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IMPACT OF ARTIFICIAL INTELLIGENCE, MACHINE LEARNING, AND AUTOMATION IN OPERATIONS MANAGEMENT: AN ANALYSIS OF HEALTHCARE, MANUFACTURING, AND RETAIL SECTORS

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IMPACT OF ARTIFICIAL INTELLIGENCE, MACHINE LEARNING, AND AUTOMATION IN OPERATIONS MANAGEMENT: AN ANALYSIS OF HEALTHCARE, MANUFACTURING, AND RETAIL SECTORS

by

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Abstract

In this thesis, we study the impacts of artificial intelligence (AI), machine learning (ML), and automation on operations management (OM). We specifically target the industries of healthcare, retail, and manufacturing in our analysis since each sector has distinct dynamics and concerns regarding the structural changes imposed by advancements in AI. We analyze 120 high-quality peer-reviewed journal articles to capture recent research trends in healthcare, retail, and manufacturing. Using respected business analytics reports, we compare academic efforts to industry initiatives. We find that growing interest in AI research in academia is consistent with growing research and development (R&D) investment and patent acquisition on AI technologies. We conclude that the industry that is likely to be impacted the most is manufacturing due to the large amounts of machinery and technology that are used in production, followed by retail and healthcare. We show that the impacts of AI, ML, and automation will change the landscape of OM and how businesses operate and make decisions in the near future. We provide some insights for students, academic institutions, and business organizations that operate in healthcare, manufacturing, and retail sectors. We recommend possible avenues of exploration to researchers interested in AI research.

Keywords: artificial intelligence (AI), machine learning (ML), automation, operations management (OM), healthcare, retail, manufacturing

Dedication

This thesis is dedicated to my beloved parents,

Christina Lea Kelley and John David Kelley;

to my grandmothers,

Ivanee Raybourn and Elizabeth “Bonnie” Morgan;

to my grandfathers,

Adren Raybourn, Gregory Morgan, Dennis Workman, William Blazo,

Samuel “Ed” Rogers, and Doug Kelley;

to my great grandparents,

Johnny Smith, Mildred Smith, Ralph Mullins, Mable Mullins, Phyllis Workman,

Raymond Workman, and Eloise Blazo;

to my uncles,

Gregory Morgan, Doug Kelley, and Tommy Kelley;

to my aunts,

Billie Jo Morgan, Barbara Smith Gill, Kattie Jones, and Martha Lalonde;

to my cousins,

Allye Kelley, Andrew Kelley, Amberlyn Kelley, Braxton Kelley, and

Devin Kenmar;

and our wonderful family cat,

Rex.

We have come so far together.

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Next, I would like to thank the faculty and staff of the University of Southern Mississippi. Even though I have not worked with all of you, I am appreciative of everything that you contribute to our academic institution. I am so glad that I chose to attend the University of Southern Mississippi for my undergraduate education, and I believe that this institution gave me a well-rounded education, beautiful friendships, and memories that will last a lifetime. I am especially grateful for the faculty/staff of the Economics Department, the School of Management, and the Honors College. Thank you for helping educate me not only about academics but also about life.

Lastly, I would like to thank my family and friends. I cannot entirely express the gratitude that I have for my loved ones in writing. My family's perseverance and

everlasting love have opened doors for me that I could not open myself. Without their efforts, I would not have the opportunities in life that I have. To my family, I am so appreciative that you are my rock, and that you always support me and push me to meet my aspirations. To my friends, I am grateful for the time that you invest in me and for bringing me positivity. Thank you for everything that you add to my life.

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List of Abbreviations

AI	Artificial Intelligence
GDP	Gross Domestic Product
HR	Human Resources
IPEDS	The Integrated Postsecondary Education Data System
ML	Machine Learning
OM	Operations Management
PwC	PricewaterhouseCoopers
R&D	Research and Development

Chapter 1: Introduction

Artificial intelligence (AI) is a field within STEM that focuses on creating human-like intelligence within machinery (i.e., creating computer programs that can operate and conduct tasks that normally human beings carry out). Machine learning (ML), a related term, is a subfield of AI that strictly focuses on using statistical learning. ML aims to develop algorithms that can learn patterns in data automatically while continuing to improve associations with previous experiences (Dogru & Keskin, 2020). AI and its ML applications manifest themselves in the form of automation. Automation consists of making apparatuses, processes, or systems that operate automatically without human control (Merriam-Webster, n.d.). AI is a growing, popular topic that already has impacts in many industries across the world, such as education, healthcare, manufacturing, construction, law enforcement, politics, automotive industries, retail, and finance. In 2018, 2.06 million people in the United States had careers related to the field of AI, which grows at a rate of 4.78% annually (Data USA, 2020). The average wage in the workforce for AI-related jobs in 2018 was $99,998, which presented a 1-year growth rate of 3.98% (Data USA, 2020). In all of these industries, there is a striking impact that is happening regarding the labor market, and there is controversy about connections between job displacement and the implementation of AI in workplaces. In 2016, 36 million jobs in the United States faced high levels of disruption due to automation (Hathaway et al., 2019).

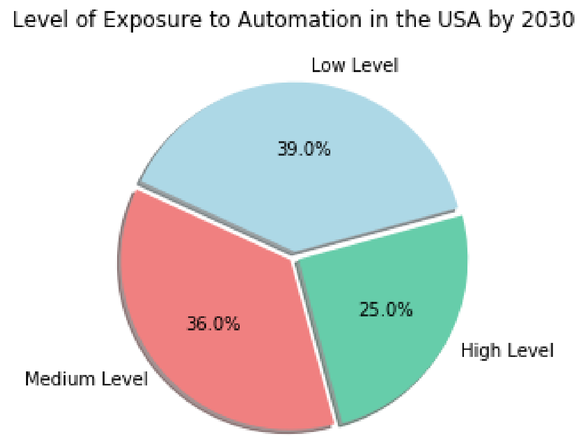

Figure 1. Level of Exposure to Automation in the USA by 2030
Source: Brookings Institution (Created using Python)

Figure 1 provides a projection on the automation level that jobs in the United States will be exposed to by 2030. The effect of automation, regardless of the level of exposure per job, could be potentially staggering. Overall, it is estimated that 145 million jobs would be impacted by automation by the year 2030, with 36 million of those jobs having high levels of exposure (Hathaway et al., 2019). To thrive in a society that is heavily exposed to AI, the workforce must adapt to automation that comes with advanced technologies. Although AI may cause job displacement, there is convincing evidence that implementing AI in the workplace may create positive job growth in the long run, especially in China and the United States. AI is predicted to benefit the global economy in the future through increased worker productivity, increased consumer demand, and increased GDP potential (PwC, 2017). Figure 2 presents a comparative impact of AI (reflected as a percent of GDP) on nations by 2030. It is predicted that most economies will benefit from AI by 2030, with the impact on China and North America being the most significant.

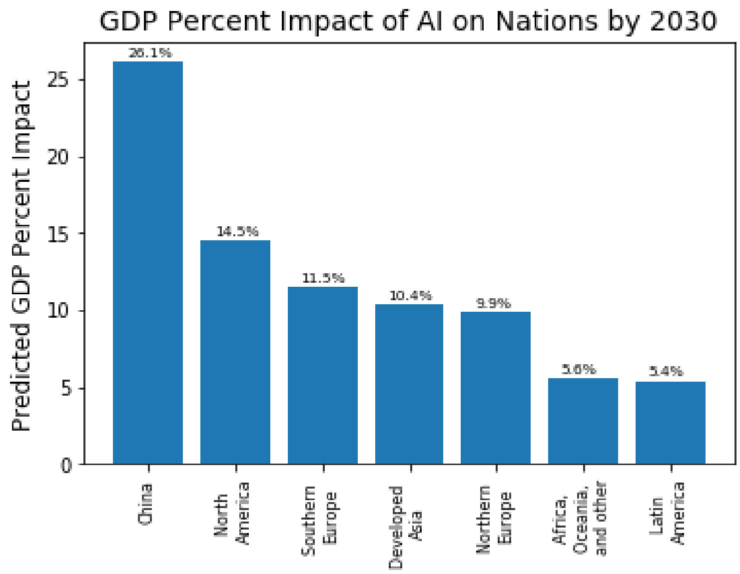

Figure 2. Impact of AI (Reflected as GDP) on Nations by 2030
Source: PwC (Created using Python)

