined as organizational processes change. Managers who might lose to the changing power balance could obstruct the introduction of AI due to opportunistic reasons [18]. Therefore, organizations should not only pay attention to the concerns of employees, but also to the potential consequences for managers, and support the transformation with active change management.

Second, organizations must ensure that functional teams are equipped with the appropriate skills and qualifications to harness the potential of AI-based applications [77]. Although the current composition of teams is often very homogeneous in terms of functional skills and qualifications, a broader range of competencies will be required within teams and departments in the future [59]. HRM, SCM, and FM professionals will need a basic technical understanding in addition to their functional subject knowledge. Increased technical understanding also tackles the issue that AI's decision-making is a "black box," which is difficult for outsiders to decipher. By increasing the understanding of AI fundamentals, this "black box" becomes more comprehensible to employees, which additionally increases the credibility of AI. However, since subject knowledge is not becoming obsolete, it should not be regarded as a replacement of essential skills, but rather as an enhancement. Therefore, employees face the ongoing task of keeping up with increasing demands. With this in mind, organizations should ensure appropriate training of their employees for the extended job requirements, thus creating more heterogeneous (cross-)functional teams with regard to their technological competencies.

Third, organizations must provide the necessary foundations for utilizing the potential of AI. Outcomes of AI-based applications are only useful and accurate if the underlying data on which the algorithms are trained is of appropriate quantity and quality. Therefore, large amounts of data (i.e., big data) and their management are irreplaceable for the diffusion of AI-based applications in businesses. The increasing amount of data, as well as its relevance, requires better data governance to ensure its accessibility at all times. Thus, organizations need to implement sufficient data governance by defining necessary processes, guidelines, and standards to transform a multitude of unstructured information sources into a unified data foundation upon which AI-based applications can be deployed [78,79]. Moreover, with the increasing relevance of data for the functioning of organizational processes, the issue of cyber risks is also growing. Corporate scandals related to the loss of (personal) data can have not only serious legal consequences, but also a negative impact on an organization's reputation [80,81]. Therefore, organizations need to ensure that the underlying data are sufficiently governed and protected against cyber risks to leverage the potential of AI-based applications across business functions.

4.3. Limitations and Future Avenues

We acknowledge that our study has limitations, which also provide avenues for future research. First, our study yielded qualitative findings as compared to quantitative results. However, this applies to the majority of synthesized studies due to the severely limited data necessary for a complementary quantitative approach. In this vein, future research might aim to develop comprehensive and applicable measures regarding the diffusion of AI in organizations. Second, we only focused on the traditional business support functions of HRM, SCM, and FM that are paramount to the organization's future success. However, future research could examine the mechanism of AI diffusion in other business functions, such as research and development, which are thought to be less affected by organizational inertia [6]. By addressing how to overcome organizational inertia in the analyzed business support functions, we derived implications for fostering the diffusion of AI. With this, we emphasized the different managerial foci necessary for the deinstitutionalization of organizational procedures through AI. Given the ongoing technological advances and the associated potential of AI for organizations, we see vast opportunities for future research in the field of AI from the perspective of an organization's management.

5. Conclusions

In this paper, we explored the potential of AI-based applications and the diffusion of these applications among different business support functions. Therefore, we examined how organizations leverage AI-based applications to exploit existing organizational processes and explore new opportunities in the domains of HRM, SCM, and FM. Based on the academic literature, we identified the great potential of AI for exploitation and exploration within business support functions. However, we observed only a moderate diffusion of AI among these functions. We noted differences in the state of diffusion across functions, which we attributed to the varying nature of the tasks and the associated resistance to adopting AI. Although management is currently focused on utilizing AI-based applications for the exploitation of existing organizational processes (horizon 1), the focus on exploring new opportunities (horizon 2) is barely existent. However, only when managers fully grasp the enormous potential of AI in organizations and shift their focus to exploring opportunities accordingly will it lead to a paradigm shift in the management of organizations. Hence, organizations need to address homogeneous cross-functional challenges to achieve the deinstitutionalization of business support functions through AI.

