# Integrated Technologies in the Graphic Communications Industry: Systematic Review, Challenges, and Outlook

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**Abstract**

This study provides a holistic overview of Integrated Technologies, such as Automation, Artificial Intelligence (AI), the Internet of Things (IoT), Big Data, Machine Learning (ML) and Neural Networks, and their applications within the Graphic Communications Industry. By leveraging a systematic literature review utilizing both quantitative and qualitative publications, this study aims to answer the following question, *"In the Graphic Communications Industry, do the implementations of Integrated Technologies have an impact on the quality of performance and customer satisfaction of organizations who have adopted them in the previous 10 years?"*.

Furthermore, identified publications were selected in order to contain a variety of different perspectives from a myriad of authors to make it abundantly clear that new approaches containing unprecedented use of the integrated technologies are bringing continuous development and change, positive and negative. They will re-shape our current approach to technology in the Graphic Communications Industry and will therefore transform the way lives are lived. Moreover, this review will be the first of its kind, shedding light on new opportunities and existing limitations, and in turn, will aid in determining the path the future of the Graphic Communications Industry will take in Industry 5.0 revolution. This paper is a part of ongoing research at The Creative School of Toronto Metropolitan University (Formerly known as Ryerson), 2022, and will serve as a basis on which further research will be conducted, as it is a neglected research topic and one that is lacking within the field of Graphic Communications.

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## Introduction

Automation, Artificial Intelligence (AI), the Internet of Things (IoT), Big Data, Machine Learning (ML), and Neural Networks are more than modern terms, these technologies have created new potential innovations within the workplace, and it has been ruling many aspects of our daily life. Essentially, automation substitutes mundane or physically difficult labor by limiting human involvement. This technological-industrial integration has been, once again, revolutionizing our means of production, increasing productivity as never before.

Businesses and economies worldwide can benefit from this integration into their workplaces. The results will not be immediate, but the long-term benefits are significant for companies. McKinsey (2019) stated that “the automation of activities can enable businesses to improve performance by reducing errors, improving quality and speed, and in some cases achieving outcomes that go beyond human capabilities”.

Industry 4.0 is here and it is growing, however, it also brings certain concerns for the general population. The substitution of workplace labor by machines has unshackled workers to focus on higher-value tasks or establish new ones, which leaves an uncertain future scenario for the availability of work. Many employees fear that there will not be enough jobs with the increasing integration of automation and artificial intelligence in the workplace or that some jobs will become obsolete. Moreover, larger firms will have an advantage over smaller businesses since there is greater access to resources, more structured data, employees with advanced technical skills to learn AI, and increased returns for cost and revenue. Seeking this, many individuals are already looking forward towards the Fifth Industrial Revolution. Nahavandi (2019) defines it as “where robots are intertwined with the human brain and work as collaborators instead of competitors”. Increased efficiency and intelligence systems are combined with human labor, which comes back to the fold 10 times over, to create revolutionary machinery in Industry 5.0. This research study will go deeper into the transition between Industry 4.0 and Industry 5.0, examining the challenges and opportunities that these technologies present to businesses in the Graphic Communications Industry.

This Technical Innovation Paper will showcase background information about promising technologies that are already taking place in the industry nowadays and discuss its use within Industry 5.0, a new production model that emerges as a favourable alternative for the future of our society. A systematic literature review will be employed in order to construct a base from different authors and perspectives, and draw conclusions based on the evidence presented. The research question to be answered is as follows, *“In the Graphic Communications Industry, do the implementations of Integrated Technologies have an impact on the quality of performance and customer satisfaction of organizations who have adopted* *them in the previous 10 years?"*. The paper will employ a systematic review to critically evaluate relevant literature and focus on contemporary applications in various Graphic Communication Industry Sectors such as Graphic Art, Graphic Design, Packaging, Printing, and others. This information will benefit those within the Graphic Communications Industries and those who are considering the implementation of integrated technologies within their respective businesses. It will explore the numerous benefits and drawbacks associated with the usage of Integrated Technologies, as well as their impact within the Graphic Communications Industry, focusing on performance quality and customer satisfaction.