The expansion of AI intimidates and scares many individuals due to concerns about the effects of technology on the wellbeing of humans. According to a global PwC survey, 37% of workers are concerned about being replaced by AI (PwC, 2018). Although AI does present work-related problems, there are also benefits that result from the use of AI in different fields. One of these fields is operations management (OM). OM is the management of systems and processes that create goods and/or services (Stevenson, 2020). OM focuses on increasing efficiency in production and service systems by applying scientific and mathematical methods (including AI and ML) to transform data into business insights to make better decisions. Automation and robotics are also at the center of OM. Therefore, advancements in AI, ML, and automation have impacts on OM research and practice. Increased human-computer interactions in the service sector and hybrid manufacturing systems that bring traditional labor and robotics together have attracted research and development (R&D) of AI and ML systems. Three areas that AI, ML, and automation have the highest value potential in are manufacturing, healthcare, and retail. Retailers spent $2 billion on AI in 2018, and that is projected to grow to $7.3 billion by 2022 (Maynard, 2019). The manufacturing sector spent $2.9 billion in 2018, and spending is predicted to reach $13.2 billion by 2025 (Omdia | Tractica, 2019). AI spending in healthcare totaled $2.1 billion in 2018, and it is predicted to increase to $36.1 billion in 2025 (MarketsandMarkets, 2018). There are a wide range of applications of AI and ML, as well as automation in manufacturing (i.e., internet of things, sensor technology, autonomous robots, 3D printing, cloud computing, augmented reality, digital twins, and blockchain), retail (i.e., smart inventory tracking systems, web-based shopping including e-groceries, smart autonomous vehicle delivery systems, and recommender engines supported by ML), and healthcare (i.e., diagnostic image analysis, appointment/surgery scheduling, and chronic disease management applications).

This thesis analyzes the impact of AI, ML, and automation on the industries of retail, manufacturing, and healthcare since collectively, these three areas have high-value potential and attract a significant level of R&D investment. Conducting a systematic review of high-quality peer-reviewed journal articles published between 2000 and 2020, and based on recent business analysis reports, we aim to draw attention to the growing need for research and practical applications in OM regarding AI, ML, and automation. By investigating recent AI teaching and research efforts by academia and the adoption of AI technologies by retail, manufacturing, and healthcare sectors, we aim to show how well research and practice are aligned. We discuss the important roles that colleges and research institutions can play in facilitating the adoption of AI technologies by these three sectors. Finally, we make managerial recommendations and provide insights into possible future research directions and application areas that these sectors need.

The remainder of the thesis is organized as follows. Section 2 provides a background on AI, ML, and automation, and their impacts on OM, students, education, and on the labor force, listing potential hazards of AI and discussing current AI integration issues in the industry. Section 3 explains our methodology in collecting our dataset, which is presented in the Appendix (please see Table 2). Section 4 analyzes the data using exploratory data analysis techniques. Section 5 discusses the results of the analysis to provide managerial insights. Section 6 provides an overview of the results of our research and makes practical recommendations from which healthcare, manufacturing, and retail sectors can benefit.

Chapter 2: Background

Growth of AI in Operations Management (OM)

The field of AI was launched in 1956 at a summer conference at Dartmouth College (Bringsjord & Govindarajulu, 2018). Although the field of AI is growing rapidly, it still is not growing at the pace that many beginning innovators of AI initially believed. Alan Turing, a father of the AI field who is famous for his *Mind* paper that questions the intellectual capabilities of machinery, predicted that AI would have intellectual capabilities indistinguishable from human capabilities (a.k.a. the Turing Test) by 2000 (Bringsjord & Govindarajulu, 2018). Despite considerable advancements in AI in the last two decades, we still could not reach that critical threshold.

OM came into being during the 19th century as a result of the industrial revolution (Sprague, 2007). Efficiency and accuracy are important performance metrics in OM. AI brings the opportunity to boost productivity via increased efficiency and improve the precision of operations via enhanced accuracy. AI can serve the needs of businesses by filling three primary needs: “automating business processes, gaining insight through data analysis, and engaging with customers and employees” (Davenport & Ronanki, 2018). It is important for firms to understand the different types of AI and what tasks each type can complete to benefit the organization (Davenport & Ronanki, 2018). For example, robotics and automation technologies can assist companies to automate tasks such as administrative and financial chores (Davenport & Ronanki, 2018).

AI can also be used to develop algorithms that can sort datasets and find patterns in data, which is crucial for business analytics (Davenport & Ronanki, 2018). ML can be used to provide chatbots or intelligent agents that interact with customers and employees. Cognitive technologies are being integrated into the labor force. However, these technologies are not currently completely replacing most human jobs (Davenport & Ronanki, 2018). The interaction between humans and AI in OM is vital to analyze to determine what type of relationship exists between the two variables. In today’s society, people and AI must coexist within the work environment, especially in businesses and organizations that want to remain competitive.

Effects of AI on Students and Education

Recent statistical data regarding degree completions in AI shows the growth of the field in education. In 2017, 212 4-year or above degrees in AI were awarded between 10 universities in the US, with Carnegie Mellon University, the University of Pennsylvania, and the University of Washington-Seattle Campus, awarding the most degrees to students (Data USA, 2020). Bachelor’s degrees in AI are relatively new, and

Carnegie Mellon University introduced the first bachelor's degree in AI in the fall of 2018 (Carnegie Mellon University, 2019).

Table 1 (please see appendix) shows the number of graduate degree completions in AI programs from 2012 to 2017. Figure 3, which provides a visual summary of Table 1, indicates a trend that private, not-for-profit institutions tend to have more AI degree completions than private for-profit and public institutions from 2012-2017.

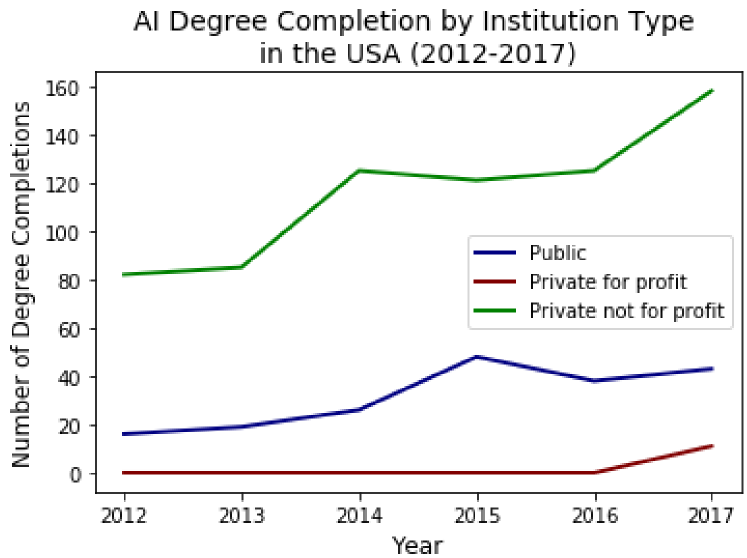

Figure 3. AI Degree Completion by Institution Type in the USA (2012-2017)
Source: IPEDS (Created using Python)

The newness of AI at the undergraduate level suggests that AI will continue to expand in education in the near future. Current and future students will progressively experience the effects of AI. AI-related technical skills will be essential for their success in the labor market. Although there are many stigmas and fears associated with the integration of AI into the daily lives of people, the growth patterns of AI in degree programs and the workplace suggest that individuals will adapt to the presence of AI, and AI will develop a sense of familiarity among large populations of people. The AI Market in the US education sector suggests that AI will continue to increase at a compound annual rate of 47.7% from the years of 2018 to 2022 (Wiley Education Services, 2020).

Since the primary goal of education is to prepare students for the job market, educators must adapt to incorporate AI in the classroom as AI has increasingly become an integral part of the work-life. Many schools, colleges, and universities are already using services driven by AI. Examples include Turnitin, a service that analyzes documents for plagiarism and offers feedback on components such as citations, and Thinkster, a math education platform that helps students visualize their learning patterns and provides coaching (Anders, 2019). It appears that this trend will go on with accelerated adoption of AI-enabled classroom technologies. Moreover, colleges and research institutions will continue to play a key role in providing human resources to business organizations and institutions with essential technical skills.

