Predictive Modeling for University Technology Transfer Success for Automation and Robotics

by

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A dissertation submitted to the Graduate Faculty of
Auburn University
in partial fulfillment of the
requirements for the Degree of
Doctor of Philosophy

Auburn, Alabama
May 4, 2024

Keywords: Technology transfer, Industry 4.0, Automation and robotics, patent licensing, Machine learning

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Abstract

Technology transfer, particularly within the context of Industry 4.0, is a complicated process full of challenges. Integrating and commercializing advanced technologies of Industry 4.0, such as automation and robotics, into industry necessitates an in-depth understanding of the factors influencing effective technology transfer. This dissertation addresses these challenges and has three primary objectives. Firstly, it aims to identify and analyze existing gaps and challenges in the technology transfer process within Industry 4.0, focusing on understanding the factors contributing to effective technology transfer. Secondly, the dissertation investigates predictors to enhance the effectiveness of Technology Transfer Offices in managing Industry 4.0 technologies, particularly in automation and robotics. These predictors provide practical guidance and proven methods for technology transfer offices to enhance patent licensing success. Lastly, the dissertation intends to build a predictive model of patent licensing success specific to automation and robotics, targeting improving university technology transfer's patent portfolio management capabilities. This model aims to increase technology transfer office performance, increase technology commercialization, and facilitate self-sustainability through revenue generation.

This dissertation employs a systematic literature review to incorporate existing knowledge, statistical analysis to explore patent variables and their relation with patent licensing, and supervised machine learning classification to develop a predictive model. These approaches enable an extensive investigation of the technology transfer process, facilitating the development of predictive models to promote innovation and enrich technology transfer effectiveness in the automation and robotics sectors within Industry 4.0. In conclusion, an Industry 4.0 Technology Transfer Model and Conceptual Framework are proposed, identifying novel predictors for automation and robotics patents, including independent claims, success rate of technology transfer office, and inventor experience. Additionally, a classification model is developed to predict patent licensing success, further contributing to the advancement of technology transfer in the Industry 4.0 era.

Acknowledgments

I would like to praise Allah the Almighty for his blessing given to me, in addition to the strength and patience to complete my Ph.D. program successfully.

I am heartily thankful to my supervisor, Dr. Konstantinos Mykoniatis, whose encouragement, guidance, and support have been from the initial to the final level. I would also like to thank my committee members, Dr. Sa'd Hamasha, Dr. Jia (Peter) Liu, Dr. Panagiotis Mistriotis, and Dr. Jorge Valenzuela, for their valuable suggestions and guidance in improving the quality of this work.

I want to thank the staff in The IP Exchange for their assistance in understanding the subject through working with them, especially Dr. Troy Brady.

I am deeply grateful to my mother, father, and sisters for everything they have given me throughout my life and for their constant prayers. I am immensely thankful to my family and in-laws for their devoted care of my daughters. Last but not least, I am dedicated to my husband Ali, my first supporter; without him, I would not have been able to bear the challenges of this journey. I also thank my daughters, Tala and Naya, for their patience during stressful times and for understanding the sacrifices required when I was away.

Table of Contents

List of Tables

List of Figures

List of Abbreviations

AI	Artificial Intelligence
AM	Advanced Manufacturing
AUTM	Association of University Technology Managers
CPC	Cooperative Patent Classification
FIP	Forecasting Innovation Pathways
HEIs	Higher Education Institutes
I4.0	Industry 4.0
ICAMS	Interdisciplinary Center for Advanced Manufacturing Systems
IoT	Internet of Things
IP	Intellectual Property
IPC	International Patent Classification
IPRs	Intellectual Property Rights
LR	Logistic Regression
ML	Machine Learning
PCT	Patent Cooperation Treaty
R&D	Research and development
R&I	Research and Innovation
r_{pb}	Point-biserial correlation coefficient
SLR	Systematic literature review
SMEs	Small and Medium-Sized Businesses

STATT	Statistics Access for Technology Transfer
TDS	Technology Delivery System
Ti	Titanium
TTA	Technology Transfer Adoption
TTO	Technology Transfer Office
UNIDO	United Nations Industrial Development Organization
USPTO	United States Patent and Trademark Office
WIPO	World Intellectual Property Organization

Chapter 1. General Introduction

1.1 Technology Transfer

1.1.1 Definitions

The Association of University Technology Managers (AUTM), which is the leading association in technology transfer, defines technology transfer as “the process of transferring scientific findings (such as academic inventions) from one organization to another (i.e., industry) for further development and commercialization” [1].

Successful collaboration between academia and industry can deliver several benefits [2]. Collaboration among organizations and universities can foster knowledge and technology transfer by sharing their intellectual property rights (IPRs), which leads to innovation. “Intellectual property (IP) refers to creations of the mind, such as inventions; literary and artistic works; designs; and symbols, names and images used in commerce” [3]. These technological and knowledge transfers assist firms in realizing their full potential, motivating them to develop new technology and improve existing ones, resulting in a productive corporate environment [4].

The most common IP used to protect scientific inventions is patent. The World Intellectual Property Organization (WIPO)[5] defines a patent as “ an exclusive right granted for an invention, which is a product or a process that provides, in general, a new way of doing something, or offers a new technical solution to a problem. To get a patent, technical information about the invention must be disclosed to the public in a patent application”.

Process, machine, article of manufacture, composition of matter, and improvement of any previous can be patented. The invention should be novel, nonobvious, useful, and not offensive to public morality. On the other hand, it can not be patented if the invention is laws of nature, physical phenomena, abstract ideas, literary, dramatic, musical, and artistic works [6].

A license agreement is the most common method of technology transfer, granting the rights to use technology through either an exclusive or non-exclusive licensing agreement. Another approach is the acquisition of technology, involving transferring IP assets like scientific inventions from a patent owner to another party, typically governed by a contractual or legal arrangement [7].

1.1.2 Technology Transfer Process

The United Nations Industrial Development Organization (UNIDO) models technology transfer as a vertical process where technology is transferred from research to production through development stages and a horizontal process where technology is transferred from one operational environment to another primarily for commercial application [8].

The typical technology transfer process at universities is illustrated in Figure 1.1 and is based on [9, 10] [11]. The simple process of technology transfer is shown in Figure 1.1. represent the three taps on the right [11]: Identifying new technologies, protecting technologies through patents and copyrights, and forming development and commercialization strategies, such as marketing and licensing to existing private sector companies or creating new start-up companies based on the technology".

Figure 1.1 illustrates the main processes from invention disclosure to patent licensing. The process starts with discovery, followed by disclosure by the inventor to the technology transfer office (TTO). The next step is to evaluate and decide whether to file a patent. The TTO does this evaluation covering two main aspects: patentability and marketability. Patentability is assessed through a prior art search to identify existing technologies and determine if patent protection is feasible. This search covers and analyzes issued patents, scientific journals, published patent applications, and other available public documents. If not, alternative forms of intellectual property protection are explored to support the invention's commercialization. Marketability is assessed by analyzing the market need for the technology, including the impact and potential demand for similar technologies [12].

If the TTO evaluation results show that the disclosure is patentable and there is a market for it, a patent application is filed. The final phase of the process involves the commercialization of the technology, either through licensing to established companies or by launching a new startup or spinoff entity [10].

It's important to note that each step within this process requires human resources for execution. As the complexity of the process increases, so does the corresponding demand for time and effort, resulting in higher associated costs [10].

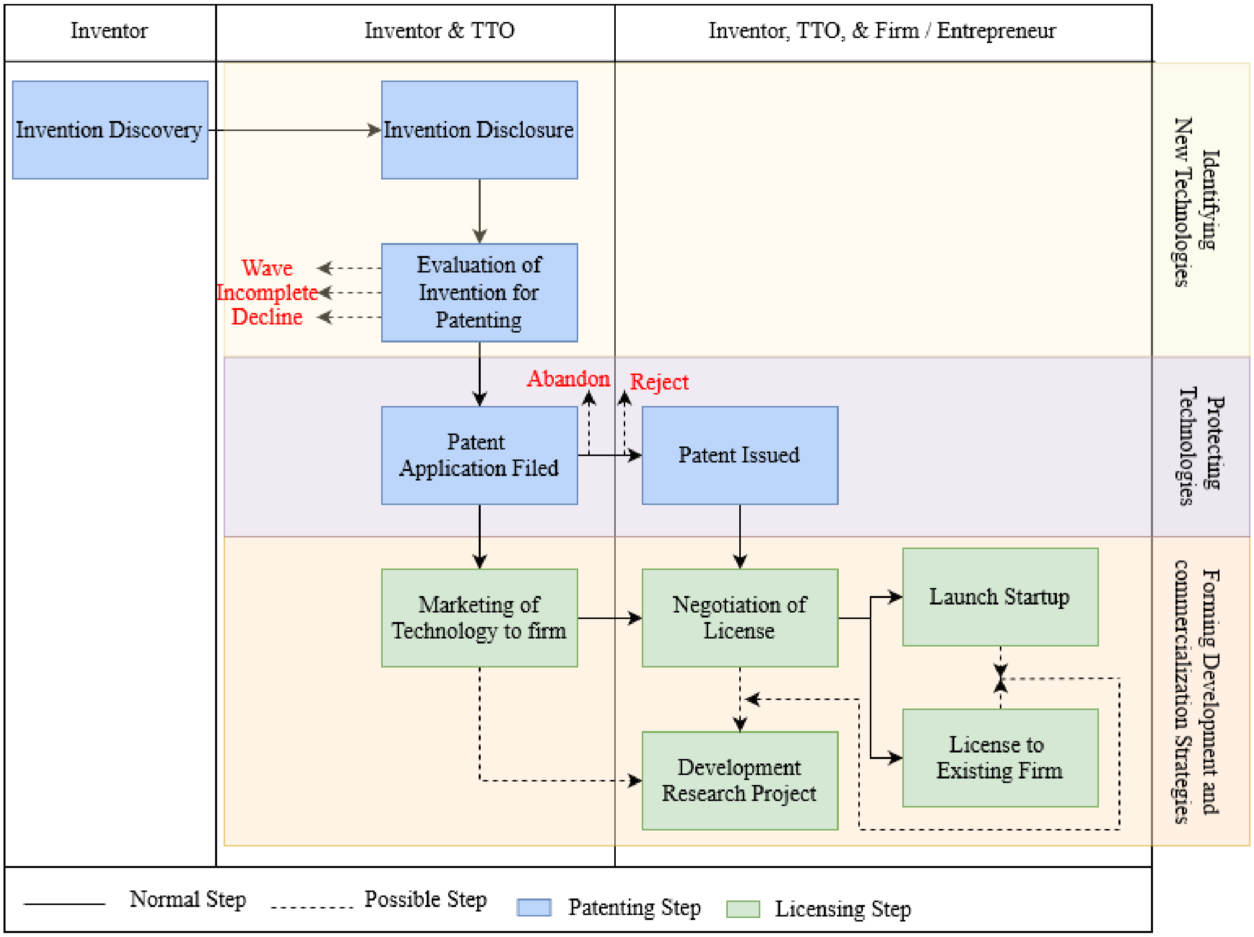

Figure 1.1: Typical process of technology transfer in the university

The timeline and milestones of the patent are presented in Figure 1.2 [13]. The process usually starts with filing a provisional application. The provisional (or "informal") patent application allows the TTO to file without a formal patent claim, oath, declaration, or any information disclosure (prior art) statement. The goal is to file at a lower initial investment, gain time (up to 12 months) before filing a nonprovisional application for a patent, and avoid initiating the 20-year patent duration [14, 15]. This step is done before filing the nonprovisional or what is known as a patent application. The provisional application provides TTO with the required time to decide whether to file a nonprovisional application after finishing the evaluation without losing the priority date and investing more than the application of the provisional fees. If TTO decides to file a nonprovisional application, they should do it before the 12 months. Patents are territorial rights [5]. Because of that, to have exclusive rights, the patent must be filed and granted in each country or region where TTO seeks to protect its technology. Filing a patent has two main options: file it only in the USA or several other countries. The decision depends on the technology and the expected market.

Preparing a nonprovisional application can take weeks to months. TTO team or External patent counsel works with inventors to gather information and scientific details for incorporation into the application, which contains two main parts: the specification, providing a detailed description of the invention, including drawings if required, and the claims, which define the scope of the patent rights. Once all the related parties approve the draft application, the attorney files the application with the United States Patent and Trademark Office (USPTO). In addition, submit the Assignment and Declaration from the inventors and an Information Disclosure Statement containing prior art information [16].

The application is published approximately 18 months (about one and a half years) after the provisional filing. The examination process for a patent application can take between 2 and 5 years. TTO can abandon the application even before the patent is granted. If the application patent is granted, issue fees must be paid. The patents are protected for 20 years after filing the nonprovisional patent application [6, 15]. Maintenance fees must be paid before the due date to maintain the enforcement of a patent. The maintenance fees in the USA due date are 3.5, 7.5, and 11.5 years after the patent is issued. The patent will be abandoned if the maintenance fees are not paid [17].

Filing a nonprovisional Patent Cooperation Treaty (PCT) application is preferable if the technology can be licensed to other countries. A private International Search Report / written opinion will be issued sixteen months after filing the provisional application. The next step is application publication to the public approximately 18 months (about 1 and a half years) after the provisional filing. TTO has up to 30 months after the provisional application date to enter the National Stage and file the application. Country selection can be made by any PCT participating state, including the USA, Europe, Japan, and China, among many others [17].

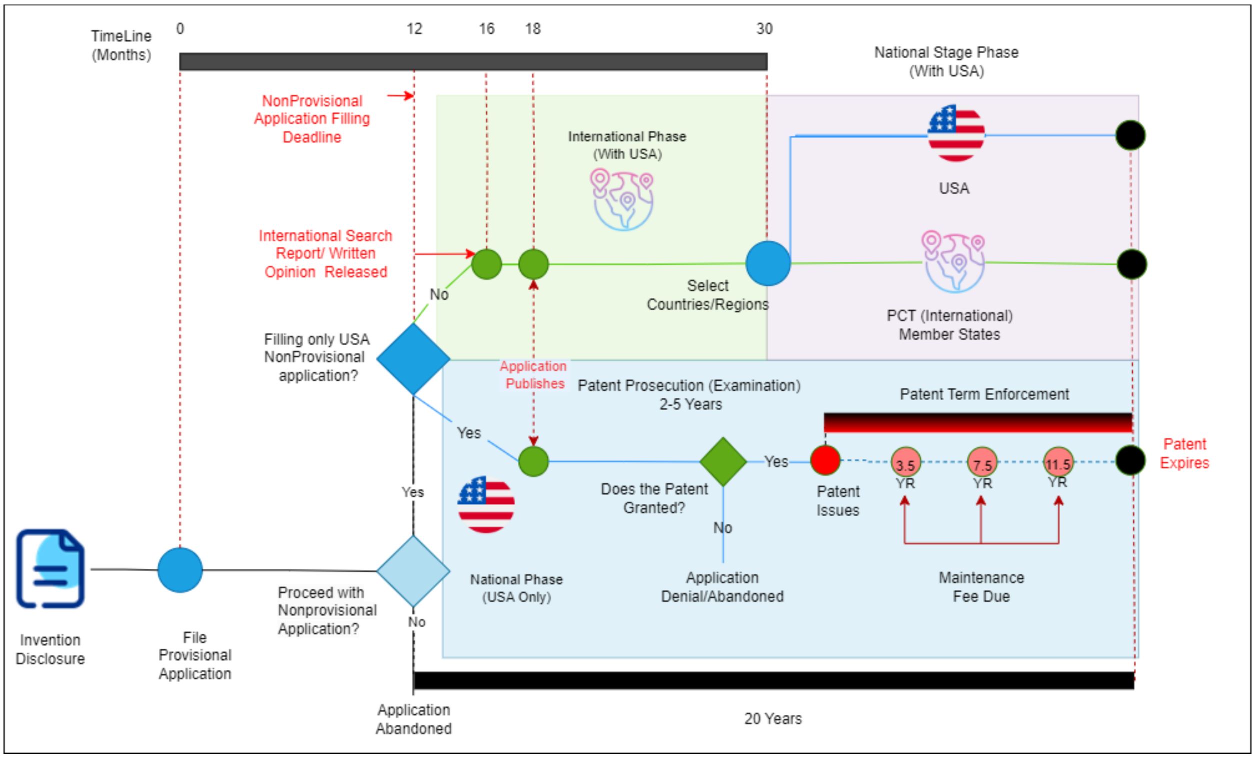

Figure 1.2: Patent timeline and milestones

1.2 Industry 4.0

Currently, the industry is driven by global competition. Because of constantly changing market demands, quick manufacturing adaption is necessary. The market has fewer delivery times, more efficient and automated processes, better quality, and customized products. These drive companies towards the so-called fourth industrial revolution, Industry 4.0 (I4.0) [18, 19]. Radical technological advances are needed for current manufacturing processes to meet these requirements. I4.0, characterized by innovative technologies fused with information and human ingenuity, can drive the next generation of intelligent production systems. The expected market share of I4.0 is more than 71.7 billion USD and is forecasted to exceed 150 billion USD [20].

A flexible production system is required to customize products [21]. Thus, I4.0 is an interdisciplinary concept with a challenging endeavor [22, 23].

Horizon integration is required at every stage of the manufacturing process, including machine interaction [18, 24]. Several technological pillars have emerged as enablers of I4.0 technologies, such as the Industrial Internet of Things, modeling and simulation, extended reality, big data and analytics, artificial intelligence (AI), cloud computing, block-chain, cybersecurity, industrial automation and robotics, and additive manufacturing [24-27].

1.3 Robotics and Automation

‘‘A robot is a reprogrammable, multifunctional manipulator designed to move material, parts, tools, or specialized devices” [28]. Robotics technology is a crucial field of the Fourth Industrial Revolution [29], which provides extensive capabilities in the field of manufacturing [30]. In the era of I4.0, technologies contributing to improving and automating processes have changed. Today, robots surpass their limits and become flexible, more sophisticated, faster, less costly, mobile, and more intelligent. Robots have become the driving force of automation, where it has never been before [30-32].

Ongoing technological advancements in robotics are increasing the accessibility and affordability of robotic solutions [30]. With the development of AI, robots can intelligently complete assignments without human feedback. Robots can master advanced skills by self-learning to achieve success, like Machine Learning (ML) through various programmed motions to perform multiple tasks [30, 32, 33]. In addition, progress in the field of robot sensors has made robots compact and more susceptible to the environment, expanding the range of their tasks [30, 32]

Robots work with employees to do routine, single, or complicated work under the employees' supervision and direction or autonomously. Robots can easily do all the hard jobs that humans can't [31], and they will replace increasingly low-paying jobs that don't require as much skill [34]. Robots can perform product disassembly, including the separation of the reusable pieces. Also, product assembly involves two or more parts, which are a subset of the assembly, and the purpose is to bring individual components together to form a new product [35].

Robots are commonly used in a range of sectors, such as life science, manufacturing, automobile, engineering, electronics, aerospace, packaging, chemicals, and healthcare, to name a few. Robots excel in making real-time decisions and navigating complex environments. These new demands robust computing power, reliable networks, and modern machine setups. Recent technological progress, such as data connectivity, parallel processing, edge computing, and AI distribution, empowers robots to make rapid decisions and ensure stability and efficiency [30].

1.4 Problem Statement

Technology transfer is pivotal for the commercialization of inventions, with billions of dollars in licensing revenue generated annually [36]. Nevertheless, the process from disclosure to commercialization is resource-intensive and faces substantial challenges. Startlingly, 90% of U.S.

patents remain unlicensed [37], including many high-quality patented inventions developed by universities. Consequently, a substantial amount of the $5 trillion spent on research and development in the U.S. in the past two decades has led to unlicensed patents [38].

Moreover, technology transfer programs face financial difficulties, with over half operating at a loss and only 16% self-sustaining [39]. Given the complexity of technology transfer, addressing this issue demands multidisciplinary research approaches [40].

Technology transfer is a unique multidisciplinary research approach that can be tackled effectively from various scholarly and methodological viewpoints [40]. Consequently, technology transfer complexity must be addressed in research and practice. By examining it from different points of view, we might learn more about the problems we face.

One of the key challenges in technology transfer is the successful transfer of complex technology [41], particularly within the domain of I4.0, encompassing automation, robotics, and additional intricate technologies like AI and the Internet of Things (IoT). The complexity of this technology necessitates extensive training, apprenticeship, and significant interpersonal interactions [41]. The involvement and selection of skilled personnel are vital to successful technology transfer [42-44].

The global IT robotic automation market was valued at US$ 5.3 billion in 2022 and is expected to expand at a compound annual growth rate of 15.7% by 2032, reaching US$ 22.8 billion [45]. Also, the Interdisciplinary Center for Advanced Manufacturing Systems (ICAMS) Smart Manufacturing Adoption Study found that automation is the most important technology in smart manufacturing for dealing with business problems [46].

Furthermore, I4.0 is transforming from the single-provider model to a network of integrated technology providers [47]. This shift underscores the evolving landscape of technology transfer within the context of I4.0. Despite the undeniable importance of these technologies and the changing dynamics of technology providers, limited studies have focused on studying technology transfer within this domain or investigating the critical success factors affecting it.

1.5 Research Objectives

The aims of this research are:

1. To identify and analyze the existing gaps and challenges in the technology transfer process within the context of I4.0. This objective aims to understand the factors that enhance effective technology transfer comprehensively.
2. To create strategies and suggestions that improve the effectiveness of TTOs in handling I4.0 technologies, particularly in the field of automation and robotics. This objective aims to offer practical guidance and proven methods for TTOs to facilitate the transfer of these advanced technologies.
3. Build a predictive model of patent licensing success in automation and robotics, specifically designed to enhance the patent portfolio management capabilities of University TTOs. This model aims to optimize TTO performance, foster increased technology commercialization, and facilitate self-sustainability through revenue generation.

Chapter 2. Background

The primary concern in predicting patent commercialization revolves around pinpointing the key factors and variables that influence patent commercialization. To address this, I conducted a comprehensive literature review to identify the significant factors associated with patent licensing success.

2.1 Institution Factors

The higher education landscape is highly heterogeneous. In other words, not all universities address their objective function similarly. Differences in size, territorial scope, legal status, academic level, subject mix, or entrepreneurial approach shape how universities define their activity mix and determine their performance [48].

2.1.1 Applicant's institution affiliation

This factor is related to the type of institutions. Choi et al. [49] used five categorical values (0: National research institute, 1: Public University, 2: Private University, 3: Collaborative research, 4: Country, 5: Community college). Their study concluded that each type of institution has different significant variables for the predictive model that was built by Choi et al. [49]. Only national research institutes and public universities have the same results. This variable was also studied by Serrano [50] from another side: the type of patentees. The results showed that small- and private inventors are the most active sellers of patents. Government agencies and large innovators are the minor sellers of patents.

2.1.2 Assignee backward citations

The average number of backward citations for patents is owned by the assignee. Backward citations are the total number of cited patents in a patent [51]. This variable will measure the technology accumulation of an assignee [52]. This variable is important in Kim and Geum's [51] model, which means knowledge accumulation of the assignee is essential in predicting technology transfer.

2.1.3 Assignee forward citations

The average number of forward citations for patents is owned by the assignee. This variable represents the technological strength of the assignee. This variable was the most important in the Kim and Geum [52] model. The technological power of a company significantly impacts patent transfer. Lin et al. [53] predicts the success of licensing pharmaceutical patents registered by universities or colleges. The variable is used as an indicator of the institution's ability to attract potential licensees due to its well-established fame and reputation.

2.1.4 Assignee family patent count

Another measure used as an indicator for predicting licensing success is the count of family patents owned by the assignee. The variable is used as an indicator of the technological marketability of the assignee [52].

2.1.5 Assignee patent transfer

The count of transfer patent success related to the assignee. It explains the previous history of patent transfers [52].

2.1.6 Assignee similar patent transfers

To present the previous history of patent transfers for a technology transfer, Kim and Geum [52] use the count of success of patent transfers as a measure of the Technological Strength of the Assignee. It explains the previous history of the success of patent transfer. This variable was influential in the prediction of patent transfer.

2.2 Time Factors

2.2.1 Expiration time

Expiration time is defined as the date of a patent expired. This variable affects Choi et al.[49] predictive model for the country. Kim et al. [29] used the variable and called it the residual time to measure the value of the patent.

2.2.2 Prior filing

Present the use of the filed patent for priority [49]. This variable was insignificant in Choi et al. [49] prediction models.

2.2.3 Period

The period represents the time (number of days) between the patent issue date and the application date [54]. This variable was used by Lee et al. [54], Kim et al. [55], and Lin et al. [53] to predict if the patent was licensed/transferred or not.

2.2.4 Patent age

The grant year of the patent to the year it is up for trade or renewal. According to Serrano[50], the probability that an active patent will be traded decreases with age, except for the year immediately after a renewal date.

2.3 Collaboration Factors

Collaboration has many benefits, such as accessing strategic assets, pooling complementary technology, learning from the partner, and sharing risks and costs [51]. The collaboration measures are:

2.3.1 Assignee count

The number of original assignees owned the application in a patent [51]. This variable has a positive influence on the predictive model presented by Huang et al. [51] . Kim et al. [55] also used it in the prediction model to measure the utility value of a patent.

2.3.2 Assignee country count

The number of countries of assignee presents a patent. International patent transactions have been a global issue [51]. This measure is essential when the patent data is from several countries, as in the model presented by Huang et al. [51].

2.3.3 Current owner count

The current assignee holds the patent [55]. Kim et al. [55] use the variable to measure the influence of the patent in the market.

2.3.4 Inventor count

Inventor count is the number of inventors in a patent [51]. This variable has no impact on the model presented by Choi et al. [49]. On the other hand, it positively impacts the model of Huang et al. [51].[29, 55] employ this variable to measure the development's sustainability.

2.3.5 Inventor country count

The number of countries of inventors in a patent. [51]. According to Huang et al. [51], this variable negatively affects the transaction likelihood.