Given the scarcity of previous research on the subject, the information presented in this study is especially important because it is the first of its nature and is a part of ongoing research at Toronto Metropolitan University's (TMU) (Formerly known as Ryerson) Creative School, 2022, thereby contributing to further research in this field. It is the first to provide a systematic review with clear definitions of emerging technologies such as Automation, AI, IoT, ML, and Big Data, as well as a holistic approach to discussing the implementation of Integrated Technologies in the Graphic Communications Industries, thereby making available evidence more accessible and advancing the Graphic Communications Industry forward.

## Definitions

**Automation** can contribute to productivity and in turn, increase a business's economic growth and prosperity. Automation is especially susceptible to industries that are data-reliant or low-skill (McKinsey, 2019) In Industry 4.0 automation is rather equivalent to autonomy, taking advantage of artificial intelligence to create truly smart robots with the ability to self-learn, in contrast to the currently deployed robots of Industry 3.0, subject to highly-controlled environments (Tantawi et. al, 2019; Muro et. al, 2019; International Society of Automation, n.d.).

**Artificial Intelligence (AI)** is complex in its definition because there are multiple ways of defining intelligence, as they relate to a variety of categories of intelligence. Abbass (2019) defines AI in simpler terms. "Artificial intelligence aims to design algorithms to provide computers with cognitive skills and competencies for sense-making and decision-making". This definition emphasizes AI's ability to use machine cognition to perform tasks. AI is a direct example of biomimicry, consisting of the transference of analogs from the field of biology to technology (Vincent et al., 2006). Machine learning (ML) and Neural Networks, are also considered examples of biomimicry work to explain how AI systems process information and acquire knowledge.

**The Internet of Things (IoT)** interconnects all sources of data over public or private internet (i.e., Industrial Internet), protocols, and (IP) networks (Patel and Patel, 2016), enabling a large amount of data to be collected and transmitted at a high speed. Cloud computing, Near Field Communications (NFC), intelligent sensing, Radio-Frequency Identification (RFID) tags, and wireless sensor network (WSN) are some technologies and tools that contribute to IoT technology either employ tracking and collecting data or provide a platform and tools to analyze it (Li et al, 2015). The emerging IoT applications have been widely used in many industries including Graphic Communications (Domingo, 2012; Jara, 2011; Bandyopadhyay and Sen, 2011; Li et al, 2015; Alberch, 2018; Bergman & Johansson, 2017; Tambo & Lydekaitye, 2019)

**Big Data** as defined by Zheng et al (2013) and Beyer and Laney (2012) "..are high volume, high velocity, and/or high variety information assets that require new forms of processing to enable enhanced decision making, insight discovery and process optimization". Due to the massive amounts of data collected, a secure system such as Cloud Storage is required (Nahavandi, 2019) in order to keep all information accessible and secure. The use of pre-processing information is also necessary to filter beforehand what needs to be analyzed and learned by the AI. Data modeling and Data analysis are also implemented to generate patterns and correlations in datasets that would provide solutions or potential trends (Junjun, 2020; Wei and Xiangbo 2020; Knol et al. 2019)

**Machine Learning (ML)** was defined by El Naqa and Murphy (2015) as an "evolving branch of computational algorithms that are designed to emulate human intelligence by learning from the surrounding environment". This allows ML to perceive hidden information without being explicitly programmed to do so. Different models of machine learning are implemented for distinctive purposes. There are many techniques that are to be developed, in the future however it is possible to divide the current methods into two distinct groups: the traditional learning method, and the deep learning method. Traditional learning is extremely machine-like, capable of only completing tasks it was designed to. On the other hand, deep learning allows AI systems to learn complex patterns of large data to inform future optimizations.

In the deep learning method, **Neural Networks** mimic learning modeling the way that neurons interact in the brain, loosely simulating connected neural units (Chui et al., 2019). It depends "on training data to learn and improve their accuracy over time" (IBM, 2020). The near human performance of neural networks provides companies with endless opportunities for new innovations in AI technologies. Common applications of the deep learning method include image classification and speech recognition.