Impact of AI on the Labor Force

Workplaces are progressively integrating AI technologies to increase the productivity and efficiency of their operations. AI can serve many purposes, and employees can benefit from AI in many ways. Currently, data-oriented big companies, such as Amazon, Walmart, Google, Facebook, Apple, and YouTube, use big data, ML, deep learning, and other data analysis methods that are powered by AI. Although most AI technologies still cannot completely replace human intellectual capabilities, it does improve the timeliness of tasks and allows for certain feats to become attainable with less human labor than would be required without these improved technologies. However, the impacts of AI on the labor market can be difficult to access because AI is moving progressively, and some novel technologies have not been greatly studied (Maxim et al., 2019). Empirical evidence shows that there is a relationship between a worker's education level and the magnitude of worker's AI exposure. This exposure may be positive (i.e., reduction in repetitive tasks, decrease in daily working hours, and working online) or negative (i.e., job displacement). White-collar workers are likely to be exposed to developments in AI the most (Maxim et al., 2019). This is partly because businesses and organizations that employ white-collar workers are more likely to allocate financial resources toward the R&D of AI technologies (Maxim et al., 2019). Educational-attainment may also relate to the level of AI-exposure that workers might face in the near future. Current research shows that individuals with bachelor's degrees are at the greatest likelihood of AI-exposure, with other educational-attainment groups lagging, including individuals with graduate degrees (Maxim et al., 2019). Although it seems more likely that workers with graduate degrees or higher would have greater AI-exposure due to increased salaries and increased funding, these individuals seem to be less at risk to AI-exposure due to a higher level of job security than workers with bachelor's degrees or lower educational attainment levels (Maxim et al., 2019). Research also shows that individuals with some college education face a slightly lower risk of AI-exposure compared to individuals with high school education, and individuals with less than high school education face the lowest levels of likelihood to exposure (Maxim et al., 2019).

AI is capable of becoming a substitute for certain types of labor, but the increased efficiency that AI produces could potentially be greater than the transition costs (Autor et al., 2019). AI often creates temporary productivity gains for workers who are not directly competing with the newly implemented technologies (Autor et al., 2019). As AI continues to increase in popularity, it may lead to workplaces adapting and demanding that workers adopt new skills that AI cannot replicate, such as enhanced social skills for human-to-human interactions (Autor et al., 2019). This profound difference in demand for new skills can be referred to as “creative destruction,” where an old need becomes replaced and demand for a new need rises in the market (Autor et al., 2019).

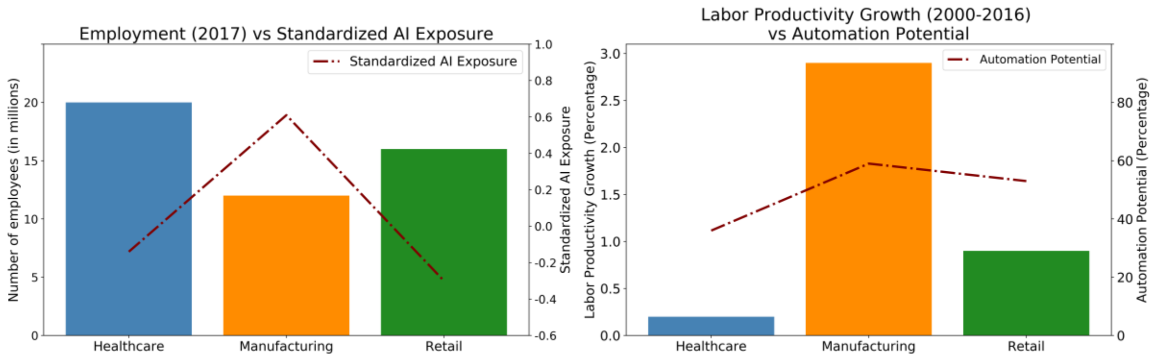

Figure 4. How sectors are affected by AI. Source: Brookings analysis of Webb (2019), OES, BLS, Census, EMSI, Moddys, and McKinsey data (Created using Python)

The combo chart with two y-axes to the left in Figure 4 (Employment (2017) vs Standardized AI Exposure) depicts the differences in total numbers of employees per OM industry, and the standardized AI exposure per area. Healthcare contains the greatest number of employees (20,208,050), retail contains the second greatest number of employees (16,009,150), and manufacturing contains the least number of employees (12,299,590). However, manufacturing has the largest level of standardized AI exposure (0.61), which could be due to the frequency that workers in manufacturing use advanced technologies and machinery to improve the overall productivity of tasks. The standardized AI exposures of healthcare (-0.14) and retail (-0.30) lag behind manufacturing potentially due to the service element of both industries that thrive on human labor and interactions. The combo chart with two y-axes to the right in Figure 4 (Labor Productivity Growth (2000-2016) vs. Automation Potential) points out that manufacturing has the largest labor productivity growth (2.9%), while healthcare (0.2%) and retail (0.9%) have lesser rates of growth. These values are consistent with the automation potential of the fields with manufacturing leading at a high rate (59%), retail trade following closely (53%), and healthcare lagging (36%). Manufacturing most likely displays high automation potential compared to other fields due to many different forms of machinery and other technologies that are implemented in the workplace for the production of goods. Retail also has high automation potential, most likely due to technologies being used in areas of retail, including inventory management, distribution of goods and services, and customer services. Healthcare shows lower levels of AI adoption with much-restricted applications such as image analysis, patient demand prediction, and appointment scheduling. In this sense, data seems to suggest that industries with high-service components (i.e. healthcare) are likely to adopt AI technologies at a slower pace than industries with lower service components (i.e. manufacturing and retail).

Risks of AI

Despite its immense benefits, AI can also pose threats to individuals (i.e., consumers and labor) and organizations (firms, government institutions, supply chains, etc.) (Cheatham et al., 2019). The risks of AI are vast. Individuals face safety issues (i.e., digital safety and privacy), ethical risks, negative effects on reputation, financial risks, threats to equity, and unfair treatment (Cheatham et al., 2019). Organizations face risks such as hindered performance (financially and non-financially), legal issues, compliance issues, negative effects on reputation, and threats to integrity (Cheatham et al., 2019). Different areas of society that can be impacted by AI include national security, the economy, politics, and infrastructure (Cheatham et al., 2019).

There have been many instances of risky situations presented from the use of AI, ML, and automation. Individual physical safety has been impacted through various events that are often due to the experimental nature of AI and the newness of its applications. For example, a pedestrian named Elaine Herzberg was killed in Tempe, Arizona by a self-driving Uber vehicle (Volvo XC90) carrying a human safety driver in March of 2018 (Wakabayashi, 2018). In 2018, IBM’s Watson, AI developed to supply answers in human language to questions, was faulted with giving incorrect recommendations that could have negatively affected the safety of cancer patients (Morris, 2018). Privacy and digital safety concerns also affect individuals. In February of 2020, Clearview AI, a company that has a database of over 3 million facial recognition images from Internet sources such as Facebook and Twitter, had its data breached, which resulted in involvement from law enforcement agencies (O'Flaherty, 2020). This breach affects individual privacy and causes concerns regarding the security and ethics of facial recognition databases for consumers and organizations. Consumers may worry about their reputation being affected by AI when information that is gathered could potentially be distributed to individuals that consumers do not want to have the data. Clearview AI’s database of consumer images also poses fair treatment concerns, since most of the individuals whose photos were in the database most likely were not aware that their photos were being collected by Clearview AI. Implementation of AI can also lead to financial health issues such as inaccurate predictions in the stock market. Different factors, such as statistical noise and constantly changing data, can make algorithm development difficult for developers seeking to improve the ability of ML to make accurate predictions in the stock market (Dewey, 2019). Inaccurate predictions can harm consumer financial health, as well as organizational financial health and performance, so algorithm-developers must take these risks into careful consideration.

Integration of AI and Industries

Although there are risks associated with implementing AI in the workplace, AI can be successfully used in labor environments in ways that can improve the efforts of employees and organizations. This subsection will discuss present applications and potential future introductions of AI to various fields of OM, including healthcare, manufacturing, and retail.