2.4 Scope Factors

Technology with greater complexity or viscosity is more challenging to transfer and requires more training or apprenticeship for successful absorption. [41]. Two patent scope measures were used:

2.4.1 IPC count

IPC count is the total number of international patent classifications present in a patent. WIPO defined the IPC as a hierarchical system of language-independent symbols for classifying patents and utility models according to their specific areas of technology [51, 56]. The technology field represents the market that can use the technology. The more diverse the market is, the more chance there is to commercialize the patent [57, 58].

Several researchers studied this, and Choi et al. [49] model results mentioned that it is crucial for the model. Huang et al. [51] also support these results, and his model presented that it positively impacts the likelihood of patent transactions. Kim et al. [55] employ the variable to represent the technology scalability. Lin et al. [53] also used it as an indicator of the potential value of the patent; the broader technological scope of a patent can have a higher potential value.

2.4.2 Count of claims

Number of claims in a patent. Each claim constitutes a unique contribution of a particular patent [59]. It indicates fundamental features of innovation [60].

The variable has no significant impact on commercialized patents. This result was supported by the predictive model by Choi et al. and Huang et al. [49, 51]. A patent with a severe legal claim implies that a patent is an appropriate asset and should not be traded [51].

On the contrary, Lee et al. [54] and Kim et al.[29, 55], and Lin et al. [53] used the claim as one of the variables to predict the patent transfer. It represents the intellectual property rights reserved by a patent[53]. Claims indicate the scope of patent rights [29].

2.5 Knowledge Factors

knowledge accumulation is crucial in understanding technology transfer [49, 52]. Technologies with high technological strength are more likely to be commercialized [52]. Patent knowledge type impacts innovation: explicit knowledge speeds it up, while tacit knowledge enhances quality [51]. For university patents, success depends on their quality, making high-quality patents more transferable in the technology market [61].

The knowledge factors are:

2.5.1 Backward citations

Backward citations present the cumulative count of previously cited patents within the prior art literature patent [51]. This variable is a critical criterion for patent quality [52]. The number of backward citations can be a suitable proxy for knowledge accumulation since it has been used to quantify how much a given technical knowledge builds on prior knowledge [62]. The number of citations used to forecast emerging technology [57] and measure the influence of technology [29].

Several studies found that this variable significantly influences the predictive mode. This result was supported by Choi et al. [49] for the national research institute and public universities' predictive model. Lee et al. [54] also used it to predict the patent transfer. Kim et al. [29, 55] used it as a technology impact measure.

In contrast with the previous research, Huang et al. [51] and Kim and Geum [52] research stated that it has no significant effect on patent commercialization.

2.5.2 Forward citations

Forward citations are the total number of patents cited by other patents. Highly cited patents can be considered technological leaders, more likely to be traded, and have a higher value [49, 50, 52, 63]. The total citation count is between 5 and 10 years [51]. Another way to deal with forward citation is using the citation-lag distribution [52].

The importance of the forward citation stands behind multiple research results that mentioned that it has a direct impact on technology transfer, as presented in the models of Choi et al. [49], Serrano[50], Huang et al. [51], and Kim et al. [55] which is represented as a technology impact measure. Lin et al. [53] use this variable to evaluate the impact or influence of a patent on other patents. On Serrano [50], younger, frequently cited, more original, and recently traded patents were more likely to be traded and renewed.

2.5.3 Number of INPADOC family patents

The INPADOC patent family comprises all the documents shared directly or indirectly (e.g., via a third document), at least one priority [64]. This variable impacts some models introduced by Choi et al. [49] for national research institutes and public universities. However, in the same study, this variable has no impact on the model for private university and county models.

2.5.4 INPADOC family countries

INPADOC family countries are the number of family countries of INPADOC Family patents [49]. This factor was presented by Choi et al. [49], and it has no significant effect on the predicted model.

2.5.5 Originality index

The strength of backward citation existing in a patent using four-level IPC as a technical field identification, a multiple IPC patent is defined by its first and primary IPC codes [51, 57, 58]. This variable decreases patent transaction likelihood in Huang et al. [51] model.

2.5.6 Generality index

The generality index is the strength of forward citations present in a patent [51]. The index measures the diversity of citing patents. The value is from zero to one; the numeric range is: 0-0.44 low, 0.45-0.65 mid, 0.66-1 high [65]. The results of Huang et al. [51] showed that this index increases a patent's transaction probability. Patents with a higher generality index represent the patent influence of many technical fields, which are prone to conduct general impact and promote its patent transfer.

2.5.7 Non-patent reference count

The non-patent reference count is the references used on a patent document from resources other than the patent document. This variable has a negative effect on the patent transaction probability, according to Huang et al. [51]. This variable was used by Lee et al. [54] to predict the transfer of a patent.

2.5.8 Foreign reference count

The foreign reference count is the number of foreign references used on the patent. This variable has a negative effect on the patent transaction probability, according to Huang et al. [51].

2.5.9 Technology topic

This Variable represents the technical description of a patent. This variable was used by Lee et al. [54] and was identified by the Latent Dirichlet allocation method. Using this variable improves the performance of the predicted model. Kim et al. [55] also used technology topics. The BERT method on abstract was used to identify the elementary technology. On the other hand, Lin et al. [53] used the same concept to clarify that more therapeutic indications are expected to have a greater interest in licensees. The main difference is that the technology topic is done manually by reading all the patents to identify the therapeutic indications.

2.5.10 Similar patents

This variable is used to measure the knowledge accumulation. The values were extracted from patent Google. It was used by Kim and Geum [52] as one of their model variables.

2.6 Protection Factors

The protection boundaries are particularly essential in predicting patent transactions since patent value is defined by how much technological knowledge may be covered by a patent.

2.6.1 Litigation

An infringement-based model that measures patent litigation properties to reveal the legal value of a patent. According to Huang et al. [51], this variable does not influence the commercialization of a patent. A litigation probability index can be a strategic factor for firms to utilize high-risk patents to acquire a competitive advantage. However, some risk-averse firms are prone to trade. Thus, the decision to hold or sell depends on risk appetite. Kim et al. [55] used the litigation status as an indicator of patent utility value

2.6.2 Family patent count

Given the application, translation, and legal costs, the number of patent families is worth considering as a proxy for technological power and protection boundaries [52, 66]. This variable was mentioned to be a good estimator input for the model of Choi et al. [49] and Lee et al. [54] model. Kim et al. [29, 55] used the variable to measure market impact.

2.6.3 Family countries count

The number of countries where a patent is covered is another essential consideration for determining protection boundaries. Because patents are only valid inside a single country, firms who wish to use the invention must submit the patent in multiple countries. As a result, the greater the number of countries in which a patent is filed, the greater the value of the patent. Given the application, translation, and legal costs, the number of patent families is worth considering as a proxy for technological power and protection boundaries [52, 66]. This result was supported by Choi et al. [49] predictive model and had a significant effect on the private university model, Kim et al. [55], and Lee et al. [54] model. In addition, Lin et al. [53] predicted the model used to measure patent recognition. Kim et al. [29] used it to represent the marketability of a patent.

2.7 Application Type Factors

2.7.1 Sole application

Indicates whether a patent application is a sole application. A sole patent is less encumbered than one in which a technology transfer and an overseas application are filed jointly, making it a measure of the utility value used only by Kim et al.[55].

2.7.2 Standard patent

A standard patent plays a vital role in the relevant technical field, so it is possible to measure the technological influence—this variable is only used by Kim et al. [55].

Chapter 3. Methodology

The methodology comprises three main components. It begins with a systematic literature review, examining the predictors employed in the patent licensing prediction model and, ultimately, developing a ML prediction model. I employed Python for data processing, visualization, data analytics techniques, and ML.

1. A systematic literature review (SLR) involves a structured process. It aimed to systematically identify the factors affecting the success of technology transfer within the contextually.

   Initially, I conducted research and identified the articles based on the search terms related to the research questions. The search was conducted over 250 databases, including but not limited to Web of Science, IEEE Xplore, ScienceDirect, SpringerLink, and EBSCO, with refinements made to search strings to ensure comprehensive coverage.

   I utilized a title review process to narrow the articles, then filtered the articles based on abstract review. I categorized the related articles based on their alignment with the research questions for my dissertation.

2. Identify the scope: I identified my scope by concentrating on one of the I4.0 technologies: automation and robotics. I also selected the patent granted to US universities.

   The selection of automation and robotic technology was driven by its substantial market size, which stood at US$ 5.3 billion in 2022 and is projected to grow at a robust compound annual growth rate of 15.7% [45].

The emphasis on university technology transfer is universities' crucial role in driving the transition towards I4.0. This transition is marked by a paradigm shift from a single-provider model to a multi-provider model, further underscoring the significance of technology transfer[47].

3. Background: A general background was done to explore the available predictor model for patent license success. The predictor was distributed into seven pillars: institution, time, collaboration, scope, knowledge, protection, and application type.
4. Data Collection: I begin by identifying the target group, followed by conducting my search. Two primary databases that I used. The first is the Patsnap website, which collects patent data. This website has an extensive database encompassing details from over 180 million global patent applications [67].

   The second one is the Statistics Access for Technology Transfer (STATT) database of AUTM. The STATT database will be used to identify the universities' TTOs, collect the data, and study the factors related to the TTOs. The database results from a voluntary yearly survey of North American universities and research centers that comprises yearly surveys [58]. The available data is for the years 1991- 2021.
5. Data cleaning: delete inaccurate data, correct the data format, eliminate duplicates, fill in missing values if possible, or remove incomplete data. I used the Google Patents website, Institution Websites, and the National Science Foundation website to fill in the missing data.
6. Data processing: Data preprocessing is an essential step in ML. Having a well-prepared dataset can improve the accuracy and efficiency of ML models. It includes transforming and integrating the data to render it suitable for analysis. Include but are not limited to

transferring the content from string to list and/or numeric. Change the data type from object to numeric. Change data type from object to date. Transfer to uppercase. The next step is to extract the predictor if further processing is required.

7. Feature selection: This involves selecting the most relevant features for the problem statement. This step will analyze the predictors used in existing research and the suggested new predictors. The selection will be using data analytics techniques.
8. ML model development: Develop a ML prediction model using logistic regression. The goal is to predict if the patent will be transferred, which is a binary output. Logistic Regression (LR) is a popular probabilistic nonlinear regression model with only two outcomes: 0 or 1. This method characterizes the data and explains the connection between one binary dependent variable and many ordinal, nominal, interval, and ratio-scale independent variables [68].
9. Model evaluation: I will use precision, recall, and F1-score to evaluate the prediction model's performance.

Chapter 4. The Success of Technology Transfer in the Industry 4.0 Era: A Systematic Literature Review

Modern innovative models have the possibility of transferring research and development (R&D) output through technology transfer from scientific and research institutions or other enterprises. The complex process of technology transfer is significantly dependent on cooperation among academia, industry, and governments in response to the technological developments driven together through Industry 4.0. As a result, numerous technology transfer factors must be addressed for I4.0 to become a reality. However, the abundance of literature on I4.0 and associated technologies, the key ingredients, and insights for executing I4.0 technology transfer are limited. This study focuses on the success factors of technology transfer for I4.0. The framework is based on systematic literature to outline significant results and factors. Furthermore, this study summarizes, analyzes, and criticizes the actual models and their influential variables for I4.0 technology transfer. One of the findings of this study is the significance of cooperation between technology recipients, agents, and inventors for I4.0 technology transfer. Another impressive finding is the significance of the ecosystem component in technology transfer. Combining I4.0 technologies and open innovation is a game-changer, enabling businesses to significantly save time and cost. This article will assist decision-makers in developing policies and strategies to improve the I4.0 technology transfer process. Furthermore, this involves identifying the kind of government assistance that will help accelerate the transition to I4.0 via technology transfer.

Keywords: technology transfer; industry 4.0; systematic literature review; barriers; models.

4.1 Introduction

Currently, the industry is driven by global competition. Because of constantly changing market demands, this necessitates quick manufacturing adaption. The market has fewer delivery times, more efficient and automated processes, better quality, and customized products. These drive companies towards the so-called fourth industrial revolution, known as I4.0 [18, 19]. To meet these requirements, radical technological advances are needed for current manufacturing processes. I4.0, which is characterized by modern technologies fused with information and human ingenuity, can drive the next generation of smart production systems. The expected market share of I4.0 is more than 71.7 billion USD and is forecasted to exceed 150 billion USD [20].

I4.0 works on transforming industrial manufacturing using by digitalizing and exploiting new technologies. A flexible production system is required to enable the customization of products [21]. Thus, I4.0 is an interdisciplinary concept with a challenging endeavor [22, 23]. This requires combining and integrating humans, technology, and organizations with established manufacturing practices across the entire production value chain. I4.0 refers to the future state of the industry in which economic and production flows have been digitized. This necessitates horizontal integration at every stage of the manufacturing process, including machine interaction [18, 24]. Several technological pillars have emerged as enablers of I4.0 technologies, such as the Industrial Internet of Things, modeling and simulation, extended reality, big data and analytics, AI, cloud computing, block-chain, cybersecurity, industrial automation and robotics, and additive manufacturing [24-27].

For a successful transition toward I4.0, collaboration between industry and universities is vital. Approximately 2.94 billion USD in licensing revenue was generated in 2018 directly from technology transfer [36]. The Association of AUTM, which is the leading association in technology transfer, defines technology transfer as, “the process of transferring scientific findings (such as academic inventions) from one organization to another (i.e., industry) for further development and commercialization” [1].

In the context of I4.0 technologies and their execution and integration, open innovation appears to be the most suitable system to promote a firm's activities for knowledge exploration and exploitation [69]. Modern innovative models give the possibility of transferring ready R&D solutions both from scientific and research institutions (vertical technology transfer) as well as from other enterprises (horizontal technology transfer) [70]. Technology transfer is a unique multidisciplinary research approach that can be tackled effectively from a variety of scholarly and methodological viewpoints [40]. As an interdisciplinary approach, problems are not separated into disciplinary silos [71]. Interdisciplinary research is becoming increasingly important. This is due to a growing focus on research designed to handle major challenges and future trends across disciplines, such as the I4.0.

Successful collaboration between academia and industry can deliver several benefits [2]. Collaboration among organizations and universities can foster knowledge and technology transfer by sharing their IPRs, which leads to innovation. These technological and knowledge transfers assist firms in realizing their full potential, motivating them to develop new technology and improve existing ones, resulting in a productive corporate environment [4].

After surveying the published articles, few studies have focused on I4.0 technology transfer. This study seeks to contribute to closing the gap in the existing literature regarding technology transfer and I4.0 and provides useful information to both practitioners and scholars. First, it improves academic and managerial understanding of how technology transfer occurs in I4.0. The second contribution is identifying factors that can improve the effectiveness of technology transfer processes in I4.0. The remainder of the paper is organized as follows. Section 2 provides an SLR of the current state of research regarding technology transfer in I4.0. Section 3 describes the factors to success in implementing I4.0 technology transfer. Section 4 synthesizes the main findings of existing models and frameworks related to I4.0 technology transfer. Finally, in Section 5, we discuss our conclusions and future work.

4.2 Systematic Literature Review Method

The need for the SLR arises from the need to summarize all existing information about technology transfer for I4.0 in a thorough and unbiased manner. This may draw more general conclusions about some factors that are possible from individual studies or be undertaken as a prelude to further research. Thus, in this study, we use SLR to answer two main research questions and systematically identify, evaluate, and interpret all relevant research. Our two main research questions are (Q1) "What are the most important factors affecting the success of technology transfer in I4.0?"; (Q2) "Are there any existing models for technology transfer targeting I4.0?". The overall objective of this SLR is to respond to the aforementioned two research questions and clearly define a path for the development of a conceptual framework comprising recommendations for effective technology transfer in I4.0.

4.2.1 Search Methodology

This section discusses the methodology and strategy used in this study. Figure 4.1 describes the search methodology process we followed in this SLR. First, we used search terms based on our research questions and identified an initial set of articles whose titles, abstracts, keywords, and subjects matched our terms. Then, we screened the results for relevance by reviewing the contents of the abstracts. If the results were deemed relevant, the full text was reviewed. Articles deemed irrelevant were excluded from the analysis.

Based on our two main research questions, we created search terms to form search strings. The search was conducted at the Auburn University Library, which subscribes to over 250 databases. The databases include but are not limited to: Web of Science, IEEE Xplore, ScienceDirect, SpringerLink, and EBSCO databases, to name a few. First, we considered the results of the following search strings: (1) “Technology transfer” AND (2) “Industry 4.0”

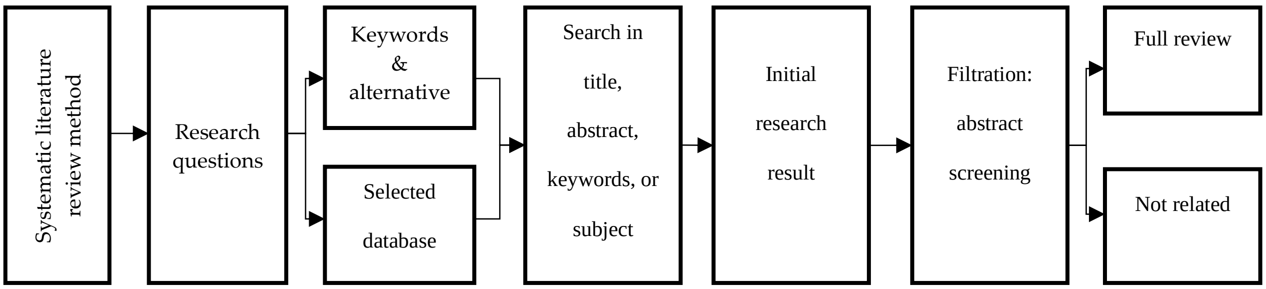

Figure 4.1: Systematic literature review method.

Other keywords and combinations arose from the first group of publications and were used to improve the literature search. For instance, some scholars from various geographical regions use the term “smart manufacturing” interchangeably with “industry 4.0.” Thus, we refined the search to ensure we did not miss any relevant articles to identify as many primary papers as possible. Table 4.1 summarizes all the possible combinations of search strings that we used. Finally, all references found in articles relevant to the review’s focus were included.

Table 4.1: Keywords and alternatives.

KEYWORDS	**Alternative KEYWORDS**
Industry 4.0	Fourth industrial revolution, advanced manufacturing, smart manufacturing
Technology Transfer	Innovation commercialization

The strategy we followed for this systematic literature review is illustrated in Figure 4. 2. Our goal was to split and categorize the content of the articles based on our two main research questions.

The first research question includes the factors affecting the success of the I4.0 technology transfer. The second research question includes existing works related to models or frameworks of technology transfer for I4.0.

In the first search, we used two keywords, “Technology Transfer” and “Industry 4.0”. Table 4.2 lists the search results of 903 peer-reviewed published articles. We then reviewed the field of the

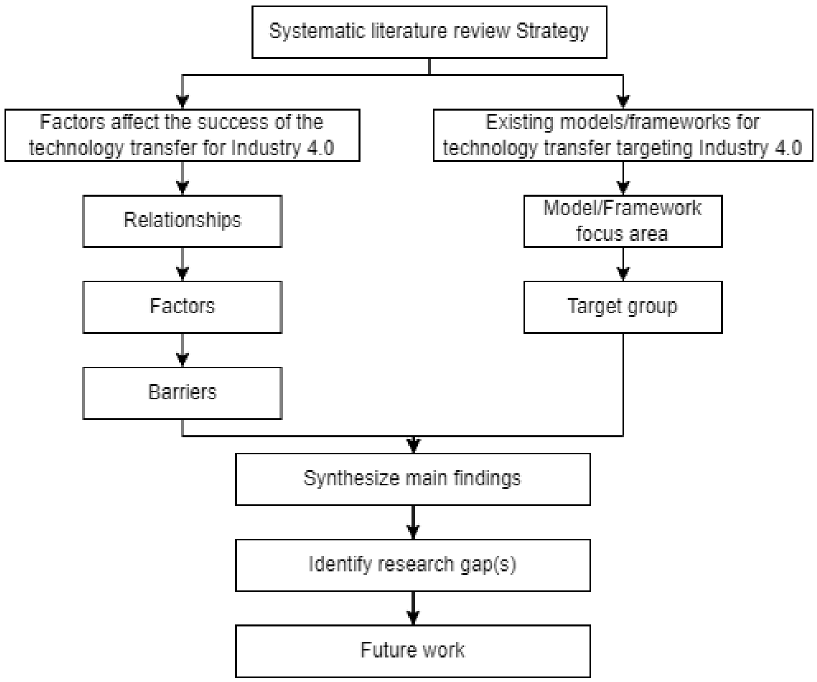

Figure 4.2: Literature review summary.

title, abstract, keywords, and subject and removed any irrelevant papers. To improve the precision of our results, we conducted an additional search using the following format (“Technology Transfer” OR “Innovation Commercialization”) AND (“Industry 4.0” OR “Fourth industrial revolution” OR “Advanced manufacturing” OR “Smart Manufacturing”). The search returned 381 articles.

Table 4.2: Article search results.

	Identified articles	**Article using precise search**	**Articles post abstract review**	**Article post full text review**
Total	903	381	72	40

For each article, we reviewed the abstract to identify whether it was relevant to the topic to be fully reviewed. Initially, we identified seventy-two relevant articles. However, only forty out of the seventy-two articles were relevant to our research questions and topic and fully reviewed. Figure

4.3 illustrates the article distribution based on the year of publication from 1985 to 2021. The articles were also categorized as unrelated/related articles. The number of articles thoroughly reviewed in a sequence relevant to the first research question alone, the second research question solely, and both research questions is 23, 12, and 5 articles, respectively.

It is worth noting that the number of articles related to this topic has been significantly increasing since 2016. Several initiatives have been launched worldwide to accelerate the transition to I4.0. The European Union published the "Industry 4.0 - European Parliament" report in 2016. According to the report, many small and medium-sized businesses (SMEs) are unprepared for the structural changes that I4.0 will entail. One way to deal with this problem is to connect these SMEs to global value networks through a comprehensive program for transferring knowledge and technology [72]. Furthermore, the World Economic Forum's 2016 Annual Meeting, which was conducted under the theme "Mastering the Fourth Industrial Revolution," mentioned that technology's role went from supporting to being the main focus [73].

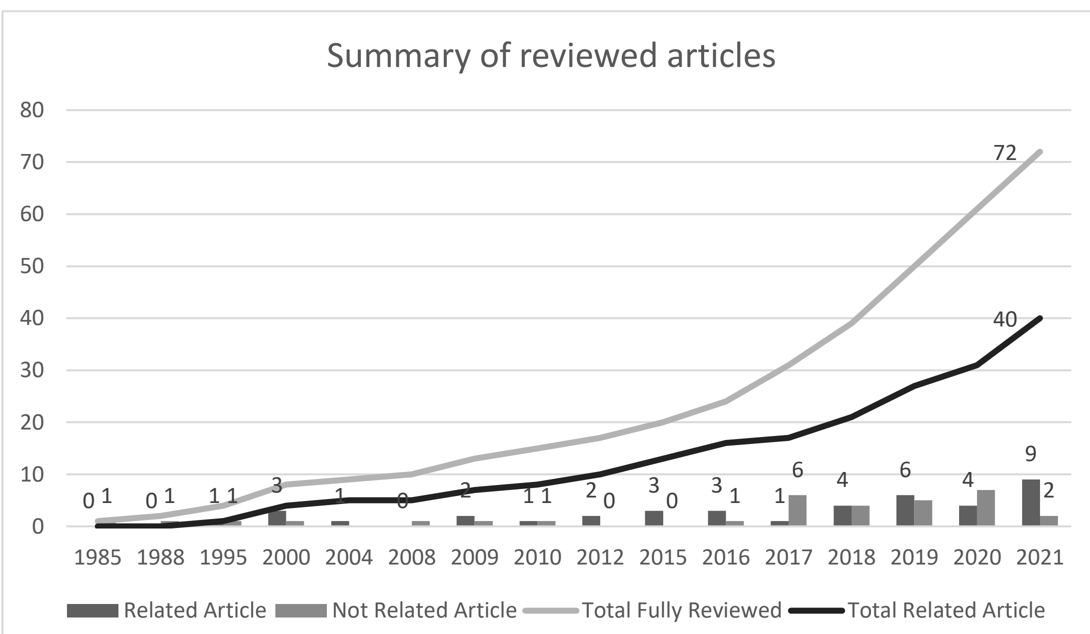

Figure 4.3 Summary of article reviewed.

Figure 4.4 illustrates a word cloud produced by the abstracts of the 40 selected manuscripts. Word clouds are graphical representations of word frequency that emphasize words that occur frequently in a source text. The bigger the term in the figure, the more frequently it appeared in the abstracts. The most commonly used terms are innovation, technology, development, manufacturing, industrial, industry 4, technology transfer, knowledge, new, and technological. This indicates that all the articles fell within our scope, which is the technology transfer of I4.0. This involves technological development and knowledge transfer to the industrial sector.