## Back-end and Front-end Interrelation

Technologies in the current industry are diverse, from AI to IoT, they all connect to each other in the automated production process, as seen in Figure 1.0. In many cases, they are not all employed at the same time, yet this whole process and information flow are leveraged by automation as it improves over time. Artificial intelligence enables the workflow to evolve as long as it learns, depending less on humans and manual programming to perform daily tasks in the production process. As technology continues to rapidly evolve, the merger of robotics and the human mind is causing huge breakthroughs in artificial intelligence, which will play a machine-independent role in Industry 5.0 allowing for a collective synergy between humans and autonomous machines.


***Figure 1.0:*** *Information process of back-end & front-end integrated technologies*

## Industry 4.0 vs. Industry 5.0

Since the end of the 18th century, four Industrial Revolutions have been historically marked and characterized. In the first one, water, steam, and fossil fuels were used as mechanical power; the factory system proposed a new way to organize work in specialized functions, and the transition from handcraft to machine fabrication allowed huge productivity and increased consumption. The 1870s inaugurated the Second Industrial Revolution. Assembly lines, mass production, the growth of the steel industry, and the utilization of electrical energy by manufacturers are some of its main characteristics (Mokyr, 1998). The Third was marked by electronics, telecommunications, and computer advancements (iED, 2019). The employment of robots in the production process enabled high-level automation. Cyber-physical systems (CPS), Cloud Computing, and the (Industrial) Internet of Things (IIoT/IoT) are major components of Industry 4.0, improving the computerization and automation started in the Third. Benefits of this digitalization include the "enhancement of operational efficiency, improved responsiveness, boosted traceability, strengthened capacity utilization and reduction in costs" (Rossini et. al, 2019, as cited in Chauhan et. al, 2021). Some believe that the Fourth Industrial Revolution has not been established yet, few even argue that it is nothing more than a marketing buzzword (Marr, 2018). Countries and their economical and technological development stages affect the industrial modes of production, which complicates any attempt to define it globally.

However, it is beyond doubt that numerous industry sectors are open and adapting to the new technologies, trusting their potential. A Grand View Research report revealed that the global artificial intelligence market was valued at 63 billion dollars in 2021, and it is expected to grow to almost a trillion USD by 2028. In 2020, most of its market share (over 40%) was concentrated in North America, and software solutions accounted for more than 38% share of the global revenue. Big companies such as Microsoft and Apple are heavily investing in AI technologies, whether forming partnerships or acquiring AI-specialized firms (ReportLinker, 2021). Moreover, beyond the tech market, the impact of Industry 4.0 is perceived in many other sectors. The packaging industry, for example, has used AI for activities such as sorting recycling goods, date labeling, inspections, shipping, and warehouse automation (PDA, 2018). Also, because of technological advancements, smart packaging has emerged, offering innovative solutions for many manufacturers and new business opportunities (Schaefer and Cheung, 2018). Machine innovation can lead to product innovation as technologies could be able to reach results humans could not (Demir et. al, 2019).

Beyond the benefits, Industry 4.0 and the quick pace of its technologies still raise concerns from the general public. Popular imaginative scenarios such as an AI takeover or a dystopia in which humans end up extinct are symptoms of a series of more realistic problems faced nowadays; unemployment seems to be the main one. Stanford (2020) looks at this fact from another perspective, affirming that "technology will not independently or inexorably determine the direction of change [...]", rather, it is the conscious and collective decisions we make as a society that will determine what the future of work will look like. Also, according to the author, the current precarization of labor caused by the so-called Gig Economy has a huge impact on unemployment. On-demand jobs are pushing workers to a growing informality, as companies get rid of paying minimum wage, assuring healthcare, among other benefits guaranteed by employment laws.

| PROS | CONS |
| --- | --- |
| • Distinctive insights<br>• Faster services<br>• Increase flexibility & scalability<br>• Improved product quality<br>  ◦ reduce or remove human error<br>• Increased savings & productivity | • Ignores human cost resulting from the optimization of processes<br>• Tendency to decrease employment numbers<br>• No strong focus on environmental protection<br>• Possible resistance from labor unions and politicians<br>  ◦ employment numbers pressure |