Healthcare

There are a variety of tasks in the healthcare industry that can be improved by implementing AI, such as precise diagnostic tools that can provide adequate recommendations for patients (Davenport & Kalakota, 2019). Other examples include using AI to gauge the engagement and behaviors of patients and for administrative work, such as billing, coding, and other business applications (Davenport & Kalakota, 2019). Robotic surgery has been increasing in popularity since its introduction in 2001 due to the assistance that it provides to surgeons, patients, and other healthcare providers (Palep, 2009). Robotic surgery can minimize the risk of error, lessen invasive surgeries, provide better visualization, provide motion scaling, and increase the convenience of surgeries to all parties involved in the process when properly executed (Palep, 2009). The introduction of surgical robots, such as Georgia Institute of Technology's "Cody," can provide bed baths to medical patients. This displays that automation and AI technologies will potentially continue to grow in the healthcare industry, which could cause the displacement of previously essential workers, such as nurses (Locsin & Pepito, 2019). However, robots and AI will most likely be used alongside human workers, since there are human characteristics such as emotions and compassion, that cannot be mimicked easily by technology (Locsin & Pepito, 2019).

Manufacturing

Manufacturing is heavily reliant on machinery and technology to allow for efficient and safe production levels. In the manufacturing industry, AI is more likely to have a presence in administration and supply chain areas when compared to being used specifically for production purposes (Charalambous et al., 2019). Cement plants were an early adopter of automation in manufacturing, and these plants often take advantage of digital controls, sensors, and signals (Charalambous et al., 2019). AI can also be useful for engineers and designers in manufacturing: one application of this is "generative design," where a user inputs a design idea into a software program and the program generates ways to reach the solution along with potential final product concepts (Forbes Insights & Intel AI, 2018). "Generative design" can provide solutions in record-timing when compared to human labor and drastically reduces the amount of time that designers and engineers use to develop ideas for research concepts (Forbes Insights & Intel AI, 2018). AI can also be used for making predictions regarding interactions in units of production, studying relationships between how different components of the manufacturing process work together, and allowing automated requests to provide updates on necessary parts, tools, maintenance, and labor for manufacturing machinery; these different forms of tasks that AI can complete provide increased efficiency for employees, which benefits the manufacturing process as a whole (Intel Corporation, n.d.).

Retail

Currently, 40% of organizations claim that they are participating in using intelligent automation (IBM Institute for Business Value and National Retail Federation, 2019). In retail, intelligent automation can be used for various purposes: some of these purposes include supply chain planning, customer intelligence, and automation capabilities (IBM Institute for Business Value and National Retail Federation, 2019). Retail often attracts consumers by defining target markets and allocating research and promotions towards the intended market or markets. A 2020 study shows that there are 4 main types of consumers that retailers can choose to target: these categories consist of value-driven (41%), purpose-driven (40%), brand-driven (13%), and product-driven (6%) consumers (IBM Institute for Business Value and National Retail Federation, 2020). AI can assist organizations in targeting certain markets by providing customer intelligence and demand forecasting (IBM Institute for Business Value and National Retail Federation, 2020). AI can improve supply chain planning via big data analysis, allowing for easier calculations of tradeoffs and developments of balanced plans (IBM Institute for Business Value and National Retail Federation, 2019).

Chapter 3: Methodology

This study analyzes a total of 120 peer-reviewed journal articles to investigate the impact of AI, ML, and automation on healthcare, manufacturing, and retail sectors in OM. We compiled these 120 articles using online academic databases, including Google Scholar, Springer, ScienceDirect, EBSCOhost, and Elsevier. A paper is selected only if 1) it show relations to the fields of manufacturing, healthcare, and retail, 2) it is related to AI, ML, and/or automation, 3) it is published sometime between 2000 and 2020, and 4) it is published in a peer-reviewed academic journal with an impact factor of at least 1.0. Papers that did not meet these criteria were eliminated from the study. After an intensive search of the abovementioned databases, we categorized the articles according to 1) number of authors, 2) year published, 3) academic journal, 4) number of citations, 5) field of OM (i.e., healthcare, manufacturing, and retail), 6) methodology, 7) software, 8) contribution, 9) contribution type, and 10) source of access. Contribution type was divided into four different categories, which consisted of review, methodological, theoretical, and application papers. It is important to note that papers with contributions in more than one area are classified according to their major contribution. For instance, if a paper has both methodological and theoretical contributions and its methodological contribution is more significant than its theoretical contribution, it is classified as a methodological paper. We identified major contributions of such papers by searching for specific contribution statements of the authors in the manuscript. If there is no such statement that clearly ranks the order of contributions of the paper, we used our subjective judgment on the matter.

Chapter 4: Analysis

In this section, we provide an extensive analysis of the dataset (please see Table 2 in the Appendix), using exploratory data analysis tools. Note that the x-axis of some charts in this section uses quarters each indicating a period of 5 years (Q1: 200-2004, Q2:2005-2009, Q3:2010-2014, and Q4:2015-2020), except Q4, which covers slightly more than 5 years, as we stopped data collection by early April 2020. Clustering academic papers in 5 year-periods enables us to reduce some of the variation in relatively long manuscript preparation, submission, revision, and publication processes (i.e., there is usually a couple of years between the actual start time of these scientific studies and the time that they are finally published).

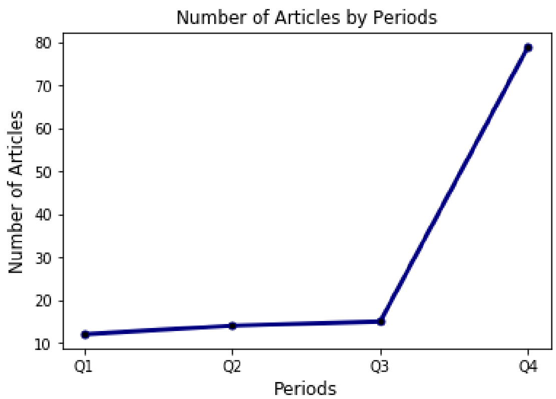

Figure 5. Number of AI articles published (2000-2020)
Q1:2000-2004, Q2:2005-2009, Q3:2010-2014, Q4:2015-2020
(Created using Python)

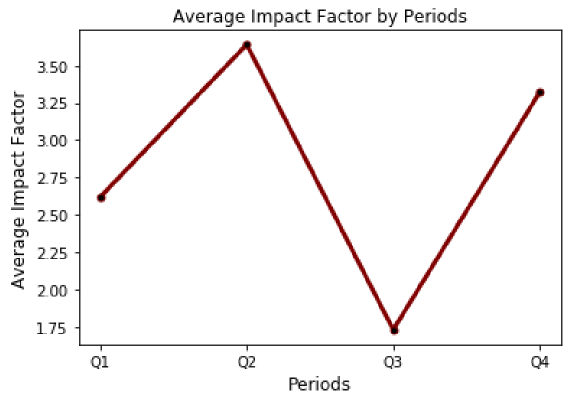

Figure 6. Average impact factor of AI articles (2000-2020)
Q1:2000-2004, Q2:2005-2009, Q3:2010-2014, Q4:2015-2020
(Created using Python)

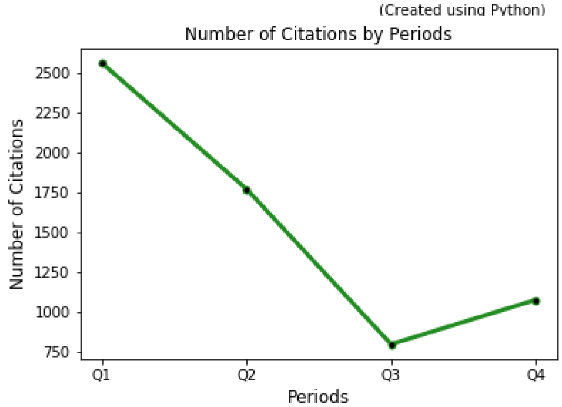

Figure 7. Total number of citations of AI articles (2000-2020)
Q1:2000-2004, Q2:2005-2009, Q3:2010-2014, Q4:2015-2020
(Created using Python)

Using line charts, Figures 5, 6, and 7 display significant trends in the last two decades (4 Quarters) regarding number of articles published, average impact factor of the academic journals that these papers were published, number of citations that published articles have received, respectively.