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References

1. Tschang, F.T.; Almirall, E. Artificial Intelligence as Augmenting Automation: Implications for Employment. *Acad. Manag. Perspect.* **2021**, *35*, 642–659. [CrossRef]
2. Chui, M.; Hall, B.; Singla, A.; Sukhrevsky, A. The State of AI in 2021. 2021. Available online: https://www.mckinsey.com/business-functions/mckinsey-analytics/our-insights/global-survey-the-state-of-ai-in-2021 (accessed on 6 June 2022).
3. Agrawal, A.; Gans, J.; Goldfarb, A. *Prediction Machines: The Simple Economics of Artificial Intelligence*; Havard Business Press: Boston, MA, USA, 2018.
4. Agrawal, A.; Gans, J.S.; Goldfarb, A. Exploring the impact of artificial Intelligence: Prediction versus judgment. *Inf. Econ. Policy* **2019**, *47*, 1–6. [CrossRef]
5. Raisch, S.; Krakowski, S. Artificial intelligence and management: The automation–augmentation paradox. *Acad. Manag. Rev.* **2021**, *46*, 192–210. [CrossRef]
6. Johnson, P.C.; Laurell, C.; Ots, M.; Sandström, C. Digital innovation and the effects of artificial intelligence on firms' research and development—Automation or augmentation, exploration or exploitation? *Technol. Forecast. Soc. Chang.* **2022**, *179*, 121636. [CrossRef]
7. Haefner, N.; Wincent, J.; Parida, V.; Gassmann, O. Artificial intelligence and innovation management: A review, framework, and research agenda☆. *Technol. Forecast. Soc. Chang.* **2021**, *162*, 120392. [CrossRef]
8. Di Vaio, A.; Palladino, R.; Hassan, R.; Escobar, O. Artificial intelligence and business models in the sustainable development goals perspective: A systematic literature review. *J. Bus. Res.* **2020**, *121*, 283–314. [CrossRef]
9. Gupta, S.; Modgil, S.; Bhattacharyya, S.; Bose, I. Artificial intelligence for decision support systems in the field of operations research: Review and future scope of research. *Ann. Oper. Res.* **2022**, *308*, 215–274. [CrossRef]
10. Martínez-López, F.J.; Casillas, J. Artificial intelligence-based systems applied in industrial marketing: An historical overview, current and future insights. *Ind. Mark. Manag.* **2013**, *42*, 489–495. [CrossRef]
11. Ransbotham, S.; Khodabandeh, S.; Kiron, D.; Candelon, F.; Chu, M.; LaFountain, B. *Expanding AI's Impact With Organizational Learning*. 2020. Available online: https://sloanreview.mit.edu/projects/expanding-ais-impact-with-organizational-learning/ (accessed on 1 June 2022).
12. McCarthy, J.; Minsky, M.L.; Rochester, N.; Shannon, C.E. A proposal for the Dartmouth summer research project on artificial intelligence. *AI Mag.* **2006**, *27*, 12–14.
13. Kaplan, A.; Haenlein, M. Siri, Siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence. *Bus. Horiz.* **2019**, *62*, 15–25. [CrossRef]
14. Tambe, P.; Cappelli, P.; Yakubovich, V. Artificial intelligence in human resources management: Challenges and A path forward. *Calif. Manag. Rev.* **2019**, *61*, 15–42. [CrossRef]
15. Bigham, T.; Nair, S.; Soral, S.; Tua, A.; Gallo, V.; Lee, M.; Mews, T.; Fouché, M. AI and Risk Management—Innovating with Confidence; Deloitte: 2018. Available online: https://www2.deloitte.com/content/dam/Deloitte/global/Documents/Financial-Services/deloitte-gx-ai-and-risk-management.pdf (accessed on 13 June 2022).