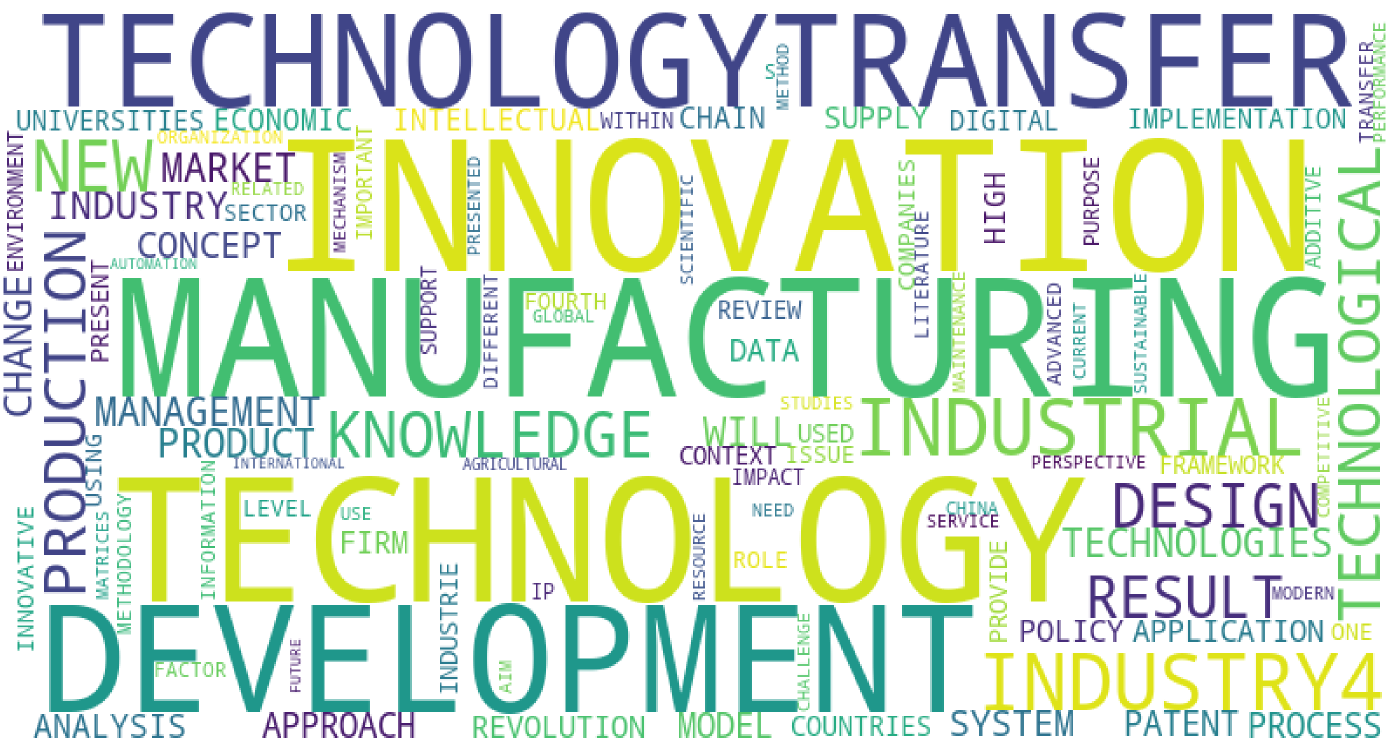

Figure 4.4:Word cloud produced by the selected abstracts.

4.3 Factors Affect the Success of the Technology Transfer for I4.0

Section 3 discusses in depth the essential aspects influencing the effectiveness of I4.0 technology transfer. These factors were classified into five categories: the I4.0 technology transfer relation, the excellence and innovation center, the manufacturing culture, human capital technical experience, and legal protection. Each factor is described in depth below.

4.3.1 Industry 4.0 Technology Transfer Relation

The focused path of technology transfer has changed over time, according to Bozeman [74]. Before 1980, most technology transfer research concentrated on cross-national technology transfer. At the beginning of the 1980s, research shifted to domestic technology transfer. In the US, interdisciplinary research holds great promise for creativity and innovation, which has become the new focus of technology transfer.

The goal of technology transfer is to bring university outcomes into the market. Relationships among universities, industries, and the government are essential. These three partners must work effectively to establish a successful process. This relationship must be contextualized because of the significant changes in productive and organizational systems in I4.0. The technology transfer process in I4.0 will mobilize the entire country based on Silva et al. [75] research. Beharry and Fai Pun [76] focus on technology-enhancing innovation in I4.0. Firms should be more adaptable and flexible in responding to client demand and market needs changes. The flexible and adaptable process is aided by new technologies of I4.0 such as 3D printing. In this vein, technology transfer is seen as a way to give small businesses and countries with less advanced industries a fair chance.

Several countries have determined the importance of technology transfer in the transition to I4.0. The UK government invested in Advanced Manufacturing (AM) research and technology transfer £95.6 million. A total of £20.5 million was invested in industry-academia collaboration projects. From 2007 to 2016, the UK government thought that technology transfer would help close the gap between what people knew about AM technology in theory and what they actually knew about it in practice [77].

According to Tan [78], the Taiwanese government plays a significant role in shaping the automation industry. The Taiwanese government established technology transfer infrastructure as part of a strategy for promoting automation, industry, infrastructure, and innovation growth. The government worked through tax incentives, favourable financing, technology development, education and training, product and equipment development, and technical assistance. The government mechanism began by transferring the core product/process technology. The transfer is from universities through licensing to automation engineering and service industries to build up supporting industries. The second is to support R&D organizations. These organizations worked as technology providers, initiating technology transfer to receivers. The main factor that affects achieving the technology transfer strategy is government and industry commitment.

Switzerland also has a government effort to support the transition to I4.0 using technology transfer. According to Ferrario [79], Switzerland is well-known for creating and applying innovative and high-value-added products. The federal government established a program targeted at technology transfer in the digitalization field. The production infrastructure must be modernized using the most advanced and efficient available technologies, focused on the I4.0 paradigm. In addition, for a more efficient approach, new and optimized manufacturing strategies were developed. As a result, Switzerland continues to rank among the top countries in this regard.

The Indonesian government realized the importance of I4.0 in agriculture (Agriculture 4.0 or Smart Agriculture). According to Suwanan et al. [19], they developed several applications to support the transition toward agriculture 4.0. The applications used I4.0 technologies. The application's targeted to monitor the cows' health, planting calendars, and plant cultivation. In addition, millennial farmers can access several sources of innovation through social media.

Another example of government involvement in I4.0 is the biotechnology sector in Ireland and Turkey. According to Simachev et al. [80], market growth models use a variety of approaches. The governments of both countries contributed the most to enhancing the biotech sector's competitiveness. In Ireland, this was accomplished through a favorable tax regime. The profit tax is among the lowest in Europe. High-tech companies can take advantage of IP tax depreciation, reimbursable R&D tax credits (25%), and patent box deductions (6.25%).

On the other hand, Turkey focuses more on the strategic level. Turkey's biotechnology strategy and action plan (2015-2018) have significantly promoted R&D. Turkey focuses on supporting innovative companies for I4.0. The R&D expenditures of commercial enterprises increased significantly between 2016 and 2019. Almost three-quarters of all spending in 2019 came from SMEs [80].

According to Kushnirenko et al. [81], technology transfer plays a pivotal role in the commercialization of new technology and skill development for students and university staff. Technology transfer creates a collaborative environment for university-industry relations. A proactive approach is required for technology transfer to involve researchers, promote technology, and encourage industrial companies to use I4.0 technologies. Technology transfer can occur through a license agreement. The license agreement lets the university keep the IP while giving the industrial party the right to develop and use the I4.0 technology under certain conditions.

On the contrary, commercialization opportunities increased if collaboration started between universities and industry as early as filing a patent application for technology development. Collaborative applications have a higher chance of success in marketing and selling technologies than technology transfer without collaboration with industry (after university technology development). The main reason is that technology development and patent applications raise various market values in several aspects of the patent, resulting in a greater possibility of commercializing the technology [82].

South Africa implemented a technology transfer road map. Alabi et al. [77] mentioned that universities must cooperate more in research with AM industries. According to the results of his survey, technology transfer creates an enabling environment to incorporate students, academics, and industry partners into AM. The road map for technology transfer will improve and accelerate industry-university collaborative research. As a result, product quality and performance will improve. Collaboration between universities and industries can also lead to new business opportunities, such as the mass customization of AM products. South Africa has a lot of titanium (Ti), and technology transfer makes it possible to make medical implants and prosthetics made of Ti.

Kushnirenko et al. [81] stated that technology transfer also includes disseminating theoretical knowledge and hands-on experience of AM processes and technologies to broader users (students, academics, and industry professionals). When it comes to AM, more collaboration between universities and the business world can improve the quality and performance of AM products.

According to Yıldırım and Tunçalp [83], the collaboration between universities and Turkey's industrial sector may produce new knowledge to solve performance problems. This research focused on how universities may help implement I4.0 technologies by developing various research and administrative policies. Digital transformations have gained momentum owing to increased digital innovations. New knowledge creation and technology transfer approaches have become critical components of innovation ecosystems.

Universities establish different units and organizations to facilitate technology transfer, such as TTOs, science parks, business incubators, and venture funds. These facilities aim to commercialize research output while dealing with challenges. Universities have the choice to commercialize technology through start-ups. Another way to do this is by developing and commercializing digital infrastructures, which are part of I4.0 technologies. Innovators need to establish multistakeholder partnerships across industries [83]. The role of universities in economic growth has altered dramatically under the I4.0 settings. Universities are considered the main engine of economic development and the critical actor in the knowledge economy. Universities have become centers for developing new high-tech enterprises [84].

India works on the collaboration between industry and higher education institutes (HEIs). Kashyap and Agrawal [85] mentioned that there is evidence to advocate how the role of HEIs has changed. In addition, HEIs participation in commercial activities has grown through technology transfer and start-ups. The focus of technology transfer is the commercialization of academic research results through the licensing and leasing of technology. There are several types of relationships between HEIs and industries for knowledge supply:

(1) Industry may look for universities as problem-solution providers.

(2) Start collaborating with the industry by submitting a research proposal from the HEIs to the industry.

(3) Industry can outsource a third party to search for the best research centers in HEIs; and

(4) The industry can receive proposals by working with a third party. The third party is the link between local R&D institutes.

Society 5.0 is a technology-driven, human-centered society that integrates cyber-physical systems and employs modern technologies to improve daily life [26]. Past and contemporary queuing systems, such as those found in supermarkets, are being replaced by Society 5.0. The private sector also significantly accelerates technology transfer in Society 5.0 based on Suwanan et al. [19].

4.3.2 Excellence and Innovation Centers

Technology transfer is vital to implementing I4.0, especially for developing countries. According to Silva et al. [86], developing countries are not established with the characteristics of I4.0. An ongoing and evolutionary process for technology transfer is needed to adopt new technologies. The resource of technology can be from specialized suppliers or their main offices. Developed countries produce knowledge and technology through contracting research centers, internal improvements, and R&D investments.

On the other hand, innovation has also played a key role in technology transfer in the new era of I4.0. Yun et al. [82] talk about how closed innovation strategies differ from the global open innovation trend, which is getting even stronger with I4.0. On the contrary, patent commercialization empowered by open innovation increases the chance of commercialization through technology transfer. Empowerment comes from the technical and economic values of the patents.

The role of the excellence centers in I4.0 discussed by Sastoque Pinilla et al. [87] shows that most SMEs do not have R&D units to support their research activities. Significant efforts are being made to upgrade students' qualifications through specialization and enhancement of local universities and excellence centers. They also work with local businesses to determine the grads' most significant problems. Two critical factors considered are: (a) The level of excellence of technology centers and universities to have a solid foundation of both primary and applied research, and (b) an appropriate level of transfer between research outcomes and industry to eliminate the interference between the production activity at the companies' and to decrease transfer cost and time.

This concept, supported by Beharry and Fai Pun [76], focused on small firms and less industrially advanced countries. The upgraded innovation model focuses on technology with an emphasis on technology transfer. Technology acquisition allows these organizations to enter the technological frontier and operate in I4.0. I4.0 technologies, on the other hand, broaden the search space, formalizing the distributed network concept and expanding on a previous open Innovation model.

Based on Kruger and Steyn [88], entrepreneurial technology in the field of I4.0 can be delivered and supported by technology transfer. Technology transfer has a significant role in the emerging technological paradigm, where strategies to address disruptions of I4.0 require coordinated activities. It should be supported by innovative spaces that offer an early access point to technological innovation. It can come from academic research and help start-up businesses grow faster by providing various resources and services.

Another example of success for better technology transfer achievements is the virtual reality laboratory "Astana Innovations" [89]. The objective is to achieve a broad and more effective use of virtual reality technologies following the latest trends. It is crucial to create appropriate conditions and promote cross-sectoral innovation culture in the private and public sectors. Based on Simachev et al. [80], Ireland established a R&D support program with a budget of 2 million euros. The Medical and Engineering Technologies Centre was set up to encourage technology transfer and the growth of new businesses. The growth is supported by simplified drug certification procedures, a high-quality business environment, a favorable tax regime, the absence of a language barrier, and the ease of access to the European market.

Innovation centers played a key role in transferring technology to farmers in the era of Agriculture 4.0; according to Suwanan et al. [19], Innovation centers aim to accelerate technology transfers to farmers. The main pillars are technology, studies to develop site-specific technology, and counselling to apply technology in the field. The location of laboratories is also essential in terms of accelerating technology transfer. Having several locations of innovation centers near farmers could help them understand, adapt, and integrate I4.0 technology.

4.3.3 Technology Transfer in the 4.0 Industrial Revolution, and Open Innovation

One of the primary drivers of open innovation and subsequent technology transfer is an innovation environment that focuses on dynamics and co-evolution [90]. Open innovation allows businesses to establish a structured innovation ecosystem that leverages external partner networks while focusing on developing core internal competencies [69]. Although the phrase "open innovation" was coined in the previous decade, the concept is not new. Open innovation is partly reflected in terms such as open source, user co-creation, user-centered innovation, and distributed innovation [69]. Dynamic open innovation is based on interactions that traverse company boundaries. Some ideas and knowledge originate from outside the company, while others are licensed to outsiders for commercialization [91].

Firms can capitalize on opportunities beyond their boundaries and limited internal resources to enhance the innovation rate in high-velocity marketplaces. Firms must have access to the resources of other organizations in addition to their own. Firms seek new ideas outside of their organizations and develop relationships with other enterprises that depend on each other [76, 92-94].

I4.0 stimulates open connections between technology and the market through open innovation [95]. I4.0 emphasized the significance for government agencies, research institutions, consultancy businesses, non-profit organizations, and entrepreneurs to form collaborative networks [96]. The most effective methods for I4.0 are dynamic open innovation business models and an open innovation culture. It is extremely beneficial to businesses in this technological era. Consequently, company collaboration may spur creativity and innovation, as well as develop novel ideas and concepts [97].

Combining I4.0 technology with open innovation is a game changer, allowing firms to drastically reduce costs and time [98]. Companies often adopt an open-source approach to building the networks associated with their products rather than a closed-source strategy [99]. The strength of local and regional research and innovation (R&I) processes regularly influences the innovative capability of SMEs. Cooperation and networking at the business and organizational levels are crucial for the growth and knowledge transfer at the core of R&I for SMEs [100]. Companies with a high level of open innovation, such as in the robotics sector, have a better chance of commercializing their patents via technology transfer [82].

Technology transfer has been a foundation of open innovation as the economic and digital industrial eras have accelerated. Open innovation improves the innovative performance of digital innovation [101-103]. By transferring knowledge, skills, technologies, and technological transfers, this type of innovation can significantly improve foreign-domestic connections and contribute to development [104]. This will boost the firm's ability to innovate and adopt new technologies [100] Open innovation also makes it simpler and less expensive for SMEs to use resources from outside their organization. This decreases risk and increases the use of external knowledge sources [104] [76].

Indeed, the era of I4.0 technologies prioritizes open innovation since incorporating external knowledge is more vital than ever in driving organizational innovation [105]. Ninety-four percent of the world's major innovators perform part of their R&D efforts abroad [106]. This indicates that companies should not depend entirely on their own ideas and in-house research but should also invite other sources to contribute. This is the outside-in branch of open innovation, sometimes called inbound open innovation [107].

4.3.4 Manufacturing Culture

The industry represents the transfer recipient in the technology transfer process. Manufacturing culture is one factor that affects the success of technology transfer. According to Gertler [108], manufacturing culture consists of firm behavior, routines, norms, and attitudes that shape it. Culture works as the link bundled with norms, traditions, and social conventions as part of informal or ‘soft’ institutions [109]. Manufacturing culture has a significant impact when we focus on technological changes, such as the transmission toward I4.0 [108]. This required an alignment between several business entities, industries, and technology strategies [110].

Manufacturing culture must be considered a key factor for a successful technology shift [108]. Based on research done by Bole [109], culture and formal institutions (rules, laws, and regulations) produced specific institutional settings. Culture is highlighted as the key element that leads to spatial variations in economic activities and performance.

Company-wide acceptability can be obtained only if senior management is explicitly committed to implementing I4.0. It is required to make faster and more effective decisions. Collaboration between departments and groups, even beyond business borders, is essential for a successful I4.0. A clear strategy and suitably trained employees can increase employee acceptance and decrease employee uncertainty about the unknown as well as the unfamiliar use of new media [111].

4.3.5 Human Capital Technical Experience

I4.0 technology transfer is a complex, interdisciplinary environment. The staff must have the knowledge and skills to deal with its complexity. The experience of the TTO staff is essential. According to Gunawardana and Jungthirapanich [42], these technologies can be 1) highly implicit or 2) the commercial application is difficult and complex, or both. This concept was supported by Bhatt [43]. She stated that special emphasis should be placed on people's involvement in technology transfer and selection. The staff includes people working on the TTO and the technology recipient (industry).

The lack of skilled staff and the necessary know-how to implement I4.0 was a crucial success factor; it was a vital barrier [44] [111]. The workforce was cited as a barrier to adopting nearly all smart manufacturing [46], which arises with the change in the manufacturing scenario and the new technologies [112].

4.3.6 Legal Protection

However, with the deployment of I4.0, the focus was on IP protection for intangibles. Some protection methods include virtual system setup, data ownership, management, storage, processing algorithms, and brand recognition. Therefore, this protection must be broadened. The deployment of I4.0 puts the existing knowledge and application of IP protection and commercialization methods to the test [113].

The creation of new techniques requires a better suited to fast-changing, highly linked corporate networks. Businesses must carefully consider ways to protect their IP. The consequences of installing interconnected communications and using application programming interfaces are more collaborative inter-company models. I4.0 outcome is a novel environment that is highly collaborative and interoperable. China recognizes that with the I4.0 technologies, countries that do not care about protecting these technologies will be less competitive and place themselves out of the world's stage for exporting end products [113].

Chandra and Liaqat [4] emphasized the need to protect I4.0 products and techniques. The protection comprises a pressing need to preserve innovative products and procedures from being easily imitated. It also erodes an organization's competitive advantage. As a result, IPRs may preserve an invention's originality, which can subsequently be marketed to promote knowledge and technology transfer for public purposes. However, a national technology transfer framework has not yet been developed. Universities and public research organizations have been recognized as having significantly contributed to technology transfer policies in numerous nations. They are both actively engaging in capacity-building and allowing the commercial application of IPs.

4.4 Industry 4.0 Technology Transfer Models and Conceptual Framework

4.4.1 Industry 4.0 Technology Transfer Models

Several institutions have successfully used a technology transfer approach for commercial profits. One of the goals of practical research on new technology innovation is to commercialize inventions. Universities have witnessed an increase in the identification of possibilities and their capacity to take inventions by boosting TTOs and innovation spaces [88].

Chih-Yi and Bou-Wen [114] examined the role of open innovation, technological crowding, and technological diversity in the relationship between competitive behaviors and firm performance. The model used in the panel set evaluates the independent, moderating, and control variables' role in firm performance. The results showed that the inbound open innovation mitigates the negative effects of vulnerability on firm performance and that external innovation through technology transfer the positive effects of competitive initiatives on firm performance. External outsourcing of technology is better suited for commercializing a company-owned technology or incorporating it into in-house applications [114].

On the other hand, Huang et al. [115] presented a conceptual model of the technology delivery system (TDS). TDS offers an essential framework for collecting information, organizing it, and concluding results regarding the implications that can be used for decisions regarding emerging technology supply chains. The TDS is a core part of the “Forecasting Innovation Pathways” (FIP) approach. FIP combines a range of future-oriented technology analysis tools to assist decision-makers in discovering opportunities (and threats) to achieve successful innovation while recognizing the inherent uncertainties of innovation pathways.

In this research, Huang et al. [115] built a TDS model for big data and analytics to emphasize technology mining as an approach to provide insights into TDSs. The model focuses on the actors and activities of institutions involved in producing and pushing to develop a new technology to emerge as a potential option for markets and society. It involved efforts to collect data, construct theories, and develop new methods to analyze technological development. A common need within these approaches is to identify the key actors and stakeholders and recognize how these elements fit together and operate as a system. The TDS model is useful in its own right. It is also connected with other frameworks to comprehensively analyze the broader socio-technical system contributing to socio-economic impacts.

Lee et al. [116] conducted an analytic hierarchy approach and correlation analysis. This approach highlights the most crucial factors in technology transfer adoption (TTA). The factors studied were TTO capabilities, technological validity, and business feasibility. The most important factors related to business feasibility are 1) commercialization, related to the profitability of the technology, and 2) marketability, including the market environment and market competitiveness.

Technical characteristics are also crucial from the technological application perspective. Their conclusion led to increased profitability through technology purchases, which is the worst criterion for a company's CEO to adopt the technology. The intangible TTA factors and dimension measurements must be used to enhance the full potential to commercialize exceptional technology with low cost and high efficiency [116].

Bliznets et al. [7] emphasized technology transmission during the current digital revolution. His research reveals that technology transfer provides new characteristics and methods for disseminating technical innovation, posing new legal theory and practice issues. Legal instruments must be adapted to address these challenges. Modern technology transfer methods include the purchase of technology, license agreement, patent pool, right to integrated technology in the legal system, direct investments, establishment of a joint venture, know-how transfer, commercial activity, and R&D agreements. Furthermore, the study showed that developing, distributing, and applying sophisticated technologies is challenging without legal IP transfer mechanisms. A vital aspect of sustainable development during the digital technology revolution is the incentive to produce and transmit new technologies.

According to Soares and Kauffman [113], new technologies establish a new ecosystem with new practices and tactics to secure and commercialize IP. Interdisciplinary collaboration is accessible through modern technologies. These collaborations could occur across the entire supply chain. Devices collaborating with various businesses will provide additional functionality, data analytics, or both to companies and customers.

This concept involves a multi-faceted and versatile IP strategy. The authors Soares and Kauffman [113] developed an IP strategy based on the company strategy and business model. Multiple businesses are involved within the I4.0 value chain. It is necessary to maintain control over the business value offers. It also maintains technological ownership, reputation, brand, and joint technological innovation. Meanwhile, preserve options for a fast route to customization, configuration, and the market.

Suwanan et al. [19] discussed a technology transfer methodology that was employed for agriculture 4.0. I4.0 may be used in a variety of industries, not just those associated with manufacturing. Where the change to agricultural digitization is concerned, agriculture may be part of it. They define agricultural digitization as developing, adopting, and enhancing digital technology in the agricultural industry. Knowledge-transfer technology has advanced significantly in recent years. Applications range from autonomous supply chain management to data and information processing as a foundation for agricultural management decision-making. The paradigm offered a partnership between the government, technology transfer (both public and commercial), and farmers, who represent technology recipients.

4.4.2 The conceptual framework for Industry 4.0 technology transfer

After finishing the I4.0 for technology transfer review. The main factors identified in this review are listed in Table 4.3. This table presents the factors, main remarks, and references.

Based on our review, the conceptual framework was developed. The framework is based on the available contingent effectiveness model by Bozeman [74] to match our finding for the I4.0 technology transfer. The framework summarized the literature on what work was done related to factors that enhance the success of the technology transfer process, elaborated in Figure 5. The contingent effectiveness model was created by Bozeman [74] and revised by Bozeman et al. [117].

The model is wide enough to cover the technology transfer process. There are two main parts of this model; 1) our major concern is the factors that influence the success of technology transfer, and 2) the measure of success (effectiveness) of technology transfer.

Table 4.3: Technology transfer for I4.0 models key factors.

Key factors	**Remarks**	**Reference**
Government support (financial)	National research funding.	[77, 79, 115]
Government support (strategic)	National promotion policies.	[19, 78, 80, 115]
Government support (Incentives)	Tax incentives	[80, 115]
Type of collaboration	Level of collaboration.	[19, 26, 77, 81-83, 85]
Source of technology	Private or public. Internal or external. Type of technology source: Excellence innovation center, research center, or university. Connection with other frameworks.	[76, 80, 82-84, 86-89]
Manufacturing culture	Manufacturing culture includes: Firm behaviour, routines, norms, and attitudes	[108, 109]
Human capital technical experience	The staff's experience and knowledge related to technology in the technology agent and recipient.	[42-44, 116]
Market factors	Productivity, profitability, marketing (this related to the effectiveness measure)	[116]
working capital funds	Fund to support the transition for the technology recipient.	[116]
Incentive mechanism	The incentive mechanism is essential for creating and transfer of new technology.	[7]
Modern legal tools	Modern legal tools support the technology transfer process to match the new technology related to the I4.0.	[4, 7, 113]
Flexible IP strategy	Implement a multi-faceted and adaptable IP strategy. The goal is to ensure they have control over the business value offer, the brand, the ownership of the technology, their reputation, and the joint development of new technologies. Preserve options for a fast route to market, configuration, and customization given the involvement of multiple businesses within the I4.0 value chain.	[113]

Six dimensions are used to categorize factors: technology agent, technology media, technology object, technology recipient, demand environment, and ecosystem. The arrows in the model indicate relations among the dimensions (dash lines indicate weaker links). These dimensions are:

The transfer agent is an entity capable of generating and transferring technology. It functioned as a transmitter. The agent can be the TTO, an institution, or an organization working on transferring technology to another entity. It includes technological niche, mission, resources, graphic location, scientific & technical human capital, organizational design, management style, political constraints, and sector [74, 117, 118].

The key elements of I4.0 technology transfer are: 1) source of technology and 2) rewards and incentives. Incentives are one of the most essential aspects that encourage people to work harder [119, 120]. According to this review, the type of organization that produces the technology can affect the success of the transition for I4.0 technologies and can increase the potential of marketing the technology object, especially for SMEs (transfer recipients). Another critical factor is the incentive mechanisms. These incentives will encourage researchers to commercialize their innovations. The remaining factors are covered by scientific and technical human capital, which is the technical experience of the TTO staff.