***Figure 2.0:*** *Industry 4.0 advantages and drawbacks, based on Chui et al. (2019), Significans Automation (2021) and Nahavandi (2019).*

Even so, other drawbacks in Industry 4.0 must be taken into consideration, involving aspects like sustainability, ethics, and politics. Also, it is difficult, in terms of employment, to acknowledge what consequence is resulting from the Gig Economy or the Industry 4.0, leading many to see the advantages of the Fourth Industrial Revolution neutralized if the jobs numbers stagnate or decrease, including political leaders pressured for results (Nahavandi, 2019; Demir et. al, 2019).

Because of this, some are already looking toward the Fifth Industrial Revolution (Martynov et. al., 2019). A far-not-so-far way of handling growing mass production with humans back in the fold. Nahavandi (2019) defines Industry 5.0 as the pairing of "human and machine to further utilize human brainpower and creativity to increase process efficiency by combining workflows with intelligent systems".

Mass customization and optimistic forecasts regarding technology progress are the main drivers behind Industry 5.0. Here are four of its main points:

- **Cobots.** Collaborative robots will have a key role in Industry 5.0. According to Nahavandi (2019), the synergy between humans and autonomous robots will allow for great productivity through cooperation. The premises are good: the cobots will be capable of helping humans by advanced machine learning (ML), making autonomous decisions to assist when necessary. State-of-the-art AI and sensing technologies will allow machines to connect to the environment as never before, getting closer to human thinking by observing and learning smartly from patterns.

- **Value-added production process and jobs.** With people back on the factory floors, creative jobs, and others that value the human unique abilities, will be significant and well-paid. Furthermore, with the advancements expected for Industry 5.0, specialists in high technology will be largely required. Among them, Nahavandi (2019) predicts the disclosure of a "Chief Robotics Officer" (CRO), defining them as individuals with expertise in human-machine interaction, mediating the robots' participation in the production process, in order to optimize performance and efficiency.

- **Human-centered.** The employment opportunities are not accompanying the global population growth. There are just not enough jobs and this scenario tends to get worse over time, mainly in low and lower-middle-income countries, where the population growth projection is above the world average (Abeliansky, 2020). Industry 5.0 will attempt to relieve it by putting humans to play a major role. While cobots assist and concentrate on repetitive and more complex mundane tasks, humans will focus on more creative and intellectual activities. With peace in mind, humans will not have to feel threatened by machines, instead, the feeling of satisfaction working alongside them is expected (Nahavandi, 2019).

- **Mass customization.** Consumption tendencies will shape the way industry manufactures. As the global population seeks more personalized and exclusive products, companies will have to adapt to employ technologies capable of attending to these demands. From the mass production of Industry 4.0 to mass customization (Østergaard, 2020), the human touch and creativity integrated with skilled robots will enable cutting-edge production and high-quality personalized goods.

Since Industry 5.0 will still leverage most technologies present in the current industry (i.e., AI, IoT, ML, neural networks), it is important to look at the human role in the industrial scenario to establish its main difference from the Fourth Industrial

Revolution. While Industry 4.0 kept evolving and improving what was brought by Industry 3.0, seeking automation to substitute workers, Industry 5.0 will do it in different manners and bring humans back to collaborate together with robots, besides embracing important questions for the future, focusing on sustainability and finding the balance between production and efficiency (see Figure 4). Martynov et. al (2019) see Industry 5.0 as "the integration of physical and virtual space to solve not only production problems, but also social problems" while Østergaard (2020) sees Industry 5.0 as the "pre-industrial form of goods production, but one that is enabled by the most advanced industrial automation technologies out there".