16. Dwivedi, Y.K.; Hughes, L.; Ismagilova, E.; Aarts, G.; Coombs, C.; Crick, T.; Duan, Y.; Dwivedi, R.; Edwards, J.; Eirug, A.; et al. Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *Int. J. Inf. Manag.* **2021**, *57*, 101994. [CrossRef]
17. Van Witteloostuijn, A. Bridging behavioral and economic theories of decline: Organizational inertia, strategic competition, and chronic failure. *Manag. Sci.* **1998**, *44*, 501–519. [CrossRef]
18. Maguire, S.; Hardy, C. Discourse and Deinstitutionalization: The Decline of DDT. *Acad. Manag. J.* **2009**, *52*, 148–178. [CrossRef]
19. Kelly, D.; Amburgey, T.L. Organizational Inertia and Momentum: A Dynamic Model of Strategic Change. *Acad. Manag. J.* **1991**, *34*, 591–612. [CrossRef]
20. DiMaggio, P.J.; Powell, W.W. The Iron Cage Revisited: Institutional Isomorphism and Collective Rationality in Organizational Fields. *Am. Sociol. Rev.* **1983**, *48*, 147. [CrossRef]
21. Meyer, J.W.; Rowan, B. Institutionalized Organizations: Formal Structure as Myth and Ceremony. *Am. J. Sociol.* **1977**, *83*, 340–363. [CrossRef]
22. Selznick, P. *Leadership in Administration: A Sociological Interpretation*; Harper & Row: New York, NY, USA, 1957.
23. Oliver, C. The Antecedents of Deinstitutionalization. *Organ. Stud.* **1992**, *13*, 563–588. [CrossRef]
24. Hargadon, A.B.; Douglas, Y. When Innovations Meet Institutions: Edison and the Design of the Electric Light. *Adm. Sci. Q.* **2001**, *46*, 476–501. [CrossRef]
25. Steve, B. McKinsey's Three Horizons Model Defined Innovation for Years. Here's Why It No Longer Applies. *Harv. Bus. Rev.* 2019. Available online: https://hbr.org/2019/02/mckinseys-three-horizons-model-defined-innovation-for-years-heres-why-it-no-longer-applies (accessed on 2 June 2022).
26. Bloch, M.; Lempres, E. From internal service provider to strategic partner: An interview with the head of Global Business Services at P&G. *McKinsey Q.* 2008. Available online: https://www.mckinsey.com/business-functions/mckinsey-digital/our-insights/from-internal-service-provider-to-strategic-partner-an-interview-with-the-head-of-global-business-services-at-p-and-g (accessed on 14 June 2022).
27. Budhwar, P.; Malik, A.; De Silva, M.T.T.; Thevisuthan, P. Artificial intelligence–challenges and opportunities for international HRM: A review and research agenda. *Int. J. Hum. Resour. Manag.* **2022**, *33*, 1065–1097. [CrossRef]

28. Goldfarb, A.; Taska, B.; Teodoridis, F. Artificial Intelligence in Health Care? Evidence from Online Job Postings. *AEA Pap. Proc.* **2020**, *110*, 400–404. [CrossRef]
29. Allal-Chérif, O.; Simón-Moya, V.; Ballester, A.C.C. Intelligent purchasing: How artificial intelligence can redefine the purchasing function. *J. Bus. Res.* **2021**, *124*, 69–76. [CrossRef]
30. Pessach, D.; Singer, G.; Avrahami, D.; Chalutz Ben-Gal, H.; Shmueli, E.; Ben-Gal, I. Employees recruitment: A prescriptive analytics approach via machine learning and mathematical programming. *Decis. Support Syst.* **2020**, *134*, 113290. [CrossRef] [PubMed]
31. Torres, E.N.; Mejia, C. Asynchronous video interviews in the hospitality industry: Considerations for virtual employee selection. *Int. J. Hosp. Manag.* **2017**, *61*, 4–13. [CrossRef]
32. Sitzmann, T.; Weinhardt, J.M. Approaching evaluation from a multilevel perspective: A comprehensive analysis of the indicators of training effectiveness. *Hum. Resour. Manag. Rev.* **2019**, *29*, 253–269. [CrossRef]
33. Nouri, H.; Parker, R.J. Career growth opportunities and employee turnover intentions in public accounting firms. *Br. Account. Rev.* **2013**, *45*, 138–148. [CrossRef]