1. The transfer agent interacts with the rest of the five dimensions. The interaction between the transfer agent and recipient is through collaboration. The earlier the collaboration starts, the better the chance of commercialization. In addition, the recipient and inventor's participation level in technology development can enhance success.

2. Transfer recipient: To whom technology is transferred. It is represented by the organization or institution that receives the transfer object. An industrial company or spinoff can be the recipient. The factors are related to scientific & technical human capital, resources,

manufacturing experience, marketing capabilities, graphic location, diversity, and business strategies.

This review concludes that a key factor in a successful I4.0 technology transfer is industrial culture. Another aspect is the flexible IP strategy; it is necessary to implement a flexible and multi-faceted IP strategy to ensure control over the business value offer and other aspects. This factor can be covered by the business strategy. The transfer recipient reacts with the all dimensions.

3. Transfer medium defines the method to transfer technology. For example, a medium could be a license agreement. It can also be formal or informal. The main points cover open literature, patents, copyrights, license, absorption, informal, and personal exchange [74, 117, 118].

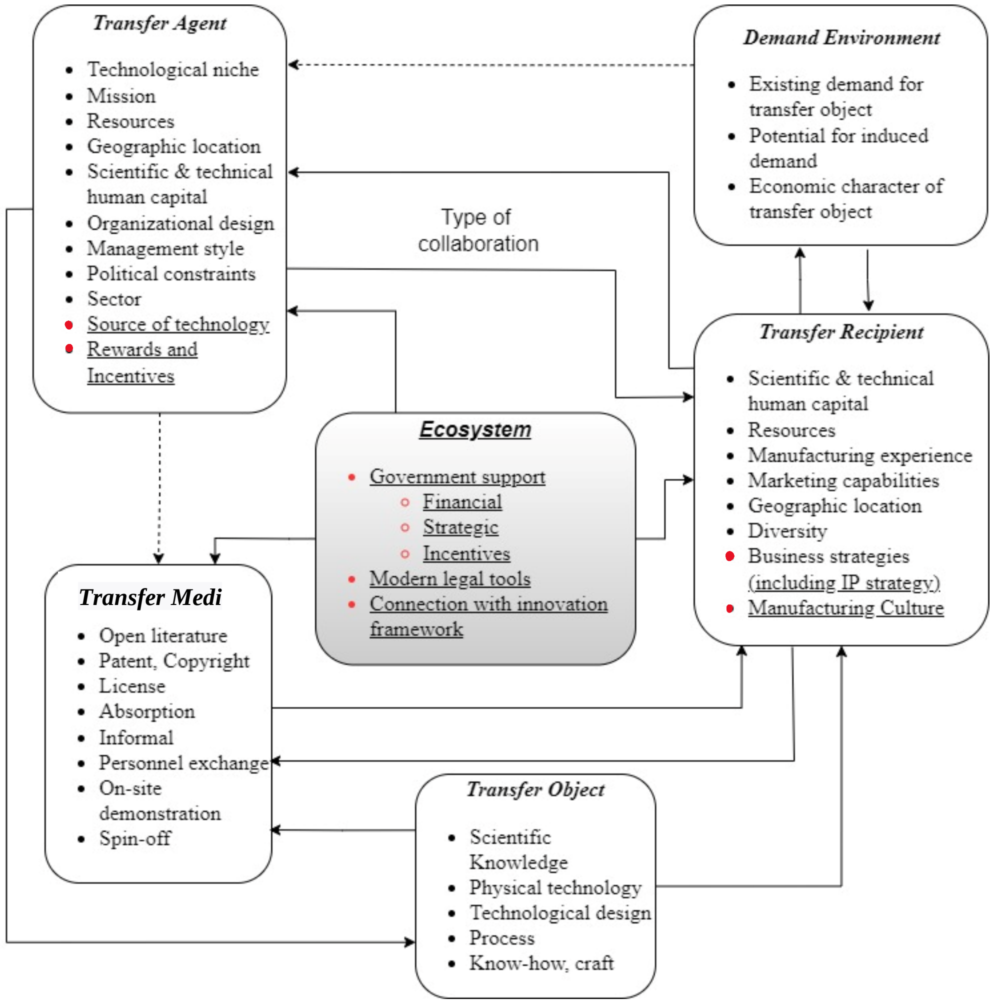

Figure 5. A conceptual framework of technology transfer for I4.0.

4. A transfer object is the content and format of what is transferred from one entity to another. It can be scientific knowledge, physical technology, technological design, process, know-how, and craft [74, 117, 118].

5. Demand environment refers to the factors that influence transfer, for example, factors of nonmarket and market about the need for the transferred object. The main is existing demand for the transfer object, the potential for induced demand, and the economic character of the transfer object [74, 117, 118].

6. Ecosystem: This is an additional dimension that coveres elements of the ecosystem for I4.0 technology transfer. The primary factors that influence and improve technology transfer performance for I4.0 are:

    - Government support: This support might be in the form of financial, strategic, incentive, or a combination of these. According to Peters et al. [46], government programs and funding can play a significant role in lowering organizational adoption barriers, and one of the recommendations is that the .S. government should develop a smart manufacturing adoption plan.
    - Modern legal tools: The legal tools need to match the new technologies related to I4.0 and support the technology transfer process.
    - Connection with the innovation framework: this will facilitate the adoption of I4.0 technology. Lack of awareness was one of the barriers to the adaptation of big data and AI [46]. To overcome adoption challenges, innovation will assist in raising awareness of I4.0 technologies.
    - This dimension interacts with the transfer agent, recipient, and media.

4.5 Summary

The technology transfer for I4.0 is reviewed in depth in this manuscript. The purpose of this article is to assist in the identification of success elements in I4.0 technology transfer, which will aid in industry, infrastructure, and innovation growth. The SLR approach was applied in this study. A conceptual framework for the I4.0 technology transfer, including the ecosystem factors, was established. The primary findings for these factors are as follows:

- The government plays a significant role in encouraging industry to strive towards I4.0 through technology transfer. The government can facilitate the transition toward I4.0 via technology transfer by enacting legislation, financing support, and offering incentives for this transition.
- A more collaborative environment must be established to enhance the effectiveness of the technology transfer process. The type and level of collaboration between technology recipients, technology agents, and inventors are required for I4.0 technology transfer. Collaborations that begin before submitting a patent application are more likely to succeed in marketing and selling inventions.
- Under I4.0, the role of universities in economic growth has shifted dramatically. Universities' duties extend beyond the commercialization of inventions to include the transfer of knowledge and skills. Universities are considered the main engine of economic development.
- The source of this technology is critical. Excellence innovation centers and laboratories support the industry (especially SMEs) in transitioning to I4.0.
- Dynamic open innovation and open innovation culture are the most effective ways to address I4.0. Technology commercialization, aided by open innovation, enhances the likelihood of commercialization via technology transfer.
- The I4.0 technology transfer environment is complex and multidisciplinary. The skills and expertise of related employees in TTO directly impact the technology transfer process of I4.0 technologies. The more availability of the skills and knowledge, the better the performance. Furthermore, the TTO requires a financial incentive structure to motivate

inventors to participate and follow up on innovation commercialization. Incentives are one of the essential aspects in motivating individuals to perform harder.

- Manufacturing culture influences the success of I4.0 technology transfer when we focus on technological advancements such as the transition to I4.0. It is vital to make quicker and more effective choices, to collaborate between departments and groups, to have a clear strategy, and to have appropriately trained staff. Consequently, employee adoption of the technology will increase, as will employee uncertainty.
- The legal tools available to protect the I4.0 technologies are inadequate. A modern legal tool is required to cover the intangibles technology with IP. These tools should be better suited for rapidly evolving technologies.
- New technologies establish a new ecosystem with new practices and tactics for securing and commercializing IP. This will facilitate the adoption of I4.0 technology.

These findings provide a roadmap for decision-makers in governments, industries, and universities, including TTOs, to establish policies and programs that will promote technology transfer for I4.0 across the board. Technology transfer is critical for assisting in the transition toward I4.0. This conclusion is supported by references from numerous nations and may be applied to various industries, including agriculture. The critical flaw is that no model focuses on predicting the success of the I4.0 technology transfer. More research is required in the future, particularly to determine how each component influences technology transfer success and how they all interact.

Chapter 5. Unveiling Predictors Influencing Patent Licensing: Analyzing Patent Scope in Robotics & Automation

Ensuring the sustainability of technology transfer offices depends on effective patent licensing strategies. This study investigates novel predictors for patent licensing prediction. It emphasizes the importance of judiciously selecting suitable patent-scope metrics to enhance the likelihood of successful patent licensing agreements. This work focuses on a critical aspect of patent scope, specifically examining the number of independent claims, the length of the first claim, the depth of the claim, the Cooperative Patent classification count, the non-US family count, and the family independent count. Additionally, we consider conventional metrics previously investigated in prior research, such as claim count, the count within the International Patent Classification, and Simple Family Application. Our empirical analysis harnesses a dataset comprising patents from university technology transfers within the robotics and automation domain. We analyze the relationship between patent scope measures and licensing outcomes using data visualization and statistical techniques, including the point-biserial correlation coefficient and the t-test. Comparative analysis of the statistical results is performed to identify the most impactful predictor. Our study reveals a correlation between the number of independent claims and the success of patent licensing. In contrast, the rest of the investigated measures do not impact the success of patent licensing.

Keywords: Patent licensing, Technology transfer, Patent scope, Predictors, Claims, Patent Metrics

5.1 Introduction

The commercialization of new technology heavily relies on technology transfer, which can be facilitated through a license agreement. This agreement allows the technology transfer office (the assignee) to retain intellectual property ownership while granting the licensee permission to utilize and develop the technology under specific conditions [121]. Many patents are abandoned before the end of their 20-year lifetime due to high maintenance fees, low demand for licensing, limited market adaptability, or the emergence of more affordable alternatives [122].

The value of patents lies in their protective capabilities. Patents that can effectively exclude competitors from valuable markets or essential technologies can lead to higher profit margins and rapid growth for the patent holder, making them highly valuable. On the other hand, patents that fail to restrict competitors may have limited value [123]. Nevertheless, the patent holder also retains the choice to grant permission to another party to exercise some or all of these exclusive rights. This action of authorizing permission is referred to as patent licensing. Through licensing, the party holding the patent rights permits another entity to engage in activities that would otherwise be restricted by the patent [124]. Recognizing patents as essential tools to distinguish technological advancements in countries, they play a crucial role in securing financial benefits through technology sales or licensing [125].

Numerous studies have explored predictors of patent licensing; one of the fields is patent scope, with indicators related to International Patent Classification (IPC) and patent claims. These predictors are commonly used to assess a patent's value for commercialization purposes. Broader patents present more opportunities to prevent competitors from introducing similar products. The technological scope of a patent is predominantly defined by its claims, underscoring the vital role of patent claims in determining patent valuation [126].

I4.0 starts with the German roadmap to include information technology in the industrial sector. It has now grown to include all major manufacturing economies globally[127]. I4.0 is characterized by hyper-connectivity, AI, software, and distributed intelligence, and it automates physical manufacturing processes and intellectual business practices [128, 129]. The digitalization of manufacturing through advanced computer integration of I4.0 revolutionary changes production processes [127]. It is expected that there will be considerable changes in the speed of development of technological innovation, as well as in the economy and social system [129].

I4.0, with its association with smart factories, has reshaped the organization of value chains through the integration of new and diverse technologies. Notably, the growth of patents related to I4.0 technologies, particularly in areas such as robotics and cloud computing, has been significant at the United States Patent and Trademark Office [125].

The Robot Institute of America defines “an industrial robot is a reprogrammable multifunctional manipulator designed to move material, parts, tools or specialized devices through variable programmed motions for the performance of a variety of tasks”. The cost-effectiveness of robotics has reached a point where it is commercially viable for a broad range of applications. The dynamic changes and potential products in this field can be effectively tracked through the analysis of numerous related patent specifications. The abundance of granted patents holds interesting implications for Intellectual Property professionals, searchers, and attorneys, considering the financial opportunities associated with some of these patents [130]. The interplay of patents within the landscape of robotics and automation underscores their significance in driving innovation and commercial viability. This research aims to uncover predictive factors influencing patent licensing by analyzing the patent scope within the field of robotics and automation.

The global IT robotic automation market was valued at US$5.3 billion in 2022 and is expected to expand at a compound annual growth rate of 15.7% by 2032, reaching US$22.8 billion [45]. Additionally, The Interdisciplinary Center for ICAMS Smart Manufacturing Adoption Study found that automation is the most important technology in smart manufacturing for dealing with business problems [46]. Furthermore, past research highlights variations in industry and universities' technology transfer prediction models. In this study, our primary focus is on patents registered by the assignees affiliated with the AUTM, the leading association in technology transfer. Universities are essential in a country's technological development [131]. Specifically, we aim to answer two main research questions:

RQ1: Can an alternative patent scope measure be identified as a potential predictor for patent licensing?

RQ2: Among the investigated patent scope measures, which ones exhibit the most robust potential as predictors for a patent licensing model?

Multiple articles have studied predictors related to patent scope when predicting licensing opportunities. The level of protection granted to a patent significantly impacts its overall value. Broad patents are particularly valuable when numerous alternative options exist within the same product category [126].

Prior studies have employed diverse empirical approaches to examine patent scope measures and their association with licensing. However, none of these studies specifically concentrated on utilizing measures of patent scope rather than count of claims and IPC subclass count or focused on patent licensing in the domains of robotics and automation, owned by AUTM assignee.

Our study addresses this gap by examining the relationship between patent scope measures and the success of patent licensing. Our methodology aims to identify the most effective scope measures for predicting patent licensing in robotics and automation, specifically among patents owned by AUTM assignees.

The remainder of this paper is organized as follows: In Section 2, we offer an overview of various methods used to measure the patent scope, including international patent classification, cooperative patent classification, claim count, independent claims count, claim depth, first claim length, simple family application count, family count, and US family independent claims count. Section 3 outlines our methodology encompassing data collection, processing, and analysis procedures, which we employed to assess various patent scope indicators using statistical and data visualization methods. In section 4, we present our experimental results and discuss our key findings and their implications. Finally, Section 5 encapsulates the conclusions of this research, where we summarize the study's contributions, highlight the identified predictor in patent licensing, address limitations, and suggest potential areas for future research and next steps.

5.2 Overview

This literature covered various methods and approaches used to measure patent scope in the context of IPC classification and patent claims.

5.2.1 International Patent Classification

The World Intellectual Property Organization created the IPC as a hierarchical system of language-independent symbols for classifying patents and utility models according to the many technological fields they apply [51, 56]. The IPC aims to identify relevant features related to a claimed invention's technical subject or multiple claimed inventions if applicable [132].

The rationale for employing this measure rests on the idea that patents encompassing a diverse range of technologies are regarded as broader, while those concentrating on a narrower scope of technology tend to be more specific. Nonetheless, a patent might be classified under multiple IPCs if it spans different technologies, even when introducing only a minor improvement over existing methods, thereby granting a limited legal right to exclude [123].

The technology field represents the technology market. The greater the chance of commercializing a patent, the more diverse the market is [57, 58]. The count of IPC has often been indicated as measuring the scope of a patent [133, 134]. According to Noh and Lee [135], technologies with more IPCs are more likely to be converging technologies. The subclass marks in the IPC reflect what the invention does rather than where it is applied in the business landscape [136]. Several scholars who have investigated this topic have noted that the IPC subclass count plays a crucial role in the technology transfer predictor model, as demonstrated by Choi et al. [49].

Furthermore, Huang et al. [51] research concludes a significant influence on the probability of patent transactions. A distinct and well-defined IPC classification offers a streamlined process when focusing on technology-oriented searches for patents with immediate solutions. However, when dealing with patents encompassing multiple IPCs, the time required to find suitable buyers significantly increases.

The Kim et al. [55] model uses the IPC count to indicate the scalability of the technology. A higher count signifies the patent's potential applicability across diverse technologies. In addition, Lin et al. [53] also utilized it as an indicator of the potential value of the patent; the broader the technological scope of a patent, the greater its potential value. In contrast, studies [51, 57, 58] have used the first and primary four digits of IPC codes for the scope, and the results from the Huang et al. [51] model results showed that having more IPCs reduced the likelihood of a patent transaction. IPC classifications play a pivotal role in measuring market diversity, assessing patent scope, and reflecting the invention's nature. They impact predicting patent success and transactions, as well as evaluating scalability and value. Their versatile use in scope measurement underlines their intricate role.

5.2.2 Cooperative Patent Classification

The Cooperative Patent Classification (CPC) is a classification system developed by the European Patent Office and the US Patent and Trademark Office. The CPC system incorporates the best classification practices of the two offices. The CPC system serves as an extension of the IPC and offers more detail than the IPC [137, 138].

The CPC is more suitable for classifying patent applications as it allows for more details[139]. The system consists of the Scheme complemented by the Definitions, which further define the subject matter and related references of the classification place under consideration [140].

5.2.3 Count of Claims

The patent claims represent the fundamental component of every patent document [126]. Each claim uniquely contributes to a particular invention [59] and describes the innovation's fundamental characteristics [60]. The claim or claims in a patent application must clearly and concisely define the subject matter for which protection is sought. These claims should be fully supported by the description provided in the application claims [141, 142]. Particularly, in a patent application, the filing fee allows for up to three independent claims and a maximum of twenty claims in total. Any additional claims incur extra fees.

Moreover, the number of claims included in a patent can also be influenced by the associated attorney fees, which often depend on the total count of claims. This fee structure incentivizes patent applicants to include fewer claims [141, 142]. In addition, a patent possessing a strong legal claim signifies its status as an owned asset and should not be subject to trade [51].

In several studies, the count of claims does not affect a patent's commercialization. This result was supported by a predictive model constructed by Huang et al. and Choi et al. [49, 51]. Since a patent's value depends on how much technological knowledge it may cover, the protection boundaries are particularly crucial in predicting patent transactions, and the protection scope is measured based on the number of claims [135].

In contrast, previous studies [29, 53-55] have employed the count of claims as an indicator for predicting patent transfer. In their research, the number of claims serves as an indicator of the intellectual property rights secured by a patent. Furthermore, the count of claims defines the scope of patent protection. Narrowing the scope of a patent significantly reduces the probability of successful licensing [143]. Finally, it is worth mentioning that while claim count indicates the scope of patent protection, it may not reliably predict patent transactions and may not be the most effective measure for a patent licensing prediction model.

5.2.4 Independent Claims Count

In the realm of patents, claims fall into two distinct categories: independent and dependent. Independent claims can stand alone and do not require reference to other claims for their interpretation. Independent claims' purpose is to outline the general technical context of the invention. It can be interpreted individually as they are considered to broaden a patent's scope based on claim construction principles. Although independent claims within a patent may overlap, they are generally not considered identical [141]. On the other hand, dependent claims must be read in conjunction with the claim they depend on [144].

According to Miyazawa and Osada, in the early stages of introducing a new product, the market leader focuses on having multiple broad and independent patent claims to capture a wide audience of innovative early adopters [145]. This strategy can secure a strong market share. On the other hand, during the later stages, the market leader emphasizes a mix of total claims, including specific dependent ones, to safeguard against competition and maintain dominance in a more mature market. This patent claim strategy directly influences licensing by initially enabling targeted licensing of groundbreaking features and transitioning to comprehensive licensing as the market evolves.

5.2.5 Claim Depth

Claim depth is a method for measuring patent scope using semantic patent claim analysis developed by Wittfoth [126]. This approach proposes a method for analyzing the interrelationships between independent and dependent claims using semantic dependency analysis to establish a patent scope indicator. The process involves several steps, including patent and claim preprocessing, identification of independent and dependent claims, creation of a dependency list for each claim, claim counting per dependency level, calculation of dependency depth, and its subsequent normalization. Finally, the patent scope is computed, as illustrated in Figure 5.1. The resulting normalized scope value falls within the range of 0 (narrow scope) to 1 (broad scope), allowing for meaningful comparisons among different patents.

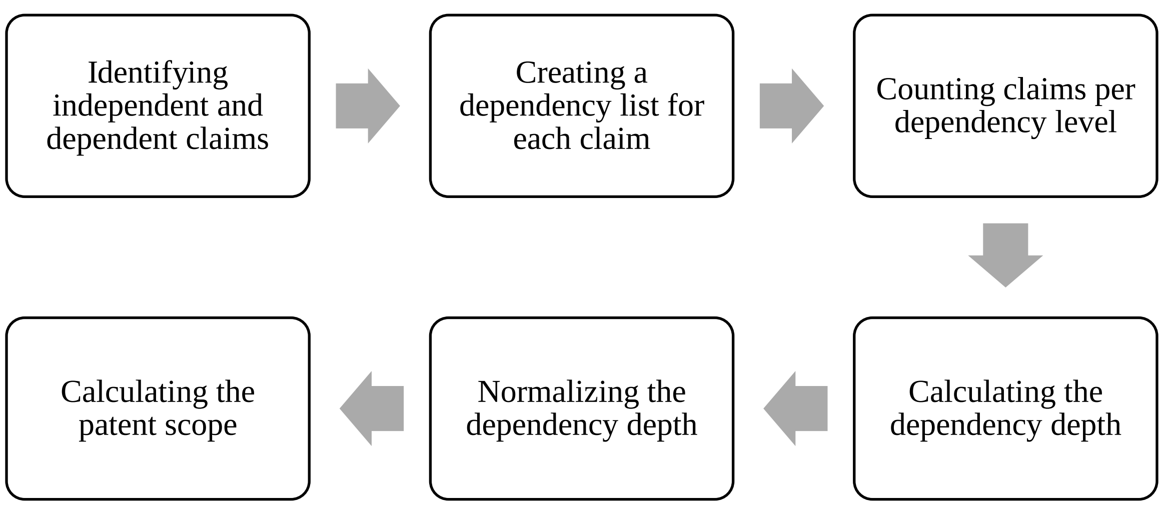

Figure 5.1:Claim depth pipeline

5.2.6 First Claim Length

In a US patent application, it is essential to incorporate at least a single independent claim, as this claim outlines the precise range of coverage being sought for the entire patent, particularly when no subsequent independent claims are present [146].

The length of the first claim serves as another valid measure of patent scope. This claim encapsulates the core of the invention and outlines its potential applications. The length of the first claim can reflect the patented invention's simplicity and the patent claim's writing style [147].

Research by Kuhn and Thompson [123] indicates that, on average, longer claims tend to be narrower than shorter ones. Longer claims often contain more specific details, which would increase the risk of infringement if they were broader. Additionally, Okada et al. [148] found that an increase in the number of elements limiting the scope of the patent right correlates with a corresponding growth in the length of the claim. This correlation highlights the substantial predictive capacity of claim breadth in assessing patent value, quantified by the reciprocal of claim length.

5.2.7 Simple Family Application Count

Patent families are a group of patents that are related to each other, stemming from a single original patent application. These related patents can include both granted patents and pending patent applications[149, 150]. Given the application, translation, and legal costs, the number of patent families is worth considering as a proxy for technological power and, hence, protection boundaries [52, 66]. This variable was mentioned to be a good estimator input for the model of Choi et al. [49] and for Lee et al. [54] model. Kim et al. [29, 55] used the variable as a measure of market impact.

Non-US Family Application Count

Non-US family patents are part of patent families that include multiple related filings in different jurisdictions. The number of countries in which a given invention is protected is often used as a measure of patent value[149]. The structure of international patent families reflects the patenting strategies of innovators and the characteristics of different patent systems [151]. The count of family outside the United States serves as an indicator of expanded market opportunities.

5.2.8 US Family Independent Claims Count

Continuation and divisional filings allow patent applicants to file new patent applications related to earlier filed applications, providing the benefit of the earlier filing dates. The written description requirement is crucial in determining the patentability of these continuing applications [152]. The proposed indicator, Family Independent Claims, is determined by the sum of independent claims granted to US family members. The indicator can serve as a robust indicator of the patent breadth.

5.3 Methodology

The methodology section outlines a comprehensive approach, encompassing data collection, processing, and analysis of diverse patent scope indicators through different statistical and data visualization methods.

5.3.1 Data Collection

Effective data collection is essential for informed decision-making and empirical analysis, enabling the construction of meaningful insights and conclusions. We begin by identifying the target group, followed by conducting our search.

The methodology starts with identifying the target group. The target group centered on robotics and automation, specifically selecting manipulators and chambers equipped with manipulation devices falling within the B25J category in IPC or CPC subclasses. Furthermore, to cover the digital data processing of the advanced robotics capabilities, we searched using the term "Robot*" to explore patent document titles, abstracts, or claims and G06F (electric digital data processing) within IPC or CPC subclasses. Next, we identified the jurisdiction as the US patent office where the sought-after patents have been granted. This choice narrows the focus to distinct regions. Additionally, we designated the original assignee to be AUTM University Assignees. Lastly, we restricted our scope to include only granted patents issued from 2001 to 2021. The data selected in The AUTM University assignees are based on the database called STATT [153]. This database contains historical data for 30 years for AUTM Assignees, including the assignee's name and information about the technology transfer office of the assignees. The original Assignee is the owner of the patent as written on the patent document [67].

The search terms.

((CPC_SUB_CLASS: B25J OR IPC_SUB_CLASS: B25J OR ((CPC_SUB_CLASS: G06F OR IPC_SUB_CLASS: G06F) AND TAC:(robot*))

AND AUTHORITY:(US)

AND PATENT_TYPE:(B)

AND AN:(AUTM). AUTM represents the list of the AUTM University Assignees

AND ISD:[20010101 TO 20211231]

We searched and retrieved data from the Patsnap website [67]. PatSnap Analytics is proficient in conducting precise worldwide patent searches and analyzing patents. PatSnap delivers a comprehensive IP analytics platform to aid businesses, researchers, and intellectual property professionals in making well-informed decisions related to patents and innovation. Their extensive database encompasses details from over 180 million global patent applications and 2.66 billion legal data sources [154]. Patsnap offers the capability to choose specific data for download, such as publication numbers, claims, CPC, IPC, and simple family.