Figure 5 compares the number of articles published per period. Most of the 120 articles collected were published during Q4, which consisted of 79 articles (66%). The second period that has the highest number of articles published, Q3, is drastically less at 15 articles (13%). This information is predictable, since AI, ML, and automation are growing topics that have gained popularity in recent years, and more information is continuously being collected about these terms and their effects on different fields of study.

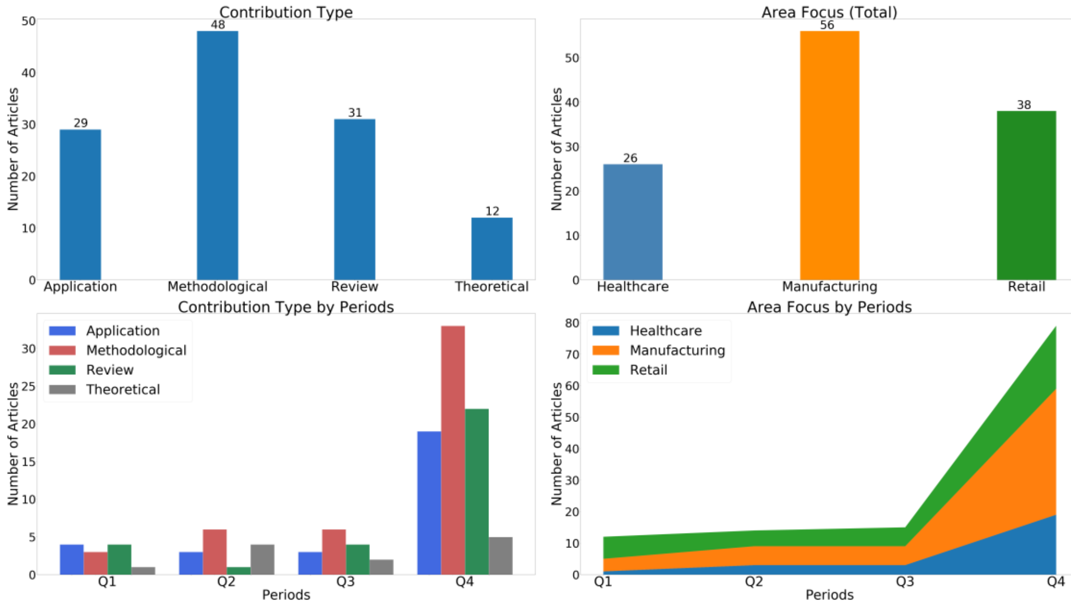

Figure 8. Contribution type and area focus of AI articles (2000-2020), Q1:2000-2004, Q2:2005-2009, Q3:2010-2014, Q4:2015-2020 (Created using Python)

Figure 6 depicts the change in the average impact factor of journals that the articles under investigation were published. The average impact factor fluctuates between 3.64 (Q2) and 1.73 in Q3, with an overall average impact factor of 2.83. However, note that we excluded articles that are published in academic journals with an impact factor of less than 1 to ensure article quality.

Figure 7 shows a steady decrease in the number of citations from Q1 to Q3, followed by a slight increase from Q3 to Q4. Q1 has received the highest number of citations. However, note that a single article published by Choi et al. (2001) in Q2 has received 1501 citations as of April 2020. Furthermore, the number of citations increases over the years, so it is quite normal to have a gradual decrease in the number of citations. An increase from Q3 to Q4 can be explained by increased recent attention to AI research, which is also supported by Figure 5 (i.e., a spike in the number of journal articles in Q4).

Figure 8 provides comparative summary statistics regarding contribution type and area focus of the 120 academic articles in our data set. The bar chart on the top left (Contribution Type) of Figure 8 compares these articles in terms of types of their contributions to the literature. The majority of papers provide either novel methodologies (40.0%) or create applications (24.2%) that use AI to solve practical business problems in healthcare, manufacturing, and retail sectors. Some papers provide relevant literature, make projections, and/or state expert opinions (these papers are classified as review papers, and they roughly account for 25.8%), whereas a relatively small number of papers make theoretical contributions (10.0%). The grouped bar chart on the bottom left (Contribution Type by Periods) of Figure 8, classifies these contributions by quarters. The chart reveals that contributions in all categories have significantly increased in Q4 (since 2015) as compared to previous quarters. The bar chart on the top right (Area Focus (Total) of Figure 8, compares these articles according to the related field that they contribute to. Not surprisingly, manufacturing takes the lead (46.7%), followed by retail (31.7%) and healthcare (21.6%) sectors, respectively. This is because of the extensive automation and employment of robotics and sensor technologies in manufacturing that comes with Industry 4.0 (Pfeiffer, 2016). Healthcare lags behind other sectors mostly due to sector-specific concerns about patient privacy, lack of trust towards AI in healthcare, and accountability issues (i.e., how to ensure accountability if a patient's health is compromised because of a decision made by an automated system? (Shah & Chircu, 2018). Finally, the area chart on the bottom right (Area Focus by Periods) of Figure 8 shows how OM researchers' interest in healthcare, manufacturing, and retail changes over time. As can be seen from the Figure, research interest in all categories has increased: manufacturing attracting the most significant interest, followed by retail and healthcare sectors. This finding is consistent with the R&D investments, as well as the number of patented ideas in each sector (please see Section 5 for a detailed discussion on industry vs academia).

Chapter 5: Discussion

In this section, we compare research efforts in academia with initiatives of industry towards the allocation of R&D investments and patenting efforts on AI technologies. Then we discuss the limitations of our research and make various recommendations for students, academic institutions and their researchers, and business organizations that operate in healthcare, manufacturing, and retail sectors. We finish this chapter with a discussion of future research directions.

Academia vs. Industry

Academia is a community that focuses on teaching, research, and scholarship. It is a network of students, faculty, staff, colleges, and research institutions. The most important function of academia is to produce new knowledge and skill sets that industry needs. Industry consists of business organizations that operate in supply chains and people (employees, and managers, etc.) who work for these organizations. Industry provides goods and services by employing human resources (HR) with required technical skills and expertise and by combining HR with software (computer programs), hardware (machines, robots, and computers), material, and energy. Therefore, the success of our economic system depends on the critical alignment of academia and industry. In other words, industry cannot fully embrace AI, ML, and automation without support from academia (Allen, 2019).

Then, how can academia support industry in terms of the healthy adoption of AI technologies? Academia can provide support in two vital areas: 1) teaching, and 2) research. First, by teaching, we mean more than instructing students. Teaching means creating a learning environment in which students naturally embrace AI to achieve the objectives of their program study. Allen (2019) states that AI could potentially increase student involvement and interest by providing them with the ability to further explore pathways of learning. Wiley Education Services (2020) estimates that AI usage in the US education sector is likely to increase at a compound annual rate of 47.7% until 2022. Student retention could become more proactive, and students' difficulties could be noticed through software recognition (Wiley Education Services, 2020). Some colleges, such as Staffordshire University and the Georgia Institute of Technology, are using chatbots to provide students with answers to commonly asked questions (Rouhiainen, 2019). Virtual assistants, such as "intelligent mood tracking" assistants like Woebot, are being used to lessen the strain on university health systems and provide students with emotional support and information (Rouhiainen, 2019). Second, academia can also support industry via research. By research, we also do not simply mean journal articles that are produced by a collaboration of faculty and graduate students. We consider research as a procedure blended with the organizational culture, in which all levels of students (both graduate and undergraduate) learn research naturally working with a faculty mentor. Therefore, it is important for academic institutions to make investments in skills and technology to create such a research environment and make sure that the educational curriculum answers the needs of industry. Historically, our academic curriculums haven been designed considering area specialization. Not surprisingly, AI and ML have long been considered as a major field under computer sciences and statistics. However, AI, ML, robotics, and automation have broader social, ethical, and psychological implications on our society that requires an interdisciplinary approach. Academia plays a key role in bringing this interdisciplinary research perspective to the field. Industry urgently needs human resources with social and technical skills that can work in analytical teams composed of experts from distinct disciplines to help managers make informed decisions through data-driven research. Finally, besides teaching and research, academia can also benefit from AI technologies to implement some administrative tasks. For instance, Wiley Education Services (2020) states that college recruiting practices are likely to be impacted by AI in the near future. Algorithms will help recruiters by suggesting which students are likely to enroll and which enrolled students might become engaged alumni (Wiley Education Services, 2020). Administrative activities for the admissions process could become automated, which would benefit processes such as student housing applications, course selection, and student visas (Wiley Education Services, 2020). Although AI, ML, and automation can be useful in academia, skills such as cognitive, emotional intelligence, and creative skills are difficult to replace with technology and will most likely provide needs in academia for human labor, such as instructors, professors, and administrative roles.