34. Mehrabad, M.S.; Brojeny, M.F. The development of an expert system for effective selection and appointment of the jobs applicants in human resource management. *Comput. Ind. Eng.* **2007**, *53*, 306–312. [CrossRef]
35. Card, D.; Mas, A.; Moretti, E.; Saez, E. Inequality at Work: The Effect of Peer Salaries on Job Satisfaction. *Am. Econ. Rev.* **2012**, *102*, 2981–3003. [CrossRef]
36. Stringer, C.; Didham, J.; Theivananthampillai, P. Motivation, pay satisfaction, and job satisfaction of front-line employees. *Qual. Res. Account. Manag.* **2011**, *8*, 161–179. [CrossRef]
37. Hammermann, A.; Mohnen, A. Who benefits from benefits? Empirical research on tangible incentives. *Rev. Manag. Sci.* **2014**, *8*, 327–350. [CrossRef]
38. Ross, J.P.; Intindola, M.L.; Boje, D.M. It Was the Best of Times; It Was the Worst of Times: The Expiration of Work–Life Balance. *J. Manag. Inq.* **2017**, *26*, 202–215. [CrossRef]
39. Stock, J.R.; Boyer, S.L. Developing a consensus definition of supply chain management: A qualitative study. *Int. J. Phys. Distrib. Logist. Manag.* **2009**, *39*, 690–711. [CrossRef]
40. Trent, R.J.; Monczka, R.M. International purchasing and global sourcing—what are the differences? *J. Supply Chain Manag.* **2003**, *39*, 26–36. [CrossRef]
41. Zimmer, K.; Fröhling, M.; Schultmann, F. Sustainable supplier management—A review of models supporting sustainable supplier selection, monitoring and development. *Int. J. Prod. Res.* **2016**, *54*, 1412–1442. [CrossRef]
42. Legenvre, H.; Gualandris, J. Innovation sourcing excellence: Three purchasing capabilities for success. *Bus. Horiz.* **2018**, *61*, 95–106. [CrossRef]
43. Fagundes, M.V.C.; Hellingrath, B.; Freires, F.G.M. Supplier Selection Risk: A New Computer-Based Decision-Making System with Fuzzy Extended AHP. *Logistics* **2021**, *5*, 13. [CrossRef]
44. Lu, R.; Hong, S.H. Incentive-based demand response for smart grid with reinforcement learning and deep neural network. *Appl. Energy* **2019**, *236*, 937–949. [CrossRef]
45. Toorajipour, R.; Sohrabpour, V.; Nazarpour, A.; Oghazi, P.; Fischl, M. Artificial intelligence in supply chain management: A systematic literature review. *J. Bus. Res.* **2021**, *122*, 502–517. [CrossRef]
46. Allal-Chérif, O.; Maira, S. Collaboration as an anti-crisis solution: The role of the procurement function. *Int. J. Phys. Distrib. Logist. Manag.* **2011**, *41*, 860–877. [CrossRef]
47. Choi, T.Y.; Krause, D.R. The supply base and its complexity: Implications for transaction costs, risks, responsiveness, and innovation. *J. Oper. Manag.* **2006**, *24*, 637–652. [CrossRef]
48. Chung, M.; Ko, E.; Joung, H.; Kim, S.J. Chatbot e-service and customer satisfaction regarding luxury brands. *J. Bus. Res.* **2020**, *117*, 587–595. [CrossRef]
49. Baryannis, G.; Validi, S.; Dani, S.; Antoniou, G. Supply chain risk management and artificial intelligence: State of the art and future research directions. *Int. J. Prod. Res.* **2019**, *57*, 2179–2202. [CrossRef]
50. van Hoek, R.I.; Weken, H.A.M. How Modular Production can Contribute to Integration in Inbound and Outbound Logistics. *Int. J. Logist. Res. Appl.* **1998**, *1*, 39–56. [CrossRef]
51. Negri, E.; Perotti, S.; Fumagalli, L.; Marchet, G.; Garetti, M. Modelling internal logistics systems through ontologies. *Comput. Ind.* **2017**, *88*, 19–34. [CrossRef]
52. Hengstler, M.; Enkel, E.; Duelli, S. Applied artificial intelligence and trust - The case of autonomous vehicles and medical assistance devices. *Technol. Forecast. Soc. Chang.* **2016**, *105*, 105–120. [CrossRef]
53. Gupta, S.; Jones, E.C. Optimizing supply chain distribution using cloud based autonomous information. *Int. J. Supply Chain Manag.* **2014**, *3*, 79–90.