5.3.2 Data Processing

Data processing and data cleaning are essential steps in analyzing data and making informed decisions, especially within domains such as data science, ML, and other relevant fields. We started with data cleaning by checking if there was a missing value. Google's patent website was also used to check the values and copy the claims. Followed by removing the outliers.

The transformation and integration process involves data preprocessing to render it suitable for analysis. The data information format is based on the content of the columns. Text data contains strings as *"str*" or lists. We employed Python for data processing, visualization, and statistical analysis.

For Text processing, first, we converted the text to a list. Each item represents a claim, and IPC and CPC represent the classification. This initial stage assists in extracting information individually, which will be subjected to subsequent processing.

Next, we identified which patents have licenses by looking for "License" in the "Legal Status & Events" column. The resulting "*licensed*" column will assume a true value if the corresponding entry in the "Legal Status & Events" column contains the term "License" and is false otherwise. Following this identification, the Boolean representation is transformed into numerical values, where 1 signifies licensed, and 0 signifies unlicensed.

To extract the for IPC and CPCsubclass, we specifically focused on the first four digits. These digits encompass the first character denoting the section, the second and third digits indicating the class, and the fourth character representing the subclass. Subsequently, we eliminated any duplicates from the extracted subclasses.

For claim identification, we utilized text processing methods to split the claims into independent and dependent claims. The pattern includes:

- Dependent claims contain one of the following words: *"of claim"*, "*to claim"*, "*claims,"* or "*claim"*.
- Independent claims do not contain the words: "*of claim"*, "*to claim"*, "*claim"*, "*claim", or* "*claims"*.

Identifying the independent and dependent claims is required to perform the claim dependency analysis and count the number of independent claims.

We used the *len()* function to return the number of items in the list to compute the Count Number of Independent Claims represented as *"Independent Claims_Count"*, and the IPC and CPC subclass as *"IPC_4_Count"* , "*CPC_4_Count"* respectively for each patent.

For counting the Length of the First Independent Claim represented as *"ind_word_count"*. We extracted the first independent claim from the independent claim list for each patent and used the *len()* function to return the number of words**.**

The last measure we need to calculate is Claim Depth, represented as **"***scope*". In this stage, we performed three key steps: dependency analysis, calculating claim depth, and calculating the patent scope. The dependency analysis method developed by Wittfoth [126] employs semantic analysis to perform dependency analysis on patent claims. Dependency analysis includes examining the relationships between different claims to understand how they depend on each other. In addition, the claim depth is determined by assessing the hierarchical level of each claim in the entire patent document. This step also involves evaluating the interdependencies among various clauses present in the claims. By analyzing these dependencies, the claim depth provides insights into the layered structure of claims. Therefore, this approach combines semantic analysis with dependency evaluation to calculate claim depth, revealing the claims' hierarchical arrangement and the interplay between their components.

As an example, dependency analysis calculation is shown in Table 5.1. The table shows the matrix dependency level for the claims and the total count for each level. Followed by the equation to calculate the depth as presented in eq. 1 [126] and sample of calculation.

Table 5.1: Matrix for the sum calculation per dependency level for US7400108B2

	Independent Claim	Subclaim Level 1	Subclaim Level 2
	1		
		2	
		3	
		4	
		5	
		6	
		7	
			8
		9	
	10		
		11	
		12	
		13	
		14	
Total Count	2	11	1

$$depth = \frac{(nIndependent + nMultiple) * 0 + nSubL1 * 1 + .. + nSubLn * n}{nClaims} \quad (1)$$

$depth(\text{US7400108B2}) = \frac{(2+0)*0+11*1+1*2}{14}$ = 0. 928571

The next step is to normalize the claim depth. This process involves standardizing claim depth values, enabling seamless comparisons across different patent documents with varying numbers of claims. By normalizing claim depths, we bring all the claims to a standard scale, making it easier to compare and assess the relative depth of claims across different patents. The normalization helps reduce noise caused by the varying number of claims and enhances the accuracy, fairness, and meaningfulness of comparisons and analyses involving patent documents. It provides a standardized metric that facilitates better understanding and evaluation of the complexity and significance inherent in patent claims across various documents. Finally, calculate the patent scope.

The patent scope we calculated based on αdep and α max. αdep as shown in Eq. (2) [126] calculated based on the arctan of the depth from eq (1) over the total number of claims minus 1. αMax presented in eq (3) [126] is the theoretical maximal depth patent. The calculation is based on the arctan of the subclaim level multiplied by one over the (max subclaim levels) over the (max subclaim level – 1). Finally, the patent scope presented in eq (4) [126] is equal to 1 minus the divided αdep over αMax.

$$\alpha\text{dep} = \arctan\left(\frac{depth}{nclaims - 1}\right) \tag{2}$$

$$\alpha Max = \arctan\left(\frac{\frac{\sum_1^a 1 * a}{a}}{a - 1}\right) \tag{3}$$

$$Patent\ Scope = 1 - \frac{\alpha dep}{\alpha Max} \tag{4}$$

a: subclaim level

depth: value calculated from Eq. (1)

nclaims: the total number of claims

The results for the given example patent, US7400108B2, were αdep = 0.071307465, αMax = 0.982793723, and a Patent Scope of 0.927444119.

To establish family indicators, we initiated the process by converting the "*simple family*" column into a list and retaining only unique values. Subsequently, we acquired the unique family patent application numbers, along with patent type, claims, and claim counts, from Patsnap [67]. For the *"family count",* we excluded data pertaining to U.S. applications and patents. We then calculated the count of rows in the family data where the 'Publication Number' matches any value in the family list.

Regarding the US Family Independent Claims Count, which is presented as *"Family Ind Count*," our approach involved first eliminating the application numbers from the simple family column if included. From the family data, we removed non-U.S. data, retaining only granted U.S. patents. Subsequently, we calculated the independent count of claims as previously done. Finally, we computed the sum of the independent count of claims where the 'Publication Number' matches any value in the family list, then added it to "*Independent Claims_Count*".

5.3.3 Statistical Tests

The characteristics of the data at hand determine the choice of the statistical method. This article's dataset comprises binary outcome, while the suggested predictors are numerical—two statistical tests employed to investigate the distinctions between the licensed and unlicensed groups.

The first selected statistical measure is the Point-biserial correlation coefficient (r_{pb}). This metric is akin to Pearson's product-moment correlation coefficient but is specifically suited for assessing the correlation between a continuous variable and a naturally occurring dichotomous variable [155]. This choice aligns with the inherent characteristics of our data, facilitating a meaningful analysis of the relationship between these variables. The decision will be based on the r_{pb} value: there is no association ($r_{pb} < 0.1$), poor ($r_{pb} = 0.1$ to 0.14), acceptable ($r_{pb} = 0.15$ to 0.19), good ($r_{pb} = 0.2$ to 0.29), and excellent ($r_{pb} \geq 0.30$) [156-158].

The second statistical method commonly used to assess differences between the means of two groups is the t-test. The hypotheses are:

- Null Hypothesis (H0): The two groups (e.g., licensed and unlicensed) have the same mean.
- Alternative Hypothesis (H1): The two groups do not have the same mean.

The tests assume the null hypothesis is true. If the resulting p-value is below a predetermined significance level (often 0.05), the null hypothesis is rejected, indicating evidence the licensed and unlicensed groups do not have the same mean. Conversely, if the p-value is above the significance level, there is insufficient evidence to reject the null hypothesis, suggesting both groups have the same meaning.

5.4 Results and Discussions

After loading and cleaning the data, 289 patents were found within the robotics and automation field granted to the AUTM assignees. Licensed patents represent 26.3% of these and unlicensed

73.3%. Figure 5.2 illustrates a bar chart of the number of licensed and unlicensed patents and a pie chart with the proportion of licensed and unlicensed patents.

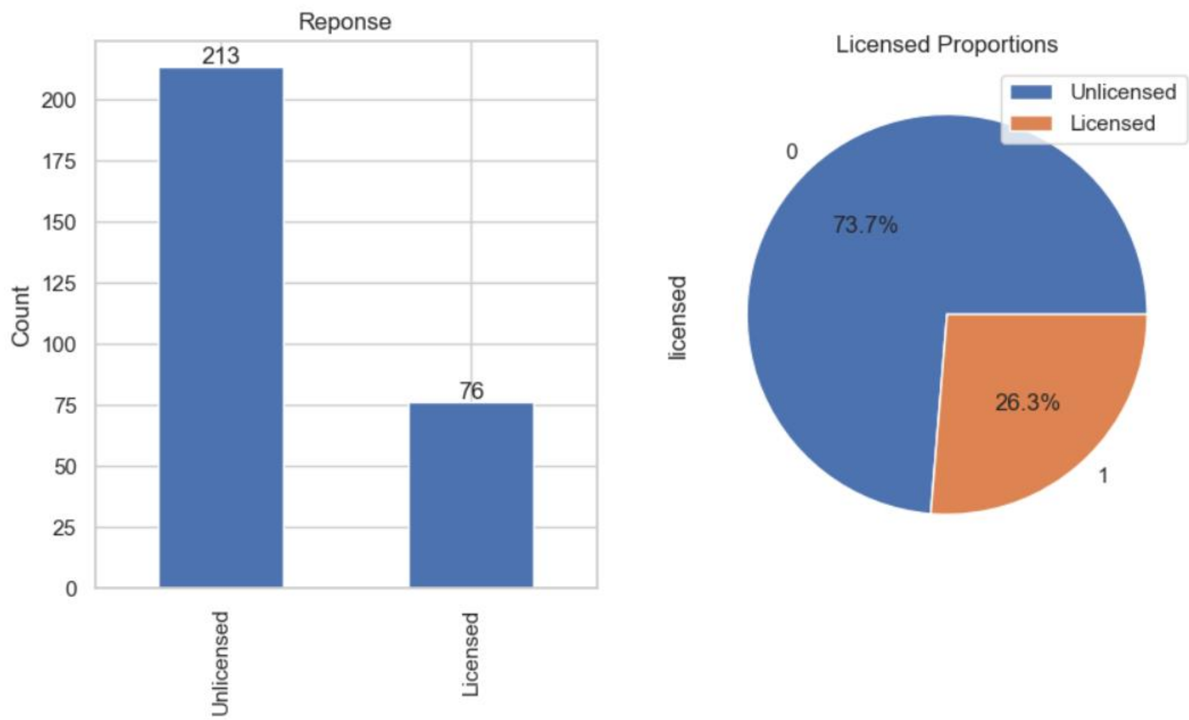

Figure 5.2: License and unlicensed patent proportion

To have a quick insight into measures correlation and patterns. Scatter plots and histograms illustrated relationships and distributions among the measures, as shown in Figure 5.3. Points on scatter plots show measurement connections, while histograms reveal individual measure distributions. Colors distinguish data points by their 'licensed' status.

A positive relationship was indicated between the count of claims and the number of independent claims. The correlation implies that as the count of independent claims increases, the overall count of claims also tends to rise. This correlation is based on the fact that the count of claims includes both dependent and independent claims, with each independent claim potentially having multiple dependent claims. In addition, a positive relation is also presented between the number of independent claims and Family Ind Count. On the other hand, there is no correlation between the other scope measures. As can be observed in Figure 5.3, we notice that the distribution for both groups, licensed and licensed, looks the same except for the independent claim count Figure 5.3 (c-3). In section 4.2, we tested if there was a significant difference in the distribution using the T-test.

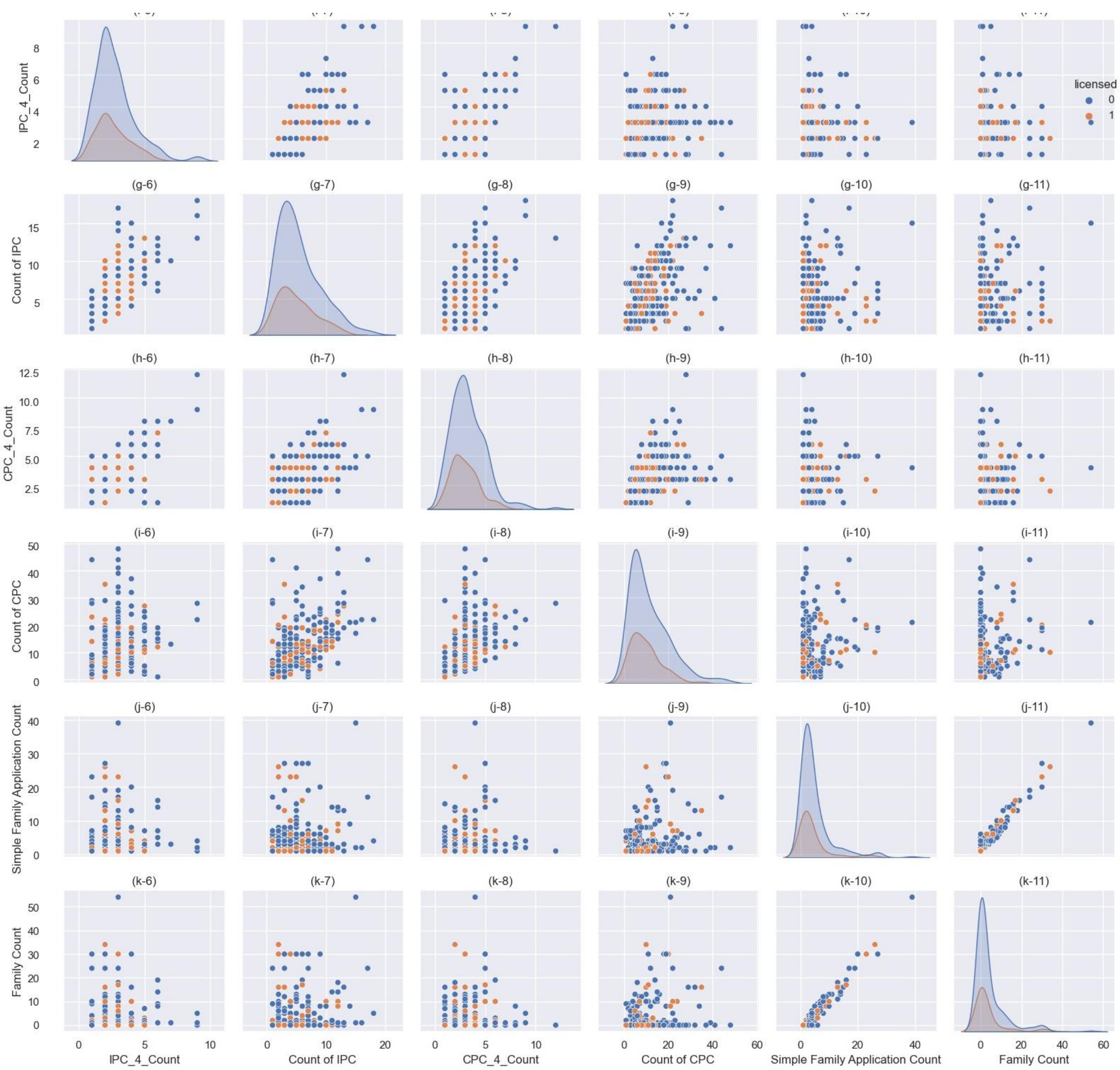

Figure 5.3: Correlations between measures (Blue: unlicensed, Orange: licensed)

5.4.1 Descriptive Statistics Results

Basic Statistics for licensed and unlicensed patent groups are presented in Table 5.2: Descriptive statistics for licensed and unlicensed patents. The "*Licensed*" group has a higher mean number of independent claims (2.91) compared to the "*Unlicensed*" group (2.53). Additionally, the standard deviation for "*Licensed*" (1.65) is greater than that of "*Unlicensed*" (1.29), suggesting greater variability in the former. The maximum value in "*Licensed*" (10) is significantly higher than "*Unlicensed*" (7). These measures indicate distinct characteristics in the mean of independent claims between the two groups, providing valuable insights and matching what was mentioned previously by Miyazawa and Osada [145] that the early adopter stage has more independent claims in the category of a product for sale.

Table 5.2: Descriptive statistics for licensed and unlicensed patents

Descriptive statistics	scope		ind_word_count		Independent Claims_Count		Count of Claims		Family Ind Count	
	Unlicensed	licensed	Unlicensed	licensed	Unlicensed	licensed	Unlicensed	licensed	Unlicensed	licensed
mean	0.911	0.914	176.87	181.84	2.53	2.91	19.62	20.91	4.31	4.62
std	0.098	0.061	92.68	79.55	1.29	1.65	9.91	10.15	4.71	3.37
min	0.122	0.568	52	46	1	1	3	4	1	1
25%	0.893	0.890	111	126.25	2	2	14	16	2	2
50%	0.933	0.925	157	175.5	2	3	19	20	3	3
75%	0.953	0.949	216	217.25	3	3	22	23	5	6
max	1	1	649	461	7	10	63	53	45	18
Descriptive statistics	IPC_4_Count		Count of IPC		CPC_4_Count		Count of CPC		Simple Family Application Count	
	Unlicensed	licensed	Unlicensed	licensed	Unlicensed	licensed	Unlicensed	licensed	Unlicensed	licensed
mean	2.72	2.58	5.41	4.99	3.31	2.96	11.62	9.70	4.84	4.21

std	1.49	1.24	3.57	3.10	1.70	1.35	9.18	6.85	5.82	5.55
min	1	1	1	1	1	1	1	1	1	1
25%	2	2	3	3	2	2	5	5	1	1
50%	2	2	5	4	3	3	9	8.5	3	2
75%	3	3	7	7	4	4	17	13	5	4
max	9	6	18	13	12	7	48	35	39	26

Descriptive statistics	Family Count	
	Unlicensed	licensed
mean	2.59	2.14
std	4.75	4.64
min	0	0
25%	0	0
50%	1	0
75%	3	1
max	32	21

The Count of Claims has a slightly higher mean (20.91) for the "*licensed*" group compared to the "*unlicensed*" group (19.62), indicating that, on average, patents in the licensed group tend to have more total claims. “*licensed*" group have a slightly higher (50th percentile) median values (20) “*unlicensed”* group median is (19).

The presented results align well with the requirement that no additional fees are needed for patents with total claims less than or equal to 20 and independent claims less than or equal to 3. Most patents in the "*Unlicensed*" and "*Licensed*" groups fall below these claim limits, indicating that most cases would not incur extra fees. However, some "*Licensed*" patents have higher claim counts, potentially suggesting that additional claims might enhance their licensing potential, warranting extra fees in such cases. The statistics support that most patents adhere to the claim limits, but certain patents may benefit from additional claims to improve their licensing prospects. This finding is also supported in the studies conducted by Huang et al. and Choi et al. [49, 51], which demonstrate that the count of claims is not a pivotal predictor for patent licensing prediction.

IPC_4_Count mean values for both groups exhibit close proximity, standing at 2.58 for the "licensed" group and 2.72 for the "*unlicensed*" group. This proximity suggests a similarity in the average number of patents encompassing the same IPC_4 subclass count across both groups. With a relatively low standard deviation for each group, the distribution of patents across the IPC_4 subclass displays a moderate degree of consistency for both groups aligned at 2 (same median values), indicating a consistent central value for patents covering IPC_4 subclass across the two categories. These outcomes deviate from prior research findings [49, 51, 53, 55, 57, 58], which emphasized the significance of this metric in predicting licensing potential.

Count of IPC mean values for "*licensed*" (4.99) for the " *unlicensed* " (5.41). Both groups have relatively moderate standard deviation for "*licensed*" (3.57) and (3.10) for " *unlicensed* " group. The distribution of patents across the *Count of IPC* displays a moderate degree of consistency for both groups aligned at 3 (same median values), indicating a consistent central value for patents covering *Count of IPC* subclass across the two categories.

On the contrasting side, the mean "*Count of CPC"* is notably higher for the *"unlicensed*" group (11.62) in comparison to the licensed group, with a mean of 9.7. This discrepancy surpasses that observed in the *"Count of IPC"*. The results exhibit substantial variability, as evidenced by the standard deviations of 9.18 and 6.85 for the *"unlicensed"* and *"licensed"* groups, respectively.

The 50% value for the *“unlicensed”* group (9) is marginally higher than that for the *“licensed”* group (8.5), suggesting a prevailing higher *“Count of CPC”* in general.

Furthermore, it is worth noting that a higher *“Count of CPC”* appears to be negatively correlated with the likelihood of being licensed. This is discerned by the expectation that a greater *“Count of CPC”* is associated with a lower likelihood of being licensed. This observation is supported by the 75th percentile values, where the *“unlicensed”* group exhibits a higher value of 17, while the *“licensed”* group has a lower value of 13. The *Count of CPC* may serve as a more effective indicator when compared to the *Count of IPC*.

The *"CPC_4_Count"* shows that the mean is higher for the *"Unlicensed"* group (3.31) compared to the *"Licensed"* group (2.96). The standard deviation is wider for *"Unlicensed"* (1.7) than for *"Licensed"* (1.35). The maximum is 12 for *"Unlicensed"* and 7 for *"Licensed."* In summary, the *"CPC_4_Count"* tends to be higher and more variable in the *"Unlicensed"* group.

The outcomes of the *scope* analysis reveal elevated values for both groups, with the same mean values hovering at approximately 0.91. These results underscore that most patents within both groups exhibit profound dependencies, nearly approaching the maximal achievable value of 1, meaning that the patents have a broad scope—relatively low variability. The standard deviation for the *“licensed”* group is (0.06), whereas the unlicensed group has a higher standard deviation (0.1); this indicates a tight clustering of scope around their respective means. Interestingly, the minimum and 25th percentile (0.89), median, and 75th (0.95) percentile values also closely approach the maximum value of 1. The max value (1) means that there are no dependent claims.

The statistical summary of the initial independent claim length presents the following insights. The "*Unlicensed*" group exhibits a slightly lower mean length at 176.87 words than the "*Licensed*" group's mean length of 181.84 words. Both groups show certain variability, as indicated by their standard deviations of 92.68 and 79.55, respectively. Looking at the lower range, the minimum, and 25th percentile lengths suggest that both groups encompass patents featuring relatively concise first independent claims, with the *"Licensed"* group demonstrating a slightly smaller minimum length of 46 words in contrast to the "*Unlicensed*" group's 52 words. On the other hand, the median and 75th percentile values shed light on a prevailing trend: most patents across both groups showcase moderately extensive to substantial lengths for their first independent claims.

In terms of *"Family Ind Count*," unlicensed cases exhibit an average of 4.31 family individuals, with a broader distribution indicated by a standard deviation of 4.71. In contrast, licensed cases have a slightly higher average of 4.62 family individuals and a lower standard deviation of 3.37, suggesting less variability. The range of family sizes spans from a minimum of 1 to a maximum of 45 for unlicensed cases and 18 for licensed cases. The median values, representing the central tendencies, are 3 for both unlicensed and licensed cases, underscoring the prevalence of cases with this family size.

The *"Simple Family Application Count"* statistics reveal differences between "*unlicensed"* and '*licensed'* groups. On average, '*unlicensed'* has a higher mean (4.84) compared to '*licensed'* (4.21). Both groups have high variability, with higher variability for the "*unlicensed"* group (5.82 vs. 5.55). Both groups share a minimum count of 1, which is mean that there is no other application or patent related to this patent, and the median is 3 for "*unlicensed"* and 2 for "*licensed"*. The 75th percentile shows that 75% of "*unlicensed"* have a count of 5 or below, while for "*licensed"*, it's 4 or below.

The *'Family Count' shows that the mean for the "unlicensed" group is slightly higher (2.59) than the "licensed" group* (2.14). Both groups display considerable variability, indicated by high standard deviations (4.75 and 4.64, respectively). The minimum *"family count"* is 0 in both groups, suggesting instances with no patent application outside the US. The median is 1 for "*unlicensed*" and 0 for "*licensed*", and the 75th percentile is 3 for "*unlicensed*" and 1 for '*licensed.*' The observed outcome may stem from difficulties in the international commercialization of patents, which may arise from challenges in aligning policies between international investment agreements and the policy choices of involved parties concerning the management of technology transfer obligations [159]. Furthermore, the complexity lies in universities' challenges in pinpointing suitable companies for particular technologies and scientists' difficulties in identifying and locating technologies of interest [160].

5.4.2 Statistic Tests Results

The point-biserial correlation coefficient was employed to assess the relationship between predictors and patent licensing outcomes. The results, detailed in Table 5.3: Statistical test results, *"Independent Claims_Count,"* appear to have the most notable associations with licensing status, with values of 0.12. This r_{pb} value represents that there is a correlation, and needs more investigation. The t-test results with a p-value of 0.041 show that the independent claim counts mean of "licensed" and "unlicensed" groups are significantly different.

In contrast, the variable " Count of CPC" has a r_{pb} value that falls in the poor range and needs more investigation. The results of the t-test (0.097) indicate that there is no statistically significant difference in the mean values between the "licensed" and "unlicensed" groups concerning the "Count of CPC" and patent licensing. It is noteworthy that, at 0.05 level of significance, we fail to reject the null hypothesis. However, it's crucial to mention that, under a more lenient significance level of 0.1 (using 90% confidence interval), the observed non-significance may be deemed acceptable.

For the *“scope,” “ind_word_count,” “Count of Claims,”“Family Ind Count,” “IPC_4_Count,” “Count of IPC,” “CPC_4_Count, ” “Simple Family Application Count,” and “Family Count”* the r_{pb} values are all below 0.1, indicating no significant correlation. Specifically, the r_{pb} values are 0.02, 0.02, 0.06, 0.03, -0.04, -0.05, -0.09, -0.05, and -0.03, respectively. These relatively low r_{pb} values imply that these indicators do not substantially influence the licensing status of patents within the provided dataset. Furthermore, the t-test outcomes show a lack of substantial mean difference. They all yield p-values exceeding 0.05, signifying that the mean does not exhibit significant differences between the "*licensed*" and "*unlicensed*" groups.