How Companies Benefit from AI

Industry is currently experiencing considerable tension due to the structural changes imposed by AI, ML, and automation. Each sector has different dynamics and concerns regarding embracing AI in its operations. Constant innovations in AI and the recentness of the technologies make workplace impact difficult to accurately assess.

Maxim et al. (2019) predict that all occupational groups will be affected by AI to some extent. There are two metrics that show the level of AI adoption in industry: 1) R&D investment on pilot programs, and 2) number of patents on AI technologies. Companies invested \$26B-\$39B on AI in 2016 alone (Allas, et al., 2017). This R&D investment corresponds to more than three times as much as in 2013 (Bughin, et al., 2017). Furthermore, a recent McKinsey report estimates the value potential of AI as \$3.5 to \$5.8 trillion, of which \$0.2-\$0.3 billion in healthcare, \$0.4-\$0.8 billion in retail, and \$0.7-\$1.0 billion in manufacturing sectors (Chui, et al., 2018).

Regarding the trends in patent acquisition, a recent report by World Intellectual Property Organization notes that AI patent families have increased by an average of 28% and scientific publications by 5.6% from 2012 to 2017 (WIPO, 2019). ML was invested in the most (grew by an average of 26% annually between 2011 and 2016 (WIPO, 2019)), with computer vision coming in second for the greatest amount of investments (Allas, et al., 2017). Natural language, autonomous vehicles, smart robotics, and virtual agents were also common areas of AI for companies to invest in (Allas, et al., 2017). Geographically, areas with heavy involvement in manufacturing will face greater disruption and exposure rates from AI, ML, and automation (Maxim et al., 2019).

Business-finance-tech industries will face high levels of exposure, along with natural resource and production industries (Maxim et al., 2019). Industry will be heavily impacted by AI, and businesses must adapt to growing trends in AI, ML, and automation if they want to thrive in the future market. These developments in industry (growing R&D investment and patents on AI, ML, and automation) are indications of significant structural changes in our economy and the resulting tension on the labor market via the displacement effect (i.e., AI replacing labor). To mitigate the negative impact of displacement (Acemoglu & Restrepo, 2018) propose creating a countervailing force via the reinstatement effect (i.e., creation of new tasks for labor). For instance, (Daugherty & Wilson, 2017) identify three new tasks for AI companies: 1) trainers who train the AI algorithms, 2) explainers who explain the AI decisions to non-technical professionals, and 3) sustainers who monitor performance and sustainability of AI technologies. Similarly, (Jha & Topol, 2016) suggest a new job description named as information specialist, which combines radiology and pathology as one specialty. They argue that the primary responsibility of an information specialist should be to oversee and analyze the outputs of AI technologies.

The creation of such new tasks for humans is vital to reduce the negative impacts of unemployment; therefore, academic institutions need to start training required human resources adapting their curriculum, education, and research. Additionally, a growing number of academic journal articles published in OM, particularly in recent years, is consistent with growing R&D investment and patent acquisition on AI and related technologies. This result provides some support that academia and industry are somewhat aligned. However, there is a need for a study to show the impacts of these journal articles on the industry.

Limitations

One limitation of our research is the number of journal articles used in our study. We analyze a set of 120 academic articles. This number could be expanded by removing some of the constraints that we have imposed (please see Section 2 Methodology) to provide a more comprehensive picture of recent trends in AI research in OM. The time-period that we analyzed also limits the results of our research. Extending the span of the research to pre-2000 could lead to a better understanding of the evolution of AI research. Finally, for papers that do not contain a specific statement of the type of contribution, we have used our subjective judgment, which presents room for error in categorical classifications.

Managerial Recommendations

Our recommendations target three main groups: 1) students entering the job market, 2) colleges and research institutions, and 3) business organizations that operate in healthcare, manufacturing, and retail sectors.

College students entering the job market should be aware that most occupations and industries will face some exposure to AI, and a background in STEM can be beneficial for this sort of market. Human characteristics that machines cannot mimic will most likely become increasingly valuable in the market. It will become important for workers to embrace the additions of AI, ML, and automation in the workplace, and workers should remember that they will be more likely to find success if they embrace upcoming technologies instead of competing with them.

Colleges and research institutions should begin to adopt AI, ML, and automation technologies to become competitive and to meet the needs of industry. Colleges and research institutions that do not adopt technological advancements could fall behind competitors and suffer from reduced admissions, higher costs, lower profit, and other devastating factors. Colleges and research institutions should remember that AI, ML, and automation should not eliminate the human aspect of education. Instead, these technologies should take the burden of repetitive tasks on human resources enabling them to focus their limited attention on higher value-added areas.

Business organizations that operate in healthcare, manufacturing, and retail sectors should also adopt AI, ML, and automation to become competitive among other business organizations. Business organizations should use ethics when determining uses for these advanced technologies and implement them in a way that enhances human labor productivity in workplaces. Business organizations should be cautious of what advanced technologies they adopt and should make sure that the AI, ML, or automation is developed in a way that is efficient, productive, accurate, and safe for use by employees.

Future Research Directions

Investigating the impact of published academic articles on industry would be an interesting research direction. Ideally, a significant portion of these academic studies are expected to be used by industries; however, this may not be the case for various reasons. If so, what can be done to achieve a better strategic alignment of research and practice?

Since AI, ML, robotics, and automation are all application-based, we believe that there is a need for more academic studies that focus on practical uses of AI. Moreover, AI is an interdisciplinary field, but only a small portion of these studies can be classified as interdisciplinary. Even though there is a growing interest in AI research, it appears that the majority of researchers prefer to collaborate with colleagues working in the same field. We believe that interdisciplinary studies provide significant value to the literature. Therefore, we invite the academic community to produce more interdisciplinary AI studies.

Another possible avenue of exploration is what new tasks can industry create to maintain labor. This research question is particularly important because the fate of our economic system depends on it. With the emergence of automated technologies, new roles need to be defined for human labor to decrease unemployment and achieve a balanced and sustainable economic growth.

Researchers may also find it interesting to explore methodologies to improve accountability and ensure trust in automated technologies. Finally, methods to eliminate algorithmic biases of AI technologies and ensuring information security of automated decision systems are other areas that need to be studied.

Chapter 6: Conclusion

This thesis investigates the impacts of AI, ML, and automation on three main fields of OM: namely, 1) healthcare, 2) manufacturing, and 3) retail. As these sectors continue to face changing landscapes due to the implementation of AI, ML, and automation, we analyze 120 high-quality peer-reviewed journal articles to capture recent research trends in these areas. Using respected business analytics reports, we compare academic efforts with industry initiatives. We find that growing interest in AI research in academia is consistent with growing R&D investment and patent acquisition on AI technologies. We conclude that the industry that is likely to be impacted the most is manufacturing due to the large amounts of machinery and technology that are used in production, followed by retail and healthcare, respectively.

Analysis of the results of this study leads to key managerial insights. First, we believe that better aligning research efforts in academia and industry would facilitate the adoption of AI technologies. Second, industry should create new tasks for human resources to mitigate the negative impact of AI’s displacement effect. Finally, academic institutions should adjust their curriculum, education, and research in line with structural changes imposed by AI, ML, and automation to create an interdisciplinary learning environment for students, who will be entering into a workforce that will increasingly be exposed to automated systems.

We also make recommendations for future research directions. We suggest researchers focus on practical uses of AI by conducting interdisciplinary studies to bring different perspectives of other disciplines to minimize potential socio-economic, physical, psychological, racial, and ethical risks, harms, and biases that automated technologies can create. Other possible avenues of exploration are: 1) what new tasks can industry create to maintain labor, 2) what is the impact of academic research on AI on industrial practice, and 3) how can industry ensure information security and increase accountability of automated systems to gain consumer trust.