54. Brynjolfsson, E.; Rock, D.; Syverson, C. Artificial Intelligence and the Modern Productivity Paradox: A Clash of Expectations and Statistics. In *The Economics of Artificial Intelligence: An Agenda*; National Bureau of Economic Research: Cambridge, MA, USA, 2019.
55. Klumpp, M. Automation and artificial intelligence in business logistics systems: Human reactions and collaboration requirements. *Int. J. Logist. Res. Appl.* **2018**, *21*, 224–242. [CrossRef]

56. Lee, C.S.; Tajudeen, F.P. Usage and impact of artificial intelligence on accounting: Evidence from Malaysian organisations. *Asian J. Bus. Account.* **2020**, *13*, 213–239. [CrossRef]
57. Bryk, A.; Lee, H.; Thibault, P.; Stewien, B. Strategies for Optimizing Your Accounts Payable. 2015. Available online: https://www2.deloitte.com/content/dam/Deloitte/ca/Documents/finance/ca-en-FA-strategies-for-optimizing-your-accounts-payable.pdf (accessed on 3 June 2022).
58. Ding, K.; Lev, B.; Peng, X.; Sun, T.; Vasarhelyi, M.A. Machine learning improves accounting estimates: Evidence from insurance payments. *Rev. Account. Stud.* **2020**, *25*, 1098–1134. [CrossRef]
59. Leitner-Hanetseder, S.; Lehner, O.M.; Eisl, C.; Forstenlechner, C. A profession in transition: Actors, tasks and roles in AI-based accounting. *J. Appl. Account. Res.* **2021**, *22*, 539–556. [CrossRef]
60. Petkov, R. Artificial intelligence (AI) and the accounting function—a revisit and a new perspective for developing framework. *J. Emerg. Technol. Account.* **2020**, *17*, 99–105. [CrossRef]
61. Oduware, U. COSO—An Approach to Internal Control Framework; Deloitte: 2015. Available online: https://www2.deloitte.com/za/en/nigeria/pages/audit/articles/financial-reporting/coso-an-approach-to-internal-control-framework.html (accessed on 1 June 2022).
62. Brands, K.; Holtzblatt, M. Business Analytics: Transforming the Role of Management Accountants. *Manag. Account. Q.* **2015**, *16*, 1–12. Available online: https://www.imanet.org/-/media/fba0ebd670414d25a467d4cff8d0c691.ashx (accessed on 9 June 2022).