Table 5.3: Statistical test results

Predictor	**Point-biserial correlation coefficient**	**t-test p-value**
scope	0.02	0.785
ind_word_count	0.02	0.678
Independent Claims_Count	0.12	0.041
Count of Claims	0.06	0.334
Family Ind Count	0.03	0.594
IPC_4_Count	-0.04	0.467
Count of IPC	-0.05	0.362
CPC_4_Count	-0.09	0.112
Count of CPC	-0.1	0.097
Simple Family Application Count	-0.05	0.417
Family Count	-0.04	0.479

Both tests consistently affirm *"Independent Claims_Count"* as the good predictor for the licensing prediction model.

5.5 Summary

The findings of this study hold promising implications for the realms of robotics and automation patents granted to AUTM University assignees. Notably, the proportion of patents issued for licensing is 26.1% of the overall patents granted. This study focused on technology transfers within these domains, demonstrating that independent claims counts are a good predictive factor within the patent licensing prediction model. Notably, the methodology adaptability extends to evaluating diverse patent metrics and assignee factors.

This study emphasizes the critical role of selecting suitable predictors from patent data and enhancing decision-making in intellectual property management and licensing strategies. Particularly noteworthy is the essential role played by the number of independent claims. Nevertheless, future endeavors should extend this analysis to encompass various technological fields and assignee groups, exploring new predictors. A more expansive investigation is poised to provide a comprehensive understanding of patent licensing outcomes across different domains, ultimately enhancing strategic decision-making and augmenting the worth of intellectual property assets.

The data analysis indicates the potency of the independent claims counts as a good predictor within the patent licensing model. This association is supported by both the point-biserial correlation coefficient and the t-tests. In contrast, variables such as Count of Claims, IPC and CPC count and subclass count, scope, first claim length, Simple Family Application, non US family count, and the family independent count exhibit no significant linkage with licensing status.

This article highlights the variability of patent licensing predictors contingent on the technological landscape and the assignee group involved. The significance of this research lies in identifying effective predictors for patent scope in a specific technological field, along with the versatile application of the same methodology for evaluating diverse predictors across different contexts.

Finally, it is essential to acknowledge a limitation in our study's scope, which centers exclusively on technology transfers in robotics and automation within AUTM university assignees. While these insights offer value within this context, generalizing the findings to other technological fields or assignee groups should be done cautiously.

In conclusion, our research results highlight the significance of independent claim counts as a pivotal predictor in patent licensing, particularly within the robotics and automation field. The main contributions lie in its potential to inform intellectual property management strategies and highlight the role of specific predictors in different technological contexts. As research progresses, a more comprehensive understanding of patent licensing dynamics across diverse fields will undoubtedly enhance decision-making and maximize the value of intellectual property.

Chapter 6. University Technology Transfer Predictive Modeling

Efficient technology transfer is crucial for successfully commercializing inventions, generating billions of dollars in licensing revenue annually. This research addresses the need for improved efficiency within technology transfer offices by developing a supervised machine learning classification model to predict patent licensing success. The feature selection was based on data on robotics and automation technology, and we used logistic regression. The predictor variables are forward citations, independent claims count, similar patents, backward citation, technology transfer success rate, and inventor experience. The selected technologies to test the model's validity were robotics and automation, image processing, and additive manufacturing. The model achieved consistent performance metrics across all three datasets, particularly in predicting success within robotics and automation, which aligned with the dataset used for exploratory data analysis and variable selection. Key variables that significantly influence the model are the forward citations representing the external recognition in licensing success and the technology transfer office's success rate emphasizing the role of technology transfer offices over the three technologies. The inventor's experience is also a critical factor in licensing success and the backward citation for image processing and robotics technologies. The results also show that even though we used the same predictor variables to build the models for all the technologies. These variables influence each model differently, meaning each technology has its characteristics that need to be investigated and considered.

6.1 Introduction

The university technology transfer process includes identifying, protecting, and marketing the university research output to transfer these into business opportunities and generate money [161]. The TTO is a unit established by universities and organizations to facilitate ideas and investment flow, including patent licensing [121, 161].

Technology transfer is critical for the commercialization of inventions, with billions of dollars in licensing revenue generated annually [36]. Nevertheless, the process from disclosure to commercialization is resource-intensive and faces substantial challenges. Some of these challenges relate to technology, which is complex and embedded in knowledge, compositions, and complex operations. In addition, challenges include the interactive context of the process, such as inefficient cooperation and communication between TTO and technology recipients [162].

On average, the time allocated to a successful invention within a TTO is evenly divided, with approximately half of the efforts dedicated to post-patent activities. The post-patent activities focused on commercialization take priority, encompassing negotiations and drafting licenses, alongside subsequent responsibilities such as monitoring and enforcing license contracts [163].

Surprisingly, 90% of United States patents remain unlicensed [37], including many high-quality patented inventions developed by universities. Consequently, approximately $5 trillion spent on research and development in the US in the past two decades has led to unlicensed patents [38]. Because of all the previous reasons, TTOs have financial difficulties, with over half operating at a loss and only 16% self-sustaining [39]. Universities' TTO is no exception, as most universities fail to secure a positive net income from their intellectual property [164].

Previous studies have limited consideration of the role of TTOs in predictor models. Additionally, to the best of my knowledge, none of the existing studies have considered any predictors related to the inventor's experience. Thus, this study introduces a model with novel predictors to classify licensing outcomes specifically within the Automation and Robotics sector for University TTOs.

The rest of this chapter is organized into four sections. Section 6.2 presents the literature review. Section 6.3 outlines the methodology, including the predictor definitions, data collection and analysis, and the development and validation of the prediction model. Section 6.4 shows the results and discussions. The last section 6.5, presents the summary.

6.2 Literature Review

To investigate the relationships between different variables and their impact on patent licensing. Choi et al. [49] conducted a patent analysis using 21 variables: applicant affiliation, time, Backward citations, Forward citations, Number of claims, number of inventors, and more. They employed Social Network Analysis (SNA), regression analysis, and decision tree modeling to analyze the data. Their research creates a general model that includes all types of institutions (nation research institute, public university, private university, collaborative research, country). In addition, Choi et al. [49] have a model for each type. The patent's novelty was the most significant influence on the public university model. For the private university model, the results showed that the most critical transfer nodes are the number of family countries, followed by the degree of the rights or the number of inventors, and then the time between the expiry date and the registered date or number of backward citations within domestic patents.

In the patent-based analysis of Huang et al. [51], their research focused on the data for the TFT-LCD technology. The methodology they used was the Multivariate probit model. The input variables considered various aspects of collaboration, knowledge, and legal protection in the context of patents. Their results show that assignee count, inventor counts, assignee country, backward citation, foreword citation, IPC count, and generality index influence the model.

In the study by Lee et al. [54], an ensemble modeling approach was employed to predict technology transfer using patent data for ML from the World Intellectual Property Services. The input variables included backward citations, period, claims count, family patent count, family country count, patent references, non-patent references, ownership transfer, and technology topic. Their study used Latent Dirichlet Allocation (LDA) to extract the technology topics, which were then integrated into different modeling ML algorithms, such as AdaBoost (AB), were used. Their findings revealed that incorporating technology topics extracted by LDA improved the predictive model's performance. Specifically, the AB Algorithm outperformed K-nearest neighbors (KNN), Support Vector Machine (SVM), and Neural Networks (NN) in accuracy, sensitivity, and specificity, indicating its efficacy in predicting patent-related outcomes.

In their work, Lin et al. [53] developed an intelligent classifier to analyze US pharmaceutical patents sourced from universities and colleges. The model focused on effectively identifying unlicensed patents within the pharmaceutical domain. The study used SVM as the classification methodology for the input variables such as assignee forward citations, IPC count, period, family countries count, forward citations, number of claims, and therapeutic indications. Results indicated that the classifier exhibited notable efficacy, particularly in its ability to discern unlicensed patents. Their model showcased satisfactory accuracy, signifying its capability to classify patents accurately, thus holding promise for enhancing patent analysis within the pharmaceutical sector.

In a study by Kim & Geum [52], they investigated the efficacy of various ML classifiers in predicting outcomes within the patents granted by the United States Patent and Trademark Office

(USPTO) and classification under G06Q (Information and Communication Technology [ICT] adapted for promoting, managing, practicing commercial, or financial activities [165]). Their model has ten variables, including patent-related variables such as forward citations, backward citations, similar patents, claims count, family patent count, and various assignee-related metrics, including backward citations, forward citations, family patent count, patent transfers, and similar patent transfers. The authors employed several ML techniques. Their findings revealed that Random Forest (RF) yielded the highest predictive performance, contrasting with Naive Bayes (NB), which exhibited the least effectiveness. Assignee-forward citations emerged as the most influential predictor. In contrast, other variables such as assignee similar patent transfers, assignee backward citations, assignee family patent count, and forward citations were identified as significant contributors to prediction accuracy.

The research of Kim et al. [29] examined the dynamics of technology commercialization patents of vascular surgery robots registered in the USPTO. The research focused on predicting technology commercialization outcomes. The study incorporated input variables such as expiration time, backward citations, forward citations, number of claims, number of inventors, family count, and family country count. Employing the Decision Tree (DT) Methodology, the findings underscored the significance of applicant rank (number of patents) in influencing technology commercialization within the domain.

In their recent study of Kim et al. [55], the authors explore the application of AI techniques within the domain of US patents, focusing on AI. Utilizing data sourced from the USPTO, the study incorporates an extensive array of input variables ranging from period, claim count, assignees count, and inventors count to various patent-related metrics such as backward citation, forward citation, family country count, family patent count, solo patent, standard patent, and litigation.

Employing advanced methodologies including but not limited to BERT, DeepInsight, Convolutional Neural Networks (CNN), RF, and AB, their study investigates the effectiveness of models trained with and without image data. Their findings reveal that models trained solely with non-image data outperform those incorporating image data, with RF exhibiting higher accuracy, AB showing the best precision, and CNN achieving the best recall and F1 score. Moreover, the study highlights the efficacy of Random Oversampling (RS) techniques compared to Synthetic Minority Oversampling (SMOTE). It underscores the advantage of employing ImageDataGenerator to train CNN models, which outperforms the accuracy of the original model.

6.3 Methodology

Chapter 6. methodology is structured around several critical subsections to facilitate a thorough examination of my research objectives. Firstly, the predictor definitions section serves as a foundational component, encompassing a comprehensive exploration of key predictors such as Forward Citations, Similar Patents, Independent Claims, Backward Citations, Technology Transfer Office Effectiveness, and Inventor Experience. This segment establishes the framework for subsequent analyses, clarifying the variables under scrutiny. Following this, the Data Collection phase outlines a systematic approach I employed to gather pertinent information, ensuring the inclusion of diverse and representative datasets. Subsequently, the Data Processing stage elucidates the methods I utilized to organize, clean, and prepare the collected data for analysis, ensuring accuracy and reliability. The Prediction Model and Validation section then details the development and assessment of predictive models, employing rigorous methodologies to evaluate model performance and validate results.

Together, these subsections form a framework that guides the research process, enabling a comprehensive exploration of my research questions and providing insightful conclusions.

6.3.1 Predictors Definitions

The model has six predictors: forward citations, similar patents, independent claims count, backward citations, TTO success rate, and inventor experience.

As mentioned in section 2.5.2, highly cited patents can be considered technological leaders, are more likely to be traded, and have a higher value [49, 50, 52, 63]. The count of forward citations increases over time. However, since the period between patent publication and issue date varies, preprocessing is required before it can be effectively used. The target is to count the forward citations before the patent issue year. The forward citation variable *“FW_C”* equals the count of forward citations calculated each year and normalized by the total forward citations in the field. The maximum value across these years represents the highest impact, as shown in equation 6.1.

$$FW\_C = \max \mathrm{FW\_ij}/\mathrm{TFW\_j} \qquad 6.1)$$

FW_C: Forward citation variable

FW_i: The count of forward citation for patent i in year j

TFW_j: The count of forward citations for patents in this field in year j

TTO will patent an invention for several reasons. One reason is that the technology has favorable market prospects [163]. Patents serve diverse purposes, covering various applications. The number of similar patents in the field helps to understand and indicate the market's size. For example, TTO may choose to patent an invention not only to secure investment for further development but also to establish themselves as industry pioneers, deter potential infringers, and facilitate technology transfer through licensing agreements. Thus, the number of similar patents in the field helps to understand and indicate the market's size. In addition, it can be used to measure the knowledge accumulation [52]. In this research, I use the number of patents issued and active five years prior to the issue date and share at least 50% of the similar technical characteristics to measure the market size. The CPC subclass will identify the technical characteristics. These similar patents provide an overview of the markets with comparable technological features. In my study, I represent this variable using the acronym *"Act_Sim"*.

The patent claims represent the fundamental component of every patent document [126]. There are two claims categories: independent and dependent. Independent Claims Count was clarified in section 5.2.4. The number of independent claims will be presented as "*Ind_Claims"* and used to demonstrate the patent's scope.

Backward citations are defined in section 2.5.1, which contains the total number of cited patents in the prior art in a patent [51]. For example, a higher number of backward citations generally indicates that the patented invention is more innovative and influential within its field, demonstrating its significance and potential for future development or commercialization. The *backward citations* variable in my research is represented as *"BW."*

The primary mission of the university TTO is to protect inventions and license technologies [166]. The skills and expertise of TTO staff directly impact the technology transfer process of I4.0 technologies [121]. The number of license and option agreements counted as one of the basic measures of the performance of TTO [167]. The measures related to licensing provide information about how many patents were licensed by the TTO [168]. In my study, TTO will be evaluated through the ratio of licensed patents to the total number of patents granted in the respective field. I present this variable as *"Assignee_Rate."*

Universities' technological inventors are primarily engaged in scientific research. These inventors often do not have experience steering the technology market, making it challenging to rapidly reach agreements on transactional specifics [169]. Collaboration and cooperation between inventors and TTOs are essential for successful commercialization, as a substantial percentage of licensed inventions require inventor involvement [170, 171]. TTO understands the inventors' important role in the commercialization process, where one of the reasons that TTO will patent an invention is the faculty inventor's experience in invention commercialization, especially the inventors' good track record of previously marketed inventions [163]. In my research, I utilize a binary metric to describe the presence or absence of prior experience among inventors in licensing patents. This variable is presented as *"Inv_exp"*.

6.3.2 Data Collection

Efficient data collection is a cornerstone for making well-informed decisions and conducting empirical analyses, facilitating the development of valuable insights and conclusions. The process commences with determining the target group, after which I execute the search.

In addition to the data set I have in Chapter 5 for robotics and automation, two more datasets were collected: G06T: Image Processing and B33Y: Additive Manufacturing. I will use the same methodology for data collection. The only difference in selecting is identifying the CPC and IPC subclass terms.

Image Processing Dataset: CPC_SUB_CLASS: G06T OR IPC_SUB_CLASS: G06T

Additive Manufacturing Dataset: CPC_SUB_CLASS: B33Y OR IPC_SUB_CLASS: B33Y

6.3.3 Data Processing

Data processing and cleaning are essential in analyzing data and making informed decisions, especially within data science and ML domains. I started with data cleaning by checking if there were any missing values.

The first step is to identify the licensed patents by looking for "*License*" in the "*Legal Status & Events*" column. The resulting "*licensed*" column will return a true value if the corresponding entry in the "Legal Status & Events" column contains the term "*License*" and false otherwise. Following this identification, the Boolean representation is transformed into numerical values, where 1 signifies licensed, and 0 indicates unlicensed.

The transformation and integration process involves data preprocessing to render it suitable for analysis. The data information format is based on the content of the columns. I used Python version (3.9.7) for data processing, visualization, and statistical analysis. I used several Python packages, including Pandas, NumPy, Matplotlib, and Seaborn.

The first step is to convert the *"str"* to list for *Cited by Patents, CPC, Claims, Standardized Original Assignee(Applicant),* and *Inventor name*. In addition, the *issue, application*, *publication, and expiry date* transformed from the "*str*" to DateTime format. Patnap provides all these columns. In addition, the *"BW" C*ount is also provided by Patsnap as *"Count of Cites Patents."* Data binning is used to solve the issue of data fluctuations for "*BW"*.

To calculate the *"FW_C,"* convert the items in Cited by Patents citation entries into individual elements by exploding the data frame. Subsequently, each cited patent's application date is identified, representing the citation date. Following this, I only select citations before the patent's issue date. Next, I calculate the count of citations for each year preceding the issue date by grouping citations based on their application dates and tallying the number of citations for each year. The citation counts obtained for each year are normalized by dividing them by the total number of forward citations in the respective field. Finally, I select the maximum normalized citation.

To calculate *"Act_Sim,"* I used CPC. My main focus is to extract the CPC subclass, represented in the first four digits, and eliminate any duplicates from the extracted subclasses. Then, I used the Jaccard similarity score for patents based on their CPC subclass codes. I search for similar patents issued and active within a five-year window in the US before the given issue year is selected. Then, I calculate the similarity scores between the CPC subclass codes of the target patent and those of the patents in the filtered five-year window. Finally, my code counts the similarity scores exceeding a threshold (0.5).

For *"Ind_Claims"*, a text processing method is used to identify the independent claims :

- Independent claims do not contain words: "*of claim*", "*to claim*", "*claim*", "*claim*", *or* "*claims*".

To calculate the *"Assignee_Rate,"* the first step is to match the Standardized Original Assignee(Applicant) with the institution in the STATT database and return the institution ID. I used the process from the rapidfuzz package to do the match and manually checked to validate the result. I used the five-year window for the number of patents issued and licensed for each ID calculation. Then, the *"Assignee_Rate"* is calculated from the number of patents licensed over the total number of patent issues.

The *"Inv_exp"* predictor is derived from the *'Inventor Name'* column. Initially, I generate binary indicators for each unique inventor's name to signify the presence or absence of patent licensing. These binary indicators are then summed across rows, considering any specified success indicators. If the cumulative sum for an inventor is equal to or greater than one, it indicates previous experience in patent licensing, and the "*Inv_exp*" value for that inventor is set to one; otherwise, it is set to zero. This binary outcome indicates an inventor's prior experience in patent licensing within the dataset.

6.3.4 Prediction Model and Validation

In this study I use a supervised ML classification algorithm, the Logistic Regression (LR). LR aims to predict class (categorical) labels, such as licensed or not licensed for a patent. Binary values represent these categories numerically [172, 173] (1: licensed, 0: not licensed). My model seeks to understand the relationship between the variables and the outcomes and the ability to interpret the data [173].

Data classification is a two-step process consisting of a learning step (where a classification model is constructed) and a classification step (where the model is used to predict class labels for given data) [172].

The first step is to prepare the dataset for modeling by separating the features from the target variable, where "*licensed*" denotes the target variable. Next, I split the dataset into training and test sets. Random Oversampling will be used to solve the class imbalance issue. This technique involved oversampling the minority class instances randomly to balance the class distribution.

Next, the logistic regression pipeline consists of two main steps: data scaling and LR classification. This pipeline served as the classification model. Following the pipeline setup, I specified a Stratified K-Fold Cross-Validation strategy with five splits. This approach ensured thorough shuffling for robustness during model evaluation.

To evaluate the performance of the classification model, I defined scoring metrics, including precision, recall, F1 score, specificity, and accuracy. These metrics provided comprehensive insights into the model's performance across various aspects of classification accuracy. The model's performance under different conditions ensures strength and generalizability.

Precision measures the model's performance to correctly classify the positive samples within all of them classified as positive. Recall is defined by the ratio of the true positive over the true positive and false negative. F1 measures the harmonic average of precision and recall. Specificity indicates the ratio of the correctly identified negative samples over the samples classified as negative by the model [53]. In addition to the previous measures, I use accuracy to assess the overall performance; this measure is considered true positive and true negative over all instances [54]. All the performance measures are presented in Table 6.1.

Table 6.1: Model performance measures equations

Measure	Equation
Precision	$\frac{TP}{TP + FP}$
Recall	$\frac{TP}{TP + FN}$
F1	$\frac{2 * \text{Recall} * \text{Precision}}{\text{Recall} + \text{Precision}}$
Specificity	$\frac{TN}{FP + TN}$
Accuracy	$\frac{TP + TN}{TP + FP + TN + FN}$
TP: True Positive, FP: False Positive, TN: True Negative, FN: False Negative	

6.4 Results and Discussions

To highlight the LR predictors and examine how these variables may influence licensing status, I need to explore their underlying structure and identify the predictors for LR. The first step is to investigate the correlation between the variables. All of my analysis is based on the Robotics and Automation dataset benchmark. The reason is having a high correlation between predictor variables can pose challenges for LR. Moreover, by focusing on a single benchmark dataset, I can control for variations in data quality, measurement techniques, and subject matter expertise, thus enhancing the reliability and validity of my analysis. The pairplot visualization presented in Figure

6.1 offers an overview examination of the relationships between variables in the dataset. I plotted graphs for each of the variable correlations against every other variable.

Upon thorough inspection of the pair plot, there is a lack of correlation between the variables. The scatter plots exhibit randomness or lack a discernible trend, indicating no linear relationships between the factors.

Upon thorough inspection of the pair plot, there is a lack of correlation between the variables. The scatter plots exhibit randomness or lack a discernible trend, indicating no linear relationships between the factors. With orange I illustrate the licensed groups, and with blue the unlicensed groups. The pair plot indicates a comparative analysis of the distributions and relationships between variables within the output for each group. This functionality enables us to evaluate whether there are any noticeable differences in patterns or distributions based on licensing status, which is crucial for understanding the impact of this variable on the output “licensed”.

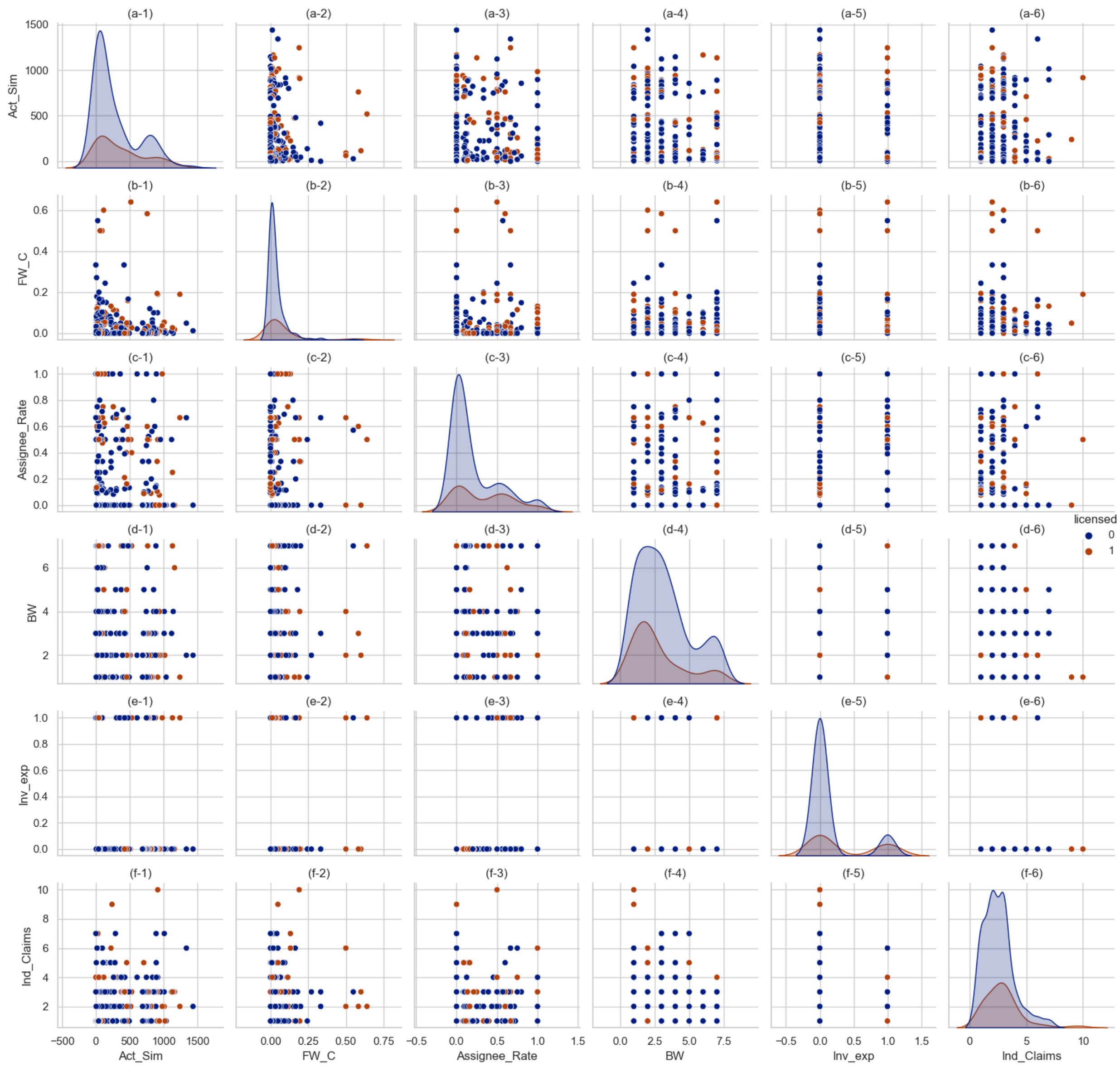

Figure 6.1: Variables pair plot

To validate and evaluate the performance of the classification model. The models will be trained and tested for three distinct datasets—Robotics and Automation, Image Processing, and Additive Manufacturing.

A general overview of datasets and patent-licensed percentages for Image Processing and Additive Manufacturing is illustrated in Figure 6.2 and Figure 6.3, respectively. There are differences in the presence of licensed patents. In the image processing dataset of 1541 patents, 406 were licensed (26.3%), while in the additive manufacturing dataset of 305 patents, 113 were licensed (37.0%). However, for the Robotics and Automation dataset, the licensed patents represent 26.3%, the same percentage as the Image processing. Nevertheless, the dataset for Image processing is much bigger. These findings highlight variations in licensing between the different technologies, suggesting potential differences in regulatory requirements or intellectual property practices.