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Appendix

Table 1. AI Degree Completions by Academic Institution Name and Type

Year	Institution Name	Institution Type	Number of Completions
2012	Carnegie Mellon University	Private not-for-profit	53
2012	University of Georgia	Public	5
2012	South Dakota School of Mines and Technology	Public	1
2012	University of Southern California	Private not-for-profit	10
2012	University of Pennsylvania	Private not-for-profit	19
2012	University of Pittsburgh-Pittsburgh Campus	Public	6
2012	Georgia Institute of Technology-Main	Public	2
2012	Eastern Michigan University	Public	2
2013	South Dakota School of Mines and Technology	Public	3
2013	University of Southern California	Private not-for-profit	3
2013	University of Pittsburgh-Pittsburgh Campus	Public	4
2013	University of Georgia	Public	9
2013	University of Pennsylvania	Private not-for-profit	34
2013	Georgia Institute of Technology-Main	Public	3
2013	Carnegie Mellon University	Private not-for-profit	48
2014	Georgia Institute of Technology-Main	Public	8
2014	Carnegie Mellon University	Private not-for-profit	85
2014	University of Pittsburgh-Pittsburgh Campus	Public	9
2014	University of Pennsylvania	Private not-for-profit	34
2014	South Dakota School of Mines and Technology	Public	5
2014	University of Georgia	Public	4
2014	University of Southern California	Private not-for-profit	6
2015	Carnegie Mellon University	Private not-for-profit	64
2015	University of Pittsburgh-Pittsburgh Campus	Public	4
2015	Syracuse University	Private not-for-profit	1
2015	Georgia Institute of Technology-Main	Public	7
2015	University of Pennsylvania	Private not-for-profit	44
2015	Eastern Michigan University	Public	1
2015	University of Southern California	Private not-for-profit	12
2015	University of Washington-Seattle Campus	Public	27
2015	University of Georgia	Public	9
2016	University of Washington-Seattle Campus	Public	19
2016	Georgia Institute of Technology-Main	Public	8
2016	University of Pittsburgh-Pittsburgh Campus	Public	8
2016	Syracuse University	Private not-for-profit	2
2016	Carnegie Mellon University	Private not-for-profit	72
2016	University of Pennsylvania	Private not-for-profit	40

2016	University of Georgia	Public	3
2016	University of Southern California	Private not-for-profit	11
2017	University of Georgia	Public	5
2017	Indiana University-Bloomington	Public	3
2017	University of Pittsburgh-Pittsburgh Campus	Public	6
2017	University of Washington-Seattle Campus	Public	28
2017	Georgia Institute of Technology-Main	Public	1
2017	University of Southern California	Private not-for-profit	9
2017	Brandeis University	Private not-for-profit	16
2017	Carnegie Mellon University	Private not-for-profit	83
2017	University of Pennsylvania	Private not-for-profit	50
2017	Full Sail University	Private for-profit	11

Table 1. AI Degree Completions by Academic Institution Name and Type
Source: IPEDS (Created using Excel)

Table 2. Academic Publications by Contribution, Year, Journal, Impact Factor, Cited, Field and Contribution Type.

Contribution	Year	Journal	Impact Factor	Cited	Field	Contribution Type
Drew et al. (2004)	2004	Ann. R. Coll. Surg. Engl.	1.268	229	Healthcare	Review
Dilsizian and Siegel (2013)	2013	Curr. Cardiol. Rep.	2.395	126	Healthcare	Review
Lee et al. (2013)	2013	Am. J. Roentgenol.	3.161	141	Healthcare	Methodological
Aydar et al. (2017)	2017	J. Am. Coll. Cardiol.	16.834	167	Healthcare	Application
Li (2006)	2006	J. Assoc. Inf. Syst.	3.103	4	Retail	Methodological
Gams and Pivk (2000)	2000	Electrotech. Rev	1.269	25	Retail	Review
Prasad (2003)	2003	J. Electron. Commer. Res.	1.667	41	Retail	Review
Chai et al. (2002)	2002	AI Mag.	1.92	70	Retail	Application
Shimazu (2002)	2002	Artif. Intell. Rev.	5.095	137	Retail	Application
McSherry (2001)	2001	Appl. Intell.	2.882	81	Retail	Application
Baykasoğlu et al. (2004)	2004	J. Intell. Manuf.	3.535	89	Manufacturing	Methodological
Holden and Serearuno (2005)	2005	J. Intell. Manuf.	3.535	11	Manufacturing	Application
Ji et al. (2016)	2016	J. Intell. Manuf.	3.535	14	Manufacturing	Application
Pesin et al. (2000)	2000	J. Intell. Manuf.	3.535	39	Manufacturing	Application
Garg et al. (2015)	2015	Int. J. Adv. Manuf. Tech.	2.601	24	Manufacturing	Application
Maris et al. (2016)	2016	Qual. Quant.	1.072	12	Manufacturing	Methodological
Agostinho et al. (2008)	2008	J. Intell. Manuf.	3.535	78	Manufacturing	Methodological
Dhada et al. (2019)	2019	J. Intell. Manuf.	3.535	0	Manufacturing	Methodological
Pallas et al. (2019)	2019	J. Intell. Manuf.	3.535	0	Manufacturing	Methodological
Cao et al. (2018)	2018	Chin. J. Mech. Eng.	1.413	1	Manufacturing	Methodological
Alam et al. (2019)	2019	Appl. Intell.	2.882	0	Manufacturing	Methodological
Hanson et al. (2019)	2019	Int. J. Intell. Rob. Appl.	2.02	0	Manufacturing	Methodological
Bäck et al. (2019)	2019	Appl. Intell.	2.882	0	Manufacturing	Methodological
Dai et al. (2019)	2019	Chin. J. Mech. Eng.	1.413	0	Manufacturing	Methodological
Chen et al. (2019)	2019	Int. J. Intell. Rob. Appl.	2.02	0	Manufacturing	Methodological
Grubinger et al. (2019)	2019	Appl. Intell.	2.882	0	Manufacturing	Methodological
Hagebring and Lennartson (2019)	2019	Discrete Event Dyn. Syst.	1.527	0	Manufacturing	Methodological
Cui et al. (2019)	2019	Int. J. Intell. Rob. Appl.	2.02	0	Healthcare	Methodological
Julvez and Oliver (2019)	2019	Discrete Event Dyn. Syst.	1.527	0	Manufacturing	Methodological
Ding et al. (2019)	2019	Chin. J. Mech. Eng.	1.413	0	Healthcare	Review
Geo et al. (2019)	2019	Chin. J. Mech. Eng.	1.413	0	Manufacturing	Methodological
Huang et al. (2019)	2019	Chin. J. Mech. Eng.	1.413	0	Manufacturing	Methodological
Aqel et al. (2019)	2019	Chin. J. Mech. Eng.	1.413	0	Manufacturing	Methodological
Mironczuk and Protasiewicz (2019)	2019	Appl. Intell.	2.882	0	Manufacturing	Methodological
Bressgott et al. (2019)	2019	J. Acad. Marketing Sci.	5.888	3	Retail	Methodological