Another way to comprehend this evolution is by looking at what industry is producing and what it could produce within the Fifth Industrial Revolution. The publishing industry, for example, has been benefiting from automation since the 70s (Amnet, 2018). Processes like authoring, editing, multimedia infusion, book design and stylesheet, artwork, final proof, and others (Impelsys, 2018) can take advantage of automated workflows in order to increase productivity in less time and reduce costs. Over time, the publishing industry had to adapt to the digitization phenomena and started delivering multiple different products and formats (i.e., XML, PDF, ePUB), besides the common printing. This seems to be a tendency: even though e-readers will become more and more popular, well-printed books will still be carried around and many more products will also become part of the publishing industry scope. This variety of products is key to what Industry 5.0 could contribute in the near future. Technologies such as AI, could meta tag images to digital publishing formats, convert print book layouts into ePUBs layouts, and help gather data from eBook readings in order to create statistics, beyond many other possibilities empowered by digitization. Mass customization enabled by Industry 5.0 will also be an important and innovative step to be taken in this industry sector, enabling readers to connect in a new way to published media. Employees could then focus on creative forms of achieving these possibilities, adding important value to the production process.

The COVID-19 pandemic has evidenced the need for a radical change in the way we produce and consume. For manufacturers, new technologies have proven to be an essential investment, as they have been providing great solutions that are keeping the industry on track. Social distancing has been facilitated by remote access technologies, part of a new normal that is transforming many companies and their workflows. Big data can be used in favor of businesses and their operations, helping to safely predict scenarios in uncertain times. According to Gamota (2021), the coronavirus pandemic has pushed people to learn new technologies and troubleshoot their problems, counting less on external help. The Virtual Age heralded by the pandemic (Mehendale and Radin, 2020 as cited in Gamota, 2021) is leading the industry to the path of the Fifth Industrial Revolution, which will require human adaptability to work collaboratively with machines. Human creativity, innovation and critical thinking alongside smart technologies are at the core of Industry 5.0.

## Findings

The findings of Performance Quality and Customer Satisfaction are classified into two subcategories with Performance Quality focusing on Process Optimization and Quality Control in the workflow, and Customer Satisfaction relating to the Decision Making Process and User Experience for consumers. However, it is important to note that these subcategories are all interrelated. For example, the research aims to work towards finding how integrated technologies like big data can inform machine learning and therefore help companies implement artificial intelligence and automate their processes, making it clear that these technologies are all interrelated and interconnected, truly shaping the next era of digital technologies.

**Performance Quality:** The Performance Quality sector includes both Process Optimization which allows these different forms of integrated technologies for optimization of workflow efficiencies, as well as the subcategory of Quality Control that is in service to answering the Performance Quality portion of the research question.

### a) Process Optimization

Big Data models and other integrated technology can be used to handle processing and visualization challenges that have previously arisen due to the Industry 4.0 revolution where machines worked independently of the human mind (Beyer, 2012). Junjun (2021) discuss how the work regarding paper roll packaging is done manually which makes it exceedingly time-consuming and inefficient. With high labour costs and security risks (Junjun, 2021) at play, the implementation of Big Data to automate a system where roll to roll high-precision packaging can be machine-driven would make the production process more efficient. Using Big Data information allows companies to enhance the visual packaging design of product paper packaging to meet the new requirements of an automated container system within a truly intelligent manufacturing environment for packaging service functions (Junjun, 2021). This not only fosters the deep integration of the packaging industry's industrialization, but also effectively improves production efficiency, product quality, cuts down the number of manual operations, and enables a more flexible response to market changes in order to best meet the industry's future needs (Junjun, 2021).

Moreover, as Industry 5.0 works to take efficiency and productivity a step further, marketers are recognizing the importance of utilizing the full capabilities of sensors such as Radio-frequency identification (RFID) that can be attached to physical products to capture large amounts of data. If used effectively, the value of converting such a high volume of data can lead to cutting-edge marketing strategies to allow businesses the opportunity to improve their promotions by targeting them specifically toward their consumer's desires (Pfeiffer, 2018). With IoT and smart packaging being used as a marketing tool, businesses are able to achieve higher levels of efficacy through tailored promotions thereby successfully integrating technology into the food packaging sector, and increasing customer satisfaction as a result of it.