63. Gentsch, P. Business KI verändert Unternehmen und Märkte. *Control. Manag. Rev.* **2019**, *63*, 24–33. [CrossRef]
64. Elbashir, M.Z.; Collier, P.A.; Sutton, S.G. The role of organizational absorptive capacity in strategic use of business intelligence to support integrated management control systems. *Account. Rev.* **2011**, *86*, 155–184. [CrossRef]
65. Batistič, S.; van der Laken, P. History, Evolution and Future of Big Data and Analytics: A Bibliometric Analysis of Its Relationship to Performance in Organizations. *Br. J. Manag.* **2019**, *30*, 229–251. [CrossRef]
66. Leo, M.; Sharma, S.; Maddulety, K. Machine learning in banking risk management: A literature review. *Risks* **2019**, *7*, 29. [CrossRef]
67. Carol, A. The present and future of financial risk management. *J. Financ. Econom.* **2005**, *3*, 3–25. [CrossRef]
68. Tsai, C.F.; Wu, J.W. Using neural network ensembles for bankruptcy prediction and credit scoring. *Expert Syst. Appl.* **2008**, *34*, 2639–2649. [CrossRef]
69. Raguseo, E.; Vitari, C.; Pigni, F. Profiting from big data analytics: The moderating roles of industry concentration and firm size. *Int. J. Prod. Econ.* **2020**, *229*, 107758. [CrossRef]
70. Sivarajah, U.; Kamal, M.M.; Irani, Z.; Weerakkody, V. Critical analysis of Big Data challenges and analytical methods. *J. Bus. Res.* **2017**, *70*, 263–286. [CrossRef]
71. Plaschke, F.; Seth, I.; Whiteman, R. Bots, Algorithms, and the Future of the Finance Function; McKinsey & Company: 2018. Available online: https://www.mckinsey.com/business-functions/strategy-and-corporate-finance/our-insights/bots-algorithms-and-the-future-of-the-finance-function (accessed on 8 June 2022).
72. Candelon, F.; di Carlo, R.C.; Mills, S. Why AI Needs a Social License; Boston Consulting Group: 2022. Available online: https://www.bcg.com/publications/2022/why-a-social-license-is-needed-for-artificial-intelligence (accessed on 7 June 2022).
73. Bhave, D.P.; Teo, L.H.; Dalal, R.S. Privacy at Work: A Review and a Research Agenda for a Contested Terrain. *J. Manag.* **2020**, *46*, 127–164. [CrossRef]
74. Alicke, K.; Dilda, V.; Görner, S.; Mori, L.; Rebuffel, P.; Reiter, S.; Samek, R. Succeeding in the AI Supply-Chain Revolution; McKinsey & Company: 2021. Available online: https://www.mckinsey.com/industries/metals-and-mining/our-insights/succeeding-in-the-ai-supply-chain-revolution (accessed on 10 June 2022).
75. Glikson, E.; Woolley, A.W. Human trust in artificial intelligence: Review of empirical research. *Acad. Manag. Ann.* **2020**, *14*, 627–660. [CrossRef]
76. Edlich, A.; Ip, F.; Whiteman, R. How Bots, Algorithms, and Artificial Intelligence Are Reshaping the Future of Corporate Support Functions. 2018. Available online: https://www.mckinsey.com/~{}/media/McKinsey/Business%20Functions/McKinsey%20Digital/Our%20Insights/How%20bots%20algorithms%20ai%20are%20reshaping/How-bots-algorithms-and-artificial-intelligence-are-reshaping-future-of-corporate-support-functions.pdf (accessed on 14 June 2022).
77. Deloitte. Talent and Workforce Effects in the Age of AI Insights from Deloitte's State of AI in the Enterprise; Deloitte Insights: 2020. Available online: https://www2.deloitte.com/content/dam/insights/us/articles/6546_talent-and-workforce-effects-in-the-age-of-ai/DI_Talent-and-workforce-effects-in-the-age-of-AI.pdf (accessed on 3 June 2022).
78. Janssen, M.; Brous, P.; Estevez, E.; Barbosa, L.S.; Janowski, T. Data governance: Organizing data for trustworthy Artificial Intelligence. *Gov. Inf. Q.* **2020**, *37*, 101493. [CrossRef]
79. Yablonsky, S. AI-driven platform enterprise maturity: From human led to machine governed. *Kybernetes* **2021**, *50*, 2753–2789. [CrossRef]
80. Confente, I.; Siciliano, G.G.; Gaudenzi, B.; Eickhoff, M. Effects of data breaches from user-generated content: A corporate reputation analysis. *Eur. Manag. J.* **2019**, *37*, 492–504. [CrossRef]
81. Gwebu, K.L.; Wang, J.; Wang, L. The Role of Corporate Reputation and Crisis Response Strategies in Data Breach Management. *J. Manag. Inf. Syst.* **2018**, *35*, 683–714. [CrossRef]