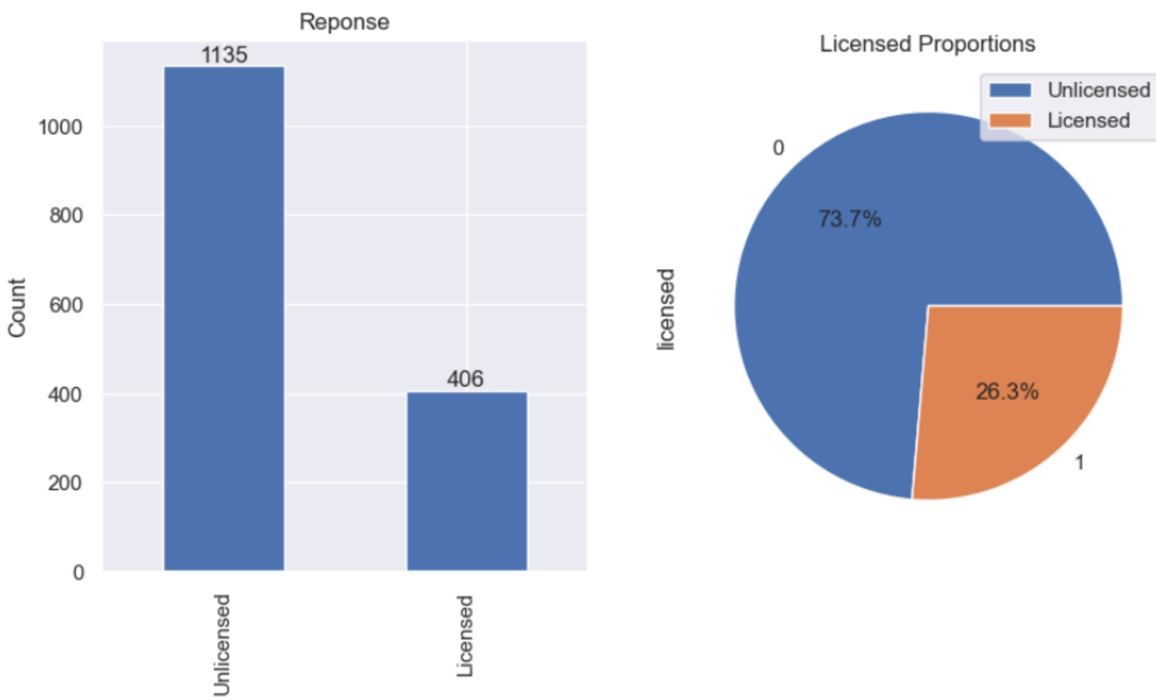

Figure 6.2: Image processing dataset and licensing percentage.

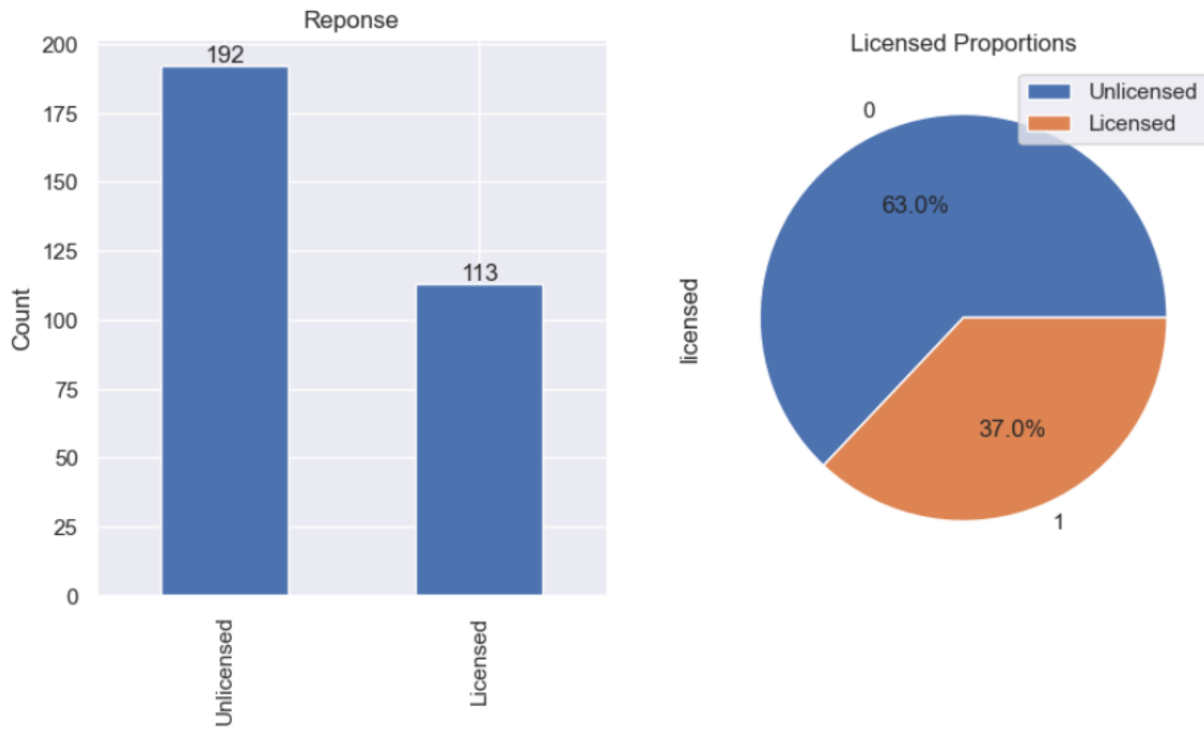

Figure 6.3: Additive manufacturing dataset and licensing percentage.

To validate and evaluate the performance of the classification model, I developed a model for each technology using the selected predictors. The model performance results are shown in Table 6.2. The precision scores for the Robotics and Automation Robotics dataset, Image Processing Model, and Additive Manufacturing dataset were 0.77, 0.67, and 0.71, respectively, indicating sufficient accuracy in correctly identifying positive instances within the Robotics and Automation Robotics dataset. However, precision scores for the Image Processing and Additive Manufacturing datasets were slightly lower, indicating a slightly lower accuracy in these domains.

Furthermore, the recall scores across the three datasets varied, with values of 0.66, 0.62, and 0.67 for the Robotics and Automation Robotics, Image Processing, and Additive Manufacturing datasets. The Additive Manufacturing dataset exhibited the highest recall score, indicating the model's effectiveness in capturing true positive instances within this domain. Similarly, the F1 scores, which combine precision and recall, reflected the model's overall performance, with values of 0.71, 0.64, and 0.68 for the Robotics and Automation, Image Processing, and Additive Manufacturing datasets.

Moreover, specificity scores were relatively higher, with values of 0.8 for the Robotics and Automation dataset. For Image Processing and Additive Manufacturing, datasets are 0.69 and 0.72, respectively, indicating the model's performance in identifying negative instances within each domain. Overall, the model's performance indicate a satisfactory level across all three datasets, with the Additive Manufacturing dataset showcasing better variations in precision, recall, and F1 scores, emphasizing the importance of tailored model adaptation for optimal results in each domain.

Table 6.2: Model performance measures

Measure	Robotics & Automation	Image Processing	Additive Manufacturing
Precision	0.77	0.67	0.71
Recall	0.66	0.62	0.67
F1	0.71	0.64	0.68
Specificity	0.8	0.69	0.72
Accuracy	0.73	0.65	0.69

The coefficients in LR are calculated after the model-fitting process to estimate the effect of each predictor variable (independent variable) on the licensing success (dependent variable). The results of the coefficients across the three datasets are presented in Table 6.3. Certain variables are the most significant and influential in predicting patent licensing success, while others are less important.

More specifically, among the most significant variables across all datasets are: the "*Assignee_Rate*", which consistently emerges as a key predictor, with positive coefficients indicating its strong positive association with the outcome in all three datasets; "*FW_C*" which demonstrates considerable importance, especially in the Robotics & Automation and Image Processing datasets, exhibiting the highest positive coefficients among all variables; and "*Inv_exp*" appears notably influential in Robotics & Automation and Image processing, with positive coefficients indicating its positive impact on the patent licensing success. "*Inv_exp*" also has a positive coefficient (0.0246) with the Additive Manufacturing model but with a less significant effect.

The "*BW*" results present the varying effects on the likelihood of patent licensing success. There is a negative effect given by the negative coefficients in the Robotics & Automation and Image Processing datasets (-0.3526 and -0.2219, respectively), suggesting that patents with fewer backward citations are more likely to show the patent licensing success, implying a potential preference for novelty and independence within these domains.

On the other hand, in the Additive Manufacturing dataset, the positive coefficient (0.0413) indicates that patents with more backward citations are likelier to show licensing success, suggesting a reliance on existing knowledge and innovations within this field. However, the effect is smaller than that for the other datasets. These perceptions emphasize the importance of considering domain-specific dynamics when interpreting the influence of backward citations on patent licensing success.

On the other hand, the variables with comparatively lesser significance include "*Ind_Claims*" and "*Act_Sim*." While still contributing to the predictability of the models, these variables exhibit smaller coefficients and less consistency in their effects across the different datasets.

Table 6.3: Variable coeficient using LR

Variable	Robotics & Automation	Image Processing	Additive Manufacturing
Act_Sim	0.0002	-8.717 e-06	-0.0041
FW_C	4.1490	3.5640	-1.3513
Assignee_Rate	1.5193	2.1600	1.3550
BW	-0.3526	-0.2219	0.0413
Inv_exp	1.5313	0.3446	0.0246
Ind_Claims	0.0131	-0.0505	-0.0098

6.5 Summary

In conclusion, my classification model has demonstrated its capability to predict patent licensing success, validated by the performance measures presented. The model shows relatively consistent performance across all three datasets, as indicated by precision, recall, F1 score, specificity, and accuracy values. The proposed model is adaptable and can handle different technologies. The model revealed the highest performance in predicting success within the Robotics and Automation field, which matches the fact that the exploratory data analysis and the variable selection are based on this dataset. The model successfully classified the licensed and unlicensed patents with a precision of 0.77 and a specificity of 0.8.

Crucial variables appeared as significant influencers in the model. Firstly, the success rate of the TTO was raised as a pivotal factor, emphasizing the essential role played by TTOs in the licensing process. Additionally, the influence of forward citations highlights the importance of external recognition and validation of patent innovations.

Moreover, my findings reveal the crucial role of inventors in the licensing process. Their active participation and understanding of the commercialization process significantly contribute to the success of patent licensing success. Furthermore, while backward citations demonstrated some influence on the model, their effect was comparatively lesser, indicating the impact of cumulative knowledge and progressive perspectives. On the other hand, The Independent Claims count and Similarity appeared less influential in the model.

My research lays a solid foundation for future research. While the current performance measures suggest the model's applicability across different technologies, further investigation into additional variables could enhance its predictive capabilities. By expanding the scope and refining the variables, I can continue to advance the understanding of patent licensing and contribute to more effective decision-making processes in technology commercialization.

Chapter 7. Conclusion

This dissertation aims to fill the gap related to the technology transfer process within the framework of I4.0, characterized by complex dynamics and challenges. Furthermore, it investigated the robotics and automation factors associated with licensing success, including the technology, TTO, and inventors factors, and predicted patent licensing. The main aim is to help TTOs enhance their performance and become self-sustainable.

Several methodologies were deployed, including a systematic literature review to synthesize the previous work-related I4.0 technology transfer and the available conceptual framework. For robotics and automation, statistical tools and analysis were used to find the factors associated with patent licensing success and feature selection. Models were developed using supervised ML to predict the patent licensing success for robotics and automation, image processing, and additive manufacturing.

My main contributions are presented by enhancing and expanding the available conceptual framework to match my findings and include the ecosystem factor to facilitate the adoption of I4.0 technologies, including clarifying the role played by the government, industry, and universities. In addition to the collaborative environment, the type and level of collaboration between technology recipients, agents, and inventors are required to succeed in the I4.0 technology transfer.

The government's role includes encouraging the industry to strive towards I4.0 through technology transfer. The government can facilitate the transition toward I4.0 via technology transfer by enacting legislation, financing support, and offering incentives for this transition. Besides that, it points out the need for modern legal tools to cover intangible technology with IP. The available legal tools are inadequate. These tools should be better suited for rapidly evolving technologies.

It is also worth mentioning that the technology recipient also needs to be considered where the manufacturing culture influences the success of I4.0 technology transfer when I focus on technological advancements such as the transition to I4.0. The skills and expertise of related employees in TTO directly impact the technology transfer process of I4.0 technologies.

Another contribution is the development of robotics and automation classification models. The model has shown its competency in predicting patent licensing success, and it has been validated and evaluated by the performance measures for three different technologies: robotics and automation, image processing, and additive manufacturing. The model shows relatively consistent performance across all three technologies, as indicated by precision, recall, F1 score, specificity, and accuracy values. The proposed model is adaptable and can handle different technologies.

In addition, the contribution presented critical factors influencing the models, which included the TTO's performance. Performance is achieved by the capabilities and skills of the TTO team to manage IP and commercialization activities. For universities looking to enhance their performance in licensing, more investment and focus should be considered TTO to improve staff experience in commercialization and enhance their networking and marketing channels.

In addition, for the model, the technology itself is also important, where external recognition and validation of patent innovations presented as forward citations are essential factors influencing the model to predict success in licensing.

The inventors have a role in most of the technology transfer process. Their role is not limited to the research part and creation of the invention; it extends to collaboration in the patent application process, TTO commercialization steps, and cooperation with industry. The model results emphasize the role of the inventor in patent licensing success. Inventor with expertise in the commercialization process has a better chance of success in patent licensing and need to be considered when managing the technology transfer process.

This dissertation also elaborates on the crucial role of selecting suitable predictors from patent data and enhancing decision-making in intellectual property management and patent licensing. The accumulation of knowledge also affects the success of patent licensing by using backward citations. Finally, the count of independent claims is considered when presenting the patent scope.

The limitation of this study is related to the boundaries of the technology transfer where national technology transfer is considered based on patents registered in the US. Feature selection was done based only on robotics and automation technology. In addition, three I4.0 technologies were tested: robotics and automation, image processing, and additive manufacturing.

By tackling these constraints, forthcoming research endeavors can improve the relevance and efficacy of predictive models by exploring more technologies from I4.0. Further development of this model can include trying other machine learning algorithms, such as deep learning algorithms, to improve the model's performance. Each technology possesses unique features, necessitating tailored feature selection approaches to effectively address specific requirements and objectives. In addition, international technology transfer can be investigated to accommodate different regulatory landscapes and cross-border transactions.

References

[1] V. L. McDevitt *et al.*, "More Than Money: The Exponential Impact of Academic Technology Transfer," *Technology & Innovation*, vol. 16, no. 1, pp. 75-84, 2014. [Online]. Available: https://dx.doi.org/10.3727/194982414x13971392823479.

[2] K.-J. Lee, T. Ohta, and K. Kakehi, "Formal boundary spanning by industry liaison offices and the changing pattern of university–industry cooperative research: the case of the University of Tokyo," *Technology Analysis & Strategic Management*, vol. 22, no. 2, pp. 189–206, 2010.

[3] World Intellectual Property Organization. "What is Intellectual Property?" https://www.wipo.int/about-ip/en/ (accessed Mar 30, 2024.

[4] G. R. Chandra and I. A. Liaqat, "Commercialization of intellectual property; an insight for technocrats," in *International Conference on Automation, Computational and Technology Management (ICACTM)*, 2019: IEEE, pp. 373-378.

[5] World Intellectual Property Organization. "Patents." https://www.wipo.int/patents/en/ (accessed Feb 5, 2024.

[6] United States Patent and Trademark Office (uspto). "Patent FAQs." https://www.uspto.gov/help/patent-help#type-browse-faqs_1902 (accessed Mar 30, 2024.

[7] I. A. y. Bliznets, A. A. Kartskhiya, and M. G. Smirnov, "Technology transfer in digital era: legal environment," *Journal of History Culture and Art Research*, vol. 7, no. 1, pp. 354-363, 2018.

[8] B. David and V. Kirit, "Meeting Technology Neds of Enterprises for National Competitiveness," presented at the Management of Technology - United Nations Industrial Development Organization, Vienna International Centre Austria, 2001.

[9] A. A. Tseng and M. Raudensky, "Assessments of technology transfer activities of US universities and associated impact of Bayh–Dole Act," *Scientometrics*, vol. 101, pp. 1851-1869, 2014.

[10] S. Bradley, C. S. Hayter, and A. Link, "Models and methods of university technology transfer," *Foundations and trends in Entrepreneurship*, vol. 9, no. 6, 2013.

[11] J. J. Davenport, *Exploring the Theory and Practice of Knowledge Exchange: intention, context and characteristics*. Lancaster University (United Kingdom), 2018.

[12] Wright State University. "Technology Transfer Process." https://www.wright.edu/research/technology-transfer/technology-transfer-process (accessed Feb 6, 2024.

[13] West Virginia University. "Patent Process." https://techtransfer.research.wvu.edu/inventor-resources/patent-process (accessed Feb 6, 2024.

[14] Pillsbury Winthrop Shaw Pittman LLP. "U.S. Provisional Patent Applications – Pros vs. Cons." https://www.pillsburylaw.com/images/content/1/0/v11/107881/FS-LifeSciences-Provisional-Patent-Applications.pdf (accessed Feb 2,2024.

[15] United States Patent and Trademark Office (uspto). "Provisional Application for Patent." https://www.uspto.gov/patents/basics/apply/provisional-application (accessed Feb 6, 2024.

[16] University of Massachusetts Amherst "Patenting Process." https://www.umass.edu/tto/inventors-artists/inventors/patenting-process (accessed Feb 6, 2024.

[17] West Virginia University. "Patent Process Figures." https://techtransfer.research.wvu.edu/inventor-resources/patent-process/patent-process-figures#ppttext (accessed Feb 6, 2024.

[18] T. Zheng, M. Ardolino, A. Bacchetti, and M. Perona, "The applications of Industry 4.0 technologies in manufacturing context: a systematic literature review," *International Journal of Production Research*, vol. 59, no. 6, pp. 1922-1954, 2021.

[19] A. F. Suwanan, A. M. Rori, and D. T. Kurniawan, "The critical review of agriculture technological transfer in the era of decentralization," in *E3S Web of Conferences*, 2021, vol. 306: EDP Sciences, p. 03021.

[20] M. Ammar, A. Haleem, M. Javaid, R. Walia, and S. Bahl, "Improving material quality management and manufacturing organizations system through Industry 4.0 technologies," *Materials Today: Proceedings*, vol. 45, 6, 2021.

[21] A. Rojko, "Industry 4.0 Concept: Background and Overview," *International Journal of Interactive Mobile Technologies (iJIM)*, vol. 11, no. 5, 2017.

[22] S. M. Weyer S, Ohmer M, Gorecky D., "Towards Industry 4.0-Standardization as the crucial challenge for highly modular, multi-vendor production systems.," *Ifac-Papersonline*, vol. 48, no. 3, pp. 579-84, 2015.

[23] J. Veile, K. Daniel, J. Müller, and K.-I. Voigt, "Lessons learned from Industry 4.0 implementation in the German manufacturing industry," *Journal of Manufacturing Technology Management*, vol. 48, no. 3, pp. 579-584, 2019.

[24] A. Angelopoulou, K. Mykoniatis, and N. R. Boyapati, "Industry 4.0: The use of simulation for human reliability assessment," *Procedia Manufacturing*, vol. 42, pp. 296-301, 2020.

[25] K. Mykoniatis, A. Angelopoulou, M. D. Proctor, and W. Karwowski, "Virtual humans for interpersonal and communication skills' training in crime investigations," in *International Conference on Virtual, Augmented and Mixed Reality*, 2014: Springer, pp. 282-292.

[26] K. Mykoniatis *et al.*, "Society 5.0: A Simulation Study of Self Checkout Operations in a Grocery Store," in *32nd European Modeling & Simulation Symposium*, 2020.

[27] K. Mykoniatis and G. A. Harris, "A digital twin emulator of a modular production system using a data-driven hybrid modeling and simulation approach," *Journal of Intelligent Manufacturing*, vol. 32, no. 7, pp. 1899-1911, 2021.

[28] G. Singh and V. Banga, "Robots and its types for industrial applications," *Materials Today: Proceedings*, vol. 60, pp. 1779-1786, 2022.

[29] Y. Kim, J. Lee, J. Kang, S. Park, and D. Jang, "A Study on the Development of Medical Robotics Technology Commercialization Model [J]," *Journal of Advances in Information Technology*, vol. 12, no. 2, 2021.

[30] M. Javaid, A. Haleem, R. P. Singh, and R. Suman, "Substantial capabilities of robotics in enhancing industry 4.0 implementation," *Cognitive Robotics*, vol. 1, pp. 58-75, 2021.

[31] J. Wen, L. He, and F. Zhu, "Swarm robotics control and communications: Imminent challenges for next generation smart logistics," *IEEE Communications Magazine*, vol. 56, no. 7, pp. 102-107, 2018.

[32] R. Galin and R. Meshcheryakov, "Automation and robotics in the context of Industry 4.0: the shift to collaborative robots," in *IOP Conference Series: Materials Science and Engineering*, 2019, vol. 537, no. 3: IOP Publishing, p. 032073.

[33] Z. Liu, Q. Liu, W. Xu, L. Wang, and Z. Zhou, "Robot learning towards smart robotic manufacturing: A review," *Robotics and Computer-Integrated Manufacturing,* vol. 77, p. 102360, 2022.

[34] R. Lässig, M. Lorenz, E. Sissimatos, I. Wicker, and T. Buchner, "Robotics outlook 2030: How intelligence and mobility will shape the future," in "Boston Consulting Group," 2021.

[35] B. Vaisi, "A review of optimization models and applications in robotic manufacturing systems: Industry 4.0 and beyond," *Decision Analytics Journal,* vol. 2, p. 100031, 2022.

[36] H. Etzkowitz and C. Zhou, "Licensing life: The evolution of Stanford university's technology transfer practice," *Technological Forecasting and Social Change,* vol. 168, p. 120764, 2021.

[37] M. K. Dinnetz and M. S. Mireles, "The promise of patent-backed finance for smes and universities, and shifting patent eligible subject matter," *Lewis & Clark L. Rev.,* vol. 26, p. 57, 2022.

[38] J. Walker and D. Fisher. "The Real Patent Crisis Is Stifling Innovation." https://www.forbes.com/sites/danielfisher/2014/06/18/13633/?sh=38dbd2c46f1c (accessed Mar 11, 2023.

[39] I. Abrams, G. Leung, and A. J. Stevens, "How are US technology transfer offices tasked and motivated-is it all about the money," *Research Management Review,* vol. 17, no. 1, pp. 1-34, 2009.

[40] D. Audretsch, E. Lehmann, S. Paleari, and S. Vismara, "Entrepreneurial finance and technology transfer," *The Journal of Technology Transfer,* vol. 41, no. 1, pp. 1-9, 2016.

[41] L. E. da Silva, S. F. Karabag, and C. Berggren, "Collaboration in international technology transfer: the role of knowledge boundaries and boundary objects," *Munich Personal RePEc Archive*. [Online]. Available: https://mpra.ub.uni-muenchen.de/83094/

[42] K. D. Gunawardana and C. Jungthirapanich. SSRN. (2012). Quantitative measurement of advanced manufacturing technology transfer from foreign-based companies to local companies. Available: https://ssrn.com/abstract=2171518

[43] N. Bhatt, "Forecasting the Implementation Success of AMT in SMEs using an Integrated AHP-TOPSIS Approach," *Global Journal of Enterprise Information System,* vol. 8, no. 4, pp. 18-28, 2016.

[44] A. Efstathiades, S. A. Tassou, G. Oxinos, and A. Antoniou, "Advanced manufacturing technology transfer and implementation in developing countries: The case of the Cypriot manufacturing industry," *Technovation,* vol. 20, no. 2, pp. 93-102, 2000.

[45] Future Market Insights. "IT Robotic Automation Market." https://www.futuremarketinsights.com/reports/it-robotics-automation-market (accessed Aug 29, 2023.

[46] C. Peters, A. C. Yarbrough, and G. A. Harris, "Smart Manufacturing Adoption Study," Auburn University's Interdisciplinary Center for Advanced Manufacturing Systems, 2022, vol. 1. [Online]. Available: https://eng.auburn.edu/icams/files/technical-report-22-01.pdf

[47] L. Agostini and A. Nosella, "The adoption of Industry 4.0 technologies in SMEs: results of an international study," *Management Decision*, vol. 58, no. 4, pp. 625-643, 2020.

[48] J. Berbegal-Mirabent, D. Gil-Doménech, and M. Eva, "Examining strategies behind universities' technology transfer portfolio: how different patterns of resource consumption

can lead to similar technology transfer profiles," *Competitiveness Review: An International Business Journal*, vol. 31, no. 3, 2020.

[49] J. Choi, D. Jang, S. Jun, and S. Park, "A predictive model of technology transfer using patent analysis," *Sustainability*, vol. 7, no. 12, pp. 16175-16195, 2015.

[50] C. J. Serrano, "The dynamics of the transfer and renewal of patents," *The RAND Journal of Economics*, vol. 41, no. 4, pp. 686-708, 2010.

[51] H.-C. Huang, H.-N. Su, and H.-Y. Shih, "Analyzing patent transactions with patent-based measures," in *2018 Portland international conference on management of engineering and technology (PICMET)*, 2018: IEEE, pp. 1-12, doi: 10.23919/PICMET.2018.8481871.

[52] M. Kim and Y. Geum, "Predicting Patent Transactions Using Patent-Based Machine Learning Techniques," *IEEE Access*, vol. 8, pp. 188833-188843, 2020.

[53] H.-H. Lin, D. Ouyang, and Y. Hu, "Intelligent classifier: a tool to impel drug technology transfer from academia to industry," *Journal of Pharmaceutical Innovation*, vol. 14, pp. 28-34, 2019.

[54] J. Lee, J.-H. Kang, S. Jun, H. Lim, D. Jang, and S. Park, "Ensemble modeling for sustainable technology transfer," *Sustainability*, vol. 10, no. 7, p. 2278, 2018.