Kohavi et al. (2004)	2004	Mach. Learn.	2.809	161	Retail	Review
Kaisers et al. (2019)	2019	Comput. Econ.	1.185	0	Retail	Theoretical
Ferrario et al. (2019)	2019	Philos. Technol.	1.32	0	Retail	Application
Jo et al. (2019)	2019	Hum.-Cent. Comput. Info.	3.212	3	Retail	Application
Grewal et al. (2019)	2019	J. Acad. Marketing Sci.	5.888	2	Retail	Theoretical
Győrffy et al. (2018)	2018	BMC Health Serv. Res.	1.932	30	Healthcare	Review
Cheng et al. (2018)	2018	Automot. Innovation	1.523	14	Retail	Review
Grüning (2014)	2014	Bus. Res	4.028	34	Retail	Theoretical
Feldman and Friedman (2010)	2010	Comput. Econ.	1.185	6	Retail	Application
Boulos et al. (2019)	2019	Int. J. Health Geographics	2.862	8	Healthcare	Application
Clark and Lomax (2018)	2018	J. Big Data	1.124	0	Retail	Methodological
Collins et al. (2013)	2013	Mach. Learn.	2.809	68	Retail	Theoretical
Jonker et al. (2007)	2007	Auton. Agents Multi-Agent Syst,	1.606	170	Retail	Theoretical
Kaczmarek et al. (2019)	2019	Eur. Food Res. Technol.	2.056	0	Retail	Methodological
Elmaghraby et al. (2006)	2006	Clin. Proteomics	3.476	10	Healthcare	Review
Huang et al. (2015)	2015	Hum.-Cent. Comput. Info.	3.212	20	Retail	Methodological
Chung et al. (2004)	2004	Mach. Learn.	2.809	65	Retail	Methodological
Chatterjee and deLeon (2015)	2015	J. Acad. Marketing Sci.	5.888	10	Retail	Methodological
Liew et al. (2017)	2017	Hum.-Cent. Comput. Info.	3.212	11	Retail	Theoretical
Sun and Zhao (2017)	2017	Fashion Text.	1.313	18	Retail	Methodological
Burstein et al. (2007)	2007	World Wide Web	1.77	628	Retail	Methodological
Hulland et al. (2019)	2019	J. Acad. Marketing Sci.	5.888	2	Retail	Theoretical
Wang (2013)	2013	Adv. Manuf.	1.603	53	Manufacturing	Methodological
Church et al. (2019)	2019	BMC Med.	8.285	20	Healthcare	Application
Kasabov and Warlow (2009)	2009	J. Direct Data Digital Marketing Pract.	1.133	8	Retail	Theoretical
Mayer et al. (2013)	2013	Bus. Res	4.028	11	Retail	Methodological
Yada (2011)	2011	J. Intell. Inf. Syst.	1.589	62	Retail	Application
Dubey et al. (2016)	2016	Global J. Flexible Syst. Manage.	3.32	28	Manufacturing	Review
Bachmann et al. (2019)	2019	Eur. J. Clin. Microbiol. Infect. Dis.	2.591	4	Healthcare	Methodological
Abeywickrama et al. (2019)	2019	Fungal Divers.	15.596	15	Retail	Application
Bansal et al. (2019)	2019	J. Mod. Transp.	1.56	11	Retail	Review
Alavi et al. (2019)	2019	J. Acad. Marketing Sci.	5.888	0	Retail	Methodological
Al-Dousari et al. (2019)	2019	J. Pet. Explor. Prod. Technol.	1.102	0	Manufacturing	Application
Blundo et al. (2017)	2017	Hum.-Cent. Comput. Info.	3.212	5	Retail	Theoretical
Arnoult et al. (2019)	2019	J. Ambient Intell. Hum. Comput.	1.598	0	Manufacturing	Application
Bustillo et al. (2017)	2017	J. Intell. Manuf.	3.535	39	Manufacturing	Methodological
Kusiak (2018)	2018	J. Intell. Manuf.	3.535	1	Manufacturing	Review
Joshi et al. (2018)	2018	J. Ind. Eng. Int.	14.63	0	Manufacturing	Application
Zhou (2013)	2013	Adv. Manuf.	2.601	48	Manufacturing	Methodological

Bruton et al. (2015)	2015	J. Big Data	1.124	100	Manufacturing	Review
Lu (2013)	2013	Adv. Manuf.	2.601	1	Manufacturing	Review
Cohen et al. (2019)	2019	Int. J. Adv. Manuf. Tech.	2.601	0	Manufacturing	Review
Wang (2014)	2014	Adv. Manuf.	2.601	34	Manufacturing	Application
Cheng and Qin (2017)	2017	Chin. J. Mech. Eng.	1.413	11	Manufacturing	Review
Lelito et al. (2015)	2015	Int. J. Adv. Manuf. Tech.	2.601	10	Manufacturing	Application
Kula et al. (2018)	2018	Neural Comput. Appl.	4.664	1	Manufacturing	Application
Mourtzis (2016)	2016	Logist. Res.	1.351	41	Manufacturing	Review
Agarwal et al. (2018)	2018	Global J. Flexible Syst. Manage.	1.73	2	Manufacturing	Review
Machado et al. (2019)	2019	Wireless Netw.	2.405	2	Manufacturing	Methodological
Gao et al. (2019)	2019	Memetic Comput.	2.674	0	Manufacturing	Review
Rauch and Rojas (2019)	2019	Int. J. Adv. Manuf. Tech.	2.601	5	Manufacturing	Methodological
Oborski (2014)	2014	Int. J. Adv. Manuf. Tech.	2.601	38	Manufacturing	Review
Holmström et al. (2019)	2019	J. Oper. Manage.	2.955	1	Manufacturing	Review
Hasija et al. (2020)	2020	Manuf. Serv. Oper. Manage.	2.667	3	Manufacturing	Review
Dande and Samant (2018)	2018	Tuberculosis	2.79	29	Healthcare	Review
Antani et al. (2019)	2019	Clin. Radiol.	2.082	7	Healthcare	Review
Akram et al. (2019)	2019	J. Mol. Liq.	4.561	23	Healthcare	Application
Chong et al. (2017)	2017	Eng. Appl. Artif. Intell.	3.526	23	Manufacturing	Methodological
Bergey and Ragsdale (2005)	2005	Omega	5.341	113	Healthcare	Theoretical
Stawowy (2006)	2006	Omega	5.341	46	Healthcare	Theoretical
Gupta and Marquez (2006)	2006	Omega	5.341	283	Manufacturing	Methodological
Chang et al. (2009)	2009	Omega	5.341	73	Manufacturing	Application
Chang et al. (2009)	2009	Omega	5.341	14	Manufacturing	Application
Mahar and Wright (2013)	2013	Omega	5.341	89	Healthcare	Methodological
Battaïa et al. (2018)	2018	Omega	5.341	12	Manufacturing	Review
Damcı-Kurt et al. (2019)	2019	Omega	5.341	3	Healthcare	Methodological
Beliën et al. (2020)	2020	Omega	5.341	5	Healthcare	Methodological
Agatz et al. (2009)	2009	Transp. Sci.	3.31	144	Retail	Methodological
Ahmadi-Javid et al. (2017)	2017	Eur. J. Oper. Res.	3.806	157	Healthcare	Review
Atun et al. (2018)	2018	J. Global Health	3.079	38	Healthcare	Review
Haferkamp and Köhler (2019)	2019	Transp. Res. Procedia	1.2	4	Retail	Methodological
Chen and Chen (2014)	2014	Transp. Res. Arena	1.758	2	Retail	Methodological
Arslan et al. (2016)	2016	Comput. Oper. Res.	3.002	77	Retail	Application
Calis and Bulkan (2013)	2013	J. Intell. Manuf.	3.535	88	Manufacturing	Review
Choi et al. (2001)	2001	J. Oper. Manage.	2.955	1501	Manufacturing	Theoretical
Olsen and Tomlin (2019)	2019	Manuf. Serv. Oper. Manage.	2.667	5	Manufacturing	Review
Davari et al. (2018)	2018	Manuf. Lett.	3.53	57	Manufacturing	Review
Kaebernick and Mazhar (2007)	2007	J. Oper. Manage.	2.955	189	Manufacturing	Methodological

Cang et al. (2002)	2002	Comput. Ind. Eng.	3.518	120	Manufacturing	Methodological
Butow and Hoque (2020)	2020	The Breast	2.381	0	Healthcare	Application
Chassagnon et al. (2020)	2020	Eur. J. Radiol.	2.948	0	Healthcare	Application
Dahdaleh et al. (2020)	2020	Clin. Neurol. Neurosurg.	1.736	0	Healthcare	Application
Pantano and Pizzi (2020)	2020	J. Retailing Consum. Serv.	3.585	0	Retail	Methodological
Bridger et al. (2020)	2020	Clin. Neurol. Neurosurg.	1.736	0	Healthcare	Application
Alsuliman et al. (2020)	2020	Curr. Res. Transl. Med.	2.353	0	Healthcare	Review

Table 2. Academic Publications by Contribution, Year, Journal, Impact Factor, Cited, Field and Contribution Type