[55] Y. Kim, S. Park, and J. Kang, "Technology Commercialization Activation Model Using Imagification of Variables," *Applied Sciences*, vol. 12, no. 16, p. 7994, 2022.

[56] World Intellectual Property Organization. "About the International Patent Classification." https://www.wipo.int/classifications/ipc/en/preface.html (accessed Aug 29, 2023.

[57] D. Harhoff, F. M. Scherer, and K. Vopel, "Citations, family size, opposition and the value of patent rights," *Research policy*, vol. 32, no. 8, pp. 1343-1363, 2003.

[58] A. Y. Aksoy, D. Pulizzotto, and C. Beaudry, "University-Industry partnerships in the smart specialisation era," *Technological Forecasting and Social Change*, vol. 176, p. 121438, 2022.

[59] W. Schoenmakers and G. Duysters, "The technological origins of radical inventions," *Research Policy*, vol. 39, no. 8, pp. 1051-1059, 2010.

[60] C. Lee, O. Kwon, M. Kim, and D. Kwon, "Early identification of emerging technologies: A machine learning approach using multiple patent indicators," *Technological Forecasting and Social Change*, vol. 127, pp. 291-303, 2018.

[61] D. Deng and T. Chen, "Prediction of University Patent Transfer Cycle Based on Random Survival Forest," *Sustainability*, vol. 15, no. 1, p. 218, 2022.

[62] G. Park and Y. Park, "On the measurement of patent stock as knowledge indicators," *Technological Forecasting and Social Change*, vol. 73, no. 7, pp. 793-812, 2006.

[63] A. Stevenson, "How much are patent citations worth? A simulation estimation based on patent renewal decisions," *Essays on the Economics of Patent Rights*, p. 76, 2022.

[64] Espacenet. "Patent Search." https://ie.espacenet.com/help?locale=en_IE&method=handleHelpTopic&topic=legalstatusqh#:~:text=An%20INPADOC%20patent%20family%20is,document)%20at%20least%20one%20priority. (accessed April 4, 2024).

[65] L. Aristodemou and F. Tietze, "Citations as a measure of technological impact: A review of forward citation-based measures," *World patent information*, vol. 53, pp. 39-44, 2018.

[66] V. Gilsing, R. Bekkers, I. M. B. Freitas, and M. Van der Steen, "Differences in technology transfer between science-based and development-based industries: Transfer mechanisms and barriers," *Technovation*, vol. 31, no. 12, pp. 638-647, 2011.

[67] PatSnap. Patent Search Database [Online] Available: https://www.patsnap.com/

[68] S. Saha, M. Saha, K. Mukherjee, A. Arabameri, P. T. T. Ngo, and G. C. Paul, "Predicting the deforestation probability using the binary logistic regression, random forest, ensemble rotational forest, REPTree: A case study at the Gumani River Basin, India," *Science of the Total Environment,* vol. 730, p. 139197, 2020.

[69] M. F. Mubarak and M. Petraite, "Industry 4.0 technologies, digital trust and technological orientation: What matters in open innovation?," *Technological Forecasting and Social Change,* vol. 161, p. 120332, 2020.

[70] K. Sachpazidu-Wojcicka, "Open innovation process via technology transfer and organizational innovation," *European Research Studies Journal,* vol. XXIII, no. 1, 2020.

[71] E. Scanlon and J. Taylor, "Is technology enhanced learning an interdisciplinary activity?," in *The 10th International Conference on Networked Learning 2016*, D. N. Cranmer S, de Laat M, Ryberg T & and J. Sime, Eds., 2016, pp. 129-133.

[72] J. Smit, S. Kreutzer, C. Moeller, and M. Carlberg. "Industry 4.0. European Parliament." https://www.europarl.europa.eu/RegData/etudes/STUD/2016/570007/IPOL_STU(2016)570007_EN.pdf (accessed Nov 17, 2022.

[73] W. E. Forum. "World Economic Forum Annual Meeting 2016 Mastering the Fourth Industrial Revolution." https://www3.weforum.org/docs/WEF_AM16_Report.pdf (accessed Nov 17, 2022.

[74] B. Bozeman, "Technology transfer and public policy: a review of research and theory," *Research Policy,* vol. 29, pp. 627–655, 2000.

[75] V. L. Silva, J. L. Kovaleski, and R. N. Pagani, "Technology transfer and human capital in the industrial 4.0 scenario: A theoretical study," *Future Studies Research Journal: Trends and Strategies*, vol. 11, no. 1, pp. 102-122, 2019.

[76] A. K. Beharry and K. Fai Pun, "Contextual Analysis of Innovation Process Models toward the Fourth Industrial Revolution," *West Indian Journal of Engineering*, vol. 43, no. 1, 2020.

[77] M. O. Alabi, D. J. de Beer, H. Wichers, and C. P. Kloppers, "Framework for effective additive manufacturing education: a case study of South African universities," *Rapid Prototyping Journal*, vol. 26, no. 5, 2020.

[78] R. R. Tan, "Establishing technology transfer infrastructure as a strategy for promoting manufacturing automation in Taiwan," *Technovation,* vol. 15, no. 7, pp. 407-421, 1995.

[79] A. Ferrario, "Design, development and applications of a learning factory at the university of applied sciences and arts of southern switzerland," Industrial Engineering, University of Parma, 2020.

[80] Y. Simachev, A. Fedyunina, M. Yurevich, M. Kuzyk, and N. Gorodny, "New Strategic Approaches to Gaining from Emerging Advanced Manufacturing Markets," *Форсайт,* vol. 15, no. 3 (eng), pp. 6-21, 2021.

[81] O. Kushnirenko, N. Gakhovich, and L. Venger, "The Impact of Industry 4.0 Technologies on Structural Transformation in the Manufacturing," in *SHS Web of Conferences*, 2021, vol. 100: EDP Sciences.

[82] J. J. Yun, E. Jeong, Y. Lee, and K. Kim, "The effect of open innovation on technology value and technology transfer: A comparative analysis of the automotive, robotics, and aviation industries of Korea," *Sustainability,* vol. 10, no. 7, p. 2459, 2018.

[83] N. Yıldırım and D. Tunçalp, "A Policy Design Framework on the Roles of S&T Universities in Innovation Ecosystems: Integrating Stakeholders' Voices for Industry 4.0," *IEEE Transactions on Engineering Management,* vol. 70, no. 7, pp. 2608 - 2625, 2023.

[84] D. Kochetkov and V. Larionova, "The Changing Role of Universities in Economic Growth," in *Proceedings of the 11th European Conference on Innovation and Entrepreneurship*, 2016, pp. 389-397.

[85] A. Kashyap and R. Agrawal, "Academia a new knowledge supplier to the industry! Uncovering barriers in the process," *Journal of Advances in Management Research*, 2019.

[86] V. L. Da Silva, J. L. Kovaleski, R. N. Pagani, J. D. M. Silva, and A. Corsi, "Implementation of Industry 4.0 concept in companies: Empirical evidences," *International Journal of Computer Integrated Manufacturing*, vol. 33, no. 4, pp. 325-342, 2020.

[87] E. L. Sastoque Pinilla, R. Llorente Rodríguez, N. Toledo Gandarias, L. N. López de Lacalle Marcaide, and M. R. Farokhad, "TRLs 5–7 Advanced Manufacturing Centres, Practical Model to Boost Technology Transfer in Manufacturing," *Sustainability,* vol. 11, no. 18, p. 4890, 2019.

[88] S. Kruger and A. A. Steyn, "Enhancing technology transfer through entrepreneurial development: practices from innovation spaces," *The Journal of Technology Transfer,* vol. 45, no. 6, pp. 1655-1689, 2020.

[89] M. Schumann, S. Leye, and A. Popov, "Virtual Reality Models and Digital Engineering Solutions for Technology Transfer," *Appl. Comput. Syst.*, vol. 17, no. 1, p. 27, 2015.

[90] K. Rong, Y. Lin, J. Yu, Y. Zhang, and A. Radziwon, "Exploring regional innovation ecosystems: an empirical study in China," *Industry and Innovation,* vol. 28, no. 5, pp. 545-569, 2021.

[91] M. Vidmar, A. Rosiello, N. Vermeulen, R. Williams, and J. Dines, "New Space and Agile Innovation: Understanding transition to open innovation by examining innovation networks and moments," *Acta astronautica,* vol. 167, pp. 122-134, 2020.

[92] N. Kumar, "The power of power in supplier-retailer relationships," *Industrial marketing management,* vol. 34, no. 8, p. 863, 2005.

[93] V. Scuotto, O. Beatrice, C. Valentina, M. Nicotra, L. Di Gioia, and M. F. Briamonte, "Uncovering the micro-foundations of knowledge sharing in open innovation partnerships: An intention-based perspective of technology transfer," *Technological forecasting and social change,* vol. 152, p. 119906, 2020.

[94] A. Shamsuzzoha, M. Al-Kindi, and N. Al-Hinai, "Open innovation in small and medium size enterprises-perspective from virtual collaboration," *International journal of engineering and technology innovation,* vol. 8, no. 3, pp. 173-190, 2018.

[95] M. Lee *et al.*, "How to respond to the fourth industrial revolution, or the second information technology revolution? Dynamic new combinations between technology, market, and society through open innovation," *Journal of Open Innovation: Technology, Market, and Complexity,* vol. 4, no. 3, p. 21, 2018.

[96] I. C. Baierle, J. C. M. Siluk, V. J. Gerhardt, C. d. F. Michelin, Á. L. N. Junior, and E. O. B. Nara, "Worldwide Innovation and Technology Environments: Research and Future Trends Involving Open Innovation," *Journal of Open Innovation: Technology, Market, and Complexity,* vol. 7, no. 4, p. 229, 2021.

[97] T. Al Amri, K. Puskas Khetani, and M. Marey-Perez, "Towards Sustainable I4. 0: Key Skill Areas for Project Managers in GCC Construction Industry," *Sustainability,* vol. 13, no. 15, p. 8121, 2021.

[98] M. Hermann, T. Pentek, and B. Otto, "Design principles for industrie 4.0 scenarios," in *2016 49th Hawaii international conference on system sciences (HICSS)*, 2016: IEEE, pp. 3928-3937.

[99] N. Fukawa, Y. Zhang, and S. Erevelles, "Dynamic capability and open-source strategy in the age of digital transformation," *Journal of Open Innovation: Technology, Market, and Complexity*, vol. 7, no. 3, p. 175, 2021.

[100] C. Henriques, C. Viseu, M. Neves, A. Amaro, M. Gouveia, and A. Trigo, "How Efficiently Does the EU Support Research and Innovation in SMEs?," *Journal of Open Innovation: Technology, Market, and Complexity*, vol. 8, no. 2, p. 92, 2022.

[101] S. Grabowska and S. Saniuk, "Development of Business Models in the Fourth Industrial Revolution: Conditions in the Context of Empirical Research on Worldwide Scope Companies Located in Poland," *Journal of Open Innovation: Technology, Market, and Complexity*, vol. 8, no. 2, p. 86, 2022.

[102] P. A. Nylund and A. Brem, "Do open innovation and dominant design foster digital innovation?," *International Journal of Innovation Management*, vol. 25, no. 09, p. 2150098, 2021.

[103] W. Sutopo, R. W. Astuti, and R. T. Suryandari, "Accelerating a technology commercialization; with a discussion on the relation between technology transfer efficiency and open innovation," *Journal of Open Innovation: Technology, Market, and Complexity*, vol. 5, no. 4, p. 95, 2019.

[104] L. Sugiharti, M. Z. Yasin, R. Purwono, M. A. Esquivias, and D. Pane, "The FDI Spillover Effect on the Efficiency and Productivity of Manufacturing Firms: Its Implication on Open

Innovation," *Journal of Open Innovation: Technology, Market, and Complexity,* vol. 8, no. 2, p. 99, 2022.

[105] M. Hizam-Hanafiah and M. A. Soomro, "The situation of technology companies in industry 4.0 and the open innovation," *Journal of open innovation: technology, market, and complexity,* vol. 7, no. 1, p. 34, 2021.

[106] B. Jaruzelski, K. Schwartz, and V. Staack, "Innovation's new world order," *strategy+ business,* vol. 27, p. 81, 2015.

[107] M. Bogers, H. Chesbrough, S. Heaton, and D. J. Teece, "Strategic management of open innovation: A dynamic capabilities perspective," *California Management Review,* vol. 62, no. 1, pp. 77-94, 2019.

[108] M. S. Gertler, *Manufacturing culture: The institutional geography of industrial practice*. Oxford University Press, 2004.

[109] D. Bole, "'What is industrial culture anyway?'Theoretical framing of the concept in economic geography," *Geography Compass,* vol. 15, no. 11, p. e12595, 2021.

[110] I. F. Ituarte, S. H. Khajavi, and J. Partanen, "Challenges to implementing additive manufacturing in globalised production environments," *International Journal of Collaborative Enterprise,* vol. 5, no. 3-4, pp. 232-247, 2016.

[111] J. M. Müller, "Assessing the barriers to Industry 4.0 implementation from a workers' perspective," *IFAC-PapersOnLine,* vol. 52, no. 13, pp. 2189-2194, 2019.

[112] F. Kovaleski, C. T. Picinin, and J. L. Kovaleski, "The Challenges of Technology Transfer in the Industry 4.0 Era Regarding Anthropotechnological Aspects: A Systematic Review," *SAGE Open,* vol. 12, no. 3, p. 21582440221111104, 2022.

[113] M. N. Soares and M. E. Kauffman, "Industry 4.0: Horizontal Integration and Intellectual Property Law Strategies In England," *Revista Opinião Jurídica (Fortaleza),* vol. 16, no. 23, pp. 268-289, 2018.

[114] S. Chih-Yi and L. Bou-Wen, "Attack and defense in patent-based competition: A new paradigm of strategic decision-making in the era of the fourth industrial revolution," *Technological Forecasting and Social Change,* vol. 167, p. 120670, 2021.

[115] Y. Huang, A. L. Porter, S. W. Cunningham, D. K. Robinson, J. Liu, and D. Zhu, "A technology delivery system for characterizing the supply side of technology emergence: Illustrated for Big Data & Analytics," *Technological Forecasting and Social Change,* vol. 130, pp. 165-176, 2018.

[116] S. Lee, W. Kim, Y. M. Kim, and K. J. Oh, "Using AHP to determine intangible priority factors for technology transfer adoption," *Expert Systems with Applications,* vol. 39, no. 7, pp. 6388-6395, 2012.

[117] B. Bozeman, H. Rimes, and J. Youtie, "The evolving state-of-the-art in technology transfer research: Revisiting the contingent effectiveness model," *Research Policy,* vol. 44, no. 1, pp. 34-49, 2015.

[118] L. Borge and S. Bröring, "Exploring effectiveness of technology transfer in interdisciplinary settings: The case of the bioeconomy," *Creative Innovation Managment,* vol. 26, pp. 311–322, 2017.

[119] R. J. Al-Khaza'aleh, G. Y. Abbasi, and A. I. Alahmer, "Project managers' motivation in the Jordanian construction industries," *International Journal of Project Organisation and Management,* vol. 8, no. 4, pp. 348-365, 2016.

[120] M. Shurrab, G. Abbasi, and R. Al Khazaleh, "Evaluating the effect of motivational dimensions on the construction project managers in Jordan," *Engineering, Construction and Architectural Management,* vol. 25, no. 3, 2018.

[121] R. Alkhazaleh, K. Mykoniatis, and A. Alahmer, "The success of technology transfer in the industry 4.0 era: A systematic literature review," *Journal of Open Innovation: Technology, Market, and Complexity,* vol. 8, no. 4, p. 202, 2022.

[122] Z. Khan, D. Kaushal, A. Dey, and A. Gupta, "Obsolescence rate of sectors in patents filed in USPTO," *World Patent Information,* vol. 74, p. 102210, 2023.

[123] J. M. Kuhn and N. C. Thompson, "How to measure and draw causal inferences with patent scope," *International Journal of the Economics of Business,* vol. 26, no. 1, pp. 5-38, 2019.

[124] M. Kasdan, "Intellectual Property Licensing," in *The Oxford Handbook of Intellectual Property Law*, R. Dreyfuss and J. Pila Eds.: Oxford University Press 2018.

[125] L. P. Santa Rita *et al.*, "Relationship between industry 4.0 and patents," *World Patent Information*, vol. 74, p. 102221, 2023.

[126] S. Wittfoth, "Measuring technological patent scope by semantic analysis of patent claims–an indicator for valuating patents," *World Patent Information,* vol. 58, p. 101906, 2019.

[127] A. J. Trappey, C. V. Trappey, U. H. Govindarajan, and A. C. Jhuang, "Construction and validation of an ontology-based technology function matrix: technology mining of cyber physical system patent portfolios," *World Patent Information,* vol. 55, pp. 19-24, 2018.

[128] S. R. Adams, "“Nothing new under the sun”; do we need new searching protocols to establish the patentability of industry 4.0 inventions?," *World Patent Information,* vol. 72, p. 102170, 2023.

[129] Y. M. Choi and D. Cho, "A study on the time-dependent changes of the intensities of factors determining patent lifespan from a biological perspective," *World Patent Information*, vol. 54, pp. 1-17, 2018.

[130] B. Spear, "Robots and patents," *World Patent Information*, vol. 23, no. 4, pp. 333-338, 2001.

[131] C. S. de Jesus, D. de Oliveira Cardoso, and C. G. de Souza, "Motivational factors for patenting: A study of the Brazilian researchers profile," *World Patent Information*, vol. 75, p. 102241, 2023.

[132] European Patent Office, "Guidelines for Examination in the European Patent Office," in "European Patent Office," Munich, Germany, 978-3-89605-338-1, 2023, vol. A6.

[133] F. Caviggioli and E. Ughetto, "Buyers in the patent auction market: Opening the black box of patent acquisitions by non-practicing entities," *Technological Forecasting and Social Change*, vol. 104, pp. 122-132, 2016.

[134] P. Belingheri, M. I. Leone, and S. Lombardi, "What's your stake when engaging in licensing? A comparison between standard and partnership-embedded licensing strategies," *IEEE Transactions on Engineering Management*, vol. 70(6), pp. 2058-2070, 2021.

[135] H. Noh and S. Lee, "What constitutes a promising technology in the era of open innovation? An investigation of patent potential from multiple perspectives," *Technological Forecasting and Social Change*, vol. 157, p. 120046, 2020.

[136] S. Adams, "Using the International Patent Classification in an online environment," *World Patent Information*, vol. 22, no. 4, pp. 291-300, 2000.

[137] B. Degroote and P. Held, "Analysis of the patent documentation coverage of the CPC in comparison with the IPC with a focus on Asian documentation," *World Patent Information*, vol. 54, pp. S78-S84, 2018.

[138] P. K. Masson, "Searching with combination sets in CPC: An efficient way to retrieve relevant documents," *World Patent Information*, vol. 54, pp. S93-S98, 2018.

[139] G. M. do Canto Cavalheiro, L. A. Joia, and A. F. Van Veenstra, "Examining the trajectory of a standard for patent classification: An institutional account of a technical cooperation between EPO and USPTO," *Technology in Society*, vol. 46, pp. 10-17, 2016.

[140] EPO and USPTO, "Guide to the CPC," www.cpcinfo.org, vol. 1.0. Accessed: Apr 1, 2024. [Online]. Available: https://link.epo.org/cpc/Guide+to+the+CPC.pdf

[141] A. C. Marco, J. D. Sarnoff, and A. Charles, "Patent claims and patent scope," *Research Policy*, vol. 48, no. 9, p. 103790, 2019.

[142] J. Lobo and D. Strumsky, "Sources of inventive novelty: two patent classification schemas, same story," *Scientometrics*, vol. 120, no. 1, pp. 19-37, 2019.

[143] H. Lee, "The heterogeneous effects of patent scope on licensing propensity," *Research Policy*, vol. 52, no. 3, p. 104696, 2023.

[144] D. V. Radack, "Reading and understanding patent claims," *JOM*, vol. 47, no. 11, pp. 69-69, 1995.

[145] T. Miyazawa and H. Osada, "Change of claim structures of market leaders' Japanese published unexamined patent applications according to the degree of technology maturity," *World Patent Information*, vol. 33, no. 2, pp. 180-187, 2011.

[146] W. Tannebaum and A. Rauber, "Learning keyword phrases from query logs of USPTO patent examiners for automatic query scope limitation in patent searching," *World Patent Information*, vol. 41, pp. 15-22, 2015.

[147] D. D. Kukolj, S. D. Nemet, M. M. Barać, and F. Benčić, "Identification of Essential Patents in AI based Automotive Patent Portfolio," in *2019 Zooming Innovation in Consumer Technologies Conference (ZINC)*, 2019: IEEE, pp. 122-125, doi: 10.1109/ZINC.2019.8769335.

[148] Y. Okada, Y. Naito, and S. Nagaoka, "Claim length as a value predictor of a patent," Citeseer, 2016. Accessed: Apr 1, 2024. [Online]. Available: http://hdl.handle.net/10086/28165

[149] N. Galli, "Patent aggregation, innovation and eu competition law," Maastricht University,

University of Augsburg, 2023.

[150] Z. Yin and Z. Sun, "Predicting the value of Chinese patents using patent characteristics: evidence based on a Chinese patent auction," *Industrial and Corporate Change*, vol. 32, no. 6, pp. 1286–1304, 2023.

[151] J. El-Ouahi. (2023). Examining the Patenting Activities of Universities in the Middle East and North Africa. Available: https://doi.org/10.21203/rs.3.rs-2895322/v1

[152] C. Righi, D. Cannito, and T. Vladasel, "Continuing patent applications at the USPTO," *Research Policy*, vol. 52, no. 4, p. 104742, 2023.

[153] AUTM. "STATT: Statistics Access for Technology Transfer Database " https://autm.net/surveys-and-tools/databases/statt (accessed Apr 1, 2024.

[154] PatSnap Analytics. "PatSnap Analytics." https://www.linkedin.com/products/patsnap-analytics/ (accessed Sep 5, 2023.

[155] T. U. Islam and M. Rizwan, "Comparison of correlation measures for nominal data," *Communications in Statistics-Simulation and Computation,* vol. 51, no. 3, pp. 698-714, 2020.

[156] S. A. Pawluk, K. Shah, R. Minhas, D. Rainkie, and K. J. Wilby, "A psychometric analysis of a newly developed summative, multiple choice question assessment adapted from Canada to a Middle Eastern context," *Currents in Pharmacy Teaching and Learning,* vol. 10, no. 8, pp. 1026-1032, 2018.

[157] A. Muyal, K. Ghadei, S. Maji, K. Pant, and T. Saklani, "Construction of A Knowledge Test for Testing the Effectiveness of Participatory Video on Virtual Marketing," *Indian Research Journal of Extension Education,* vol. 22, no. 5, 2022.

[158] J. Vallejo-Elias, "Interpretation of Discrimination Data from Multiple-Choice Test Items," *Midwestern University, Downers Grove, IL,* 2021.

[159] J. Toman and B. Klímová, "Current Challenges of the Technology Transfer Process," presented at the Hardec Economic Days, 2020.

[160] C. Schultz and D. Mietzner, *The technology transfer challenge*, 1 ed. (New Perspectives in Technology Transfer: Theories, Concepts, and Practices in an Age of Complexity). Springer Cham, 2021, pp. 1-8.

[161] T. Hockaday, *University Technology Transfer: What it is and how to Do it*. JHU Press, 2020.

[162] V. L. da Silva, J. L. Kovaleski, and R. N. Pagani, "Technology transfer in the supply chain oriented to industry 4.0: a literature review," *Technology Analysis & Strategic Management,* vol. 31, no. 5, pp. 546-562, 2019.

[163] G. Graff, A. Heiman, and D. Zilberman, "University research and offices of technology transfer," *California Management Review*, vol. 45, no. 1, pp. 88-115, 2002.

[164] I. Macho-Stadler, D. Pérez-Castrillo, and R. Veugelers, "Licensing of university inventions: The role of a technology transfer office," *International Journal of Industrial Organization*, vol. 25, no. 3, pp. 483-510, 2007.

[165] USPTO. "CPC Definition - Subclass G06Q." https://www.uspto.gov/web/patents/classification/cpc/html/defG06Q.html#G06Q (accessed Mar 19, 2024, 2024).

[166] G. D. Markman, P. H. Phan, D. B. Balkin, and P. T. Gianiodis, "Entrepreneurship and university-based technology transfer," *Journal of business venturing*, vol. 20, no. 2, pp. 241-263, 2005.

[167] T. R. Anderson, T. U. Daim, and F. F. Lavoie, "Measuring the efficiency of university technology transfer," *Technovation*, vol. 27, no. 5, pp. 306-318, 2007.

[168] V. Choudhry and T. A. Ponzio, "Modernizing federal technology transfer metrics," *The Journal of Technology Transfer*, vol. 45, no. 2, pp. 544-559, 2020.

[169] V. Arza, "Channels, benefits and risks of public—private interactions for knowledge transfer: conceptual framework inspired by Latin America," *Science and Public Policy*, vol. 37, no. 7, pp. 473-484, 2010.

[170] A. Agrawal, "Engaging the inventor: Exploring licensing strategies for university inventions and the role of latent knowledge," *Strategic Management Journal*, vol. 27, no. 1, pp. 63-79, 2006.

[171] K. Hoye and F. Pries, "Repeat Commercializers' in University-Industry Technology Transfer: A Minority oof Faculty Inventors Account for a Majority of Commercialized

Inventions," in *PICMET'07-2007 Portland International Conference on Management of Engineering & Technology*, 2007: IEEE, pp. 1840-1846.

[172] J. Han, M. Kamber, and J. Pei, *Data mining concepts and techniques*, 3 ed. Morgan Kaufmann, 2012.

[173] A. C. Müller and S. Guido, *Introduction to machine learning with Python: a guide for data scientists*. O'Reilly Media, 2016.