In relevant literature regarding the commercial printing industry, Printed Electronics (PE) are discussed and presented through printed conductive patterns and sensors on a variety of flexible substrates having a multitude of properties. These sensors are extremely important technologies employed in the industry, as they enable visualization, hearing and other types of "sensings" extracted from the environment, enabling machines to respond when necessary. The processes developed enable print companies to manufacture mechanical, environmental, chemical, and medical sensors, as well as construct specialized tools for their analysis and understanding. The measurement range of these sensors covers at least five different orders of magnitude and is required for successful human-machine interaction (Albrecht, 2018). The general print process considers a wide range of printed, smart, and electronic systems for the Internet of Things (IoT) on a variety of substrates. Today, Printed Electronics (PE) allow for new and innovative design techniques, as well as continually shift how companies create and utilize electronics, thereby having a significant impact on not only the printing industry but a myriad of industries that can benefit from printed electronics, from healthcare to manufacturing, to printing.

Additionally, the overall process of the print production workflow is analyzed, from design to printing to production to general system integration (Albrecht, 2018). Integrated technologies, in the form of software and hardware, can play an important role in many spaces in the production process. A technique such as the one described by Villalba-Diez et al. (2019) could be useful, in which a DNN (Deep Neural Network) is applied to IoT devices to develop the ability to perform complex sensing and recognition tasks supporting the quality control process of print production (Cameron, n.d.). Villalba-Diez et al. (2019) discuss the combination of a high-resolution optical camera with advanced machine learning that provides an accurate and powerful tool to compare printed assets with the original engraving file, saving companies time and repetitive work, thereby allowing IoT to create advancements in the printing industry.

Stephanie (2019) showcases a company that has truly pushed the boundaries of automation in packaging. Delta Systems has successfully implemented and embraced industry 4.0 technologies, such as IoT, more specifically, their integration of schneider Electric's PacDrive 3, which is a localized system for controlling a broad range of servo-driven production and packaging machinery (Neil, 2019). Delta systems truly serve as an example of a company that keeps up-to-date with integrated technologies in an effort to streamline workflows and focus on process optimization, and therefore enhancing the user experience without adding further layers of complexity.

Verganti et. al (2020) argue the advantages and disadvantages of design in the age of artificial intelligence (AI), questioning whether AI will transform working frameworks that humans are inadequate in performing. They discuss that AI in actuality, does not undermine or contrast the key principles of Design Thinking which are focused on a people-centered, abductive and iterative fashion, rather it encourages the defeat of previous challenges such as the lack of scope and scale (Verganti et al., 2020). It is debated that although AI within a daily operational setting will present a learning curve for employees, it will also profoundly change the way design is practised, allowing machine learning to automate algorithmic loops to simplify complicated tasks, therefore allowing problem-solving tasks to be completed by the designer. This shift in focus calls for new theories and brings design closer to a leadership standpoint, which inherently impacts the quality of performance and the customer satisfaction of a company, allowing employers to focus on higher-level thinking tasks.

The Kalman observation introduces an algorithm that precisely measures the state of the workflow system using a linear state system whilst pulling from detailed data (Liu et al., 2021). This tool aids in improving the use of colour and visual effects in images. Through deep learning methods, the technology has studied the design of colour matching and image application and aims to transform the ways visual media design is communicated. This visual communication design model that is based on AI technology is able to break through traditional colour matching and orthodox image application to redefine how colour can be used in the field of graphic arts. This inventive method will undoubtedly change day-to-day responsibilities as machines take on a bigger role in the process, optimizing the workflow, allowing employees to focus on higher-thinking tasks allowing companies to prioritize customer satisfaction.

Fortune Business Insights displays the Market Size, Share, and Global Trend of Print Equipment until 2025. With North America leading the global market in 2017, it is clear that the market is highly driven by the dynamic changes these technologies bring. The correlation between the implementation of technological advancements and the adoption of automation, to the increase of growth in the market size, is seen by the myriad of industries that are embracing these technologies (Proquest, 2019). An example that is emphasized is the use of 3D printing throughout a variety of fields, from graphic communications to automotive to healthcare. Drakontaeidis (2019) expands on the uses of 3D printing by introducing an open-source machine learning framework for large scale additive manufacturing (Drakontaeidis, 2019). 3Dprint.AI works towards overcoming the challenges of current day limitations of 3D printing which include the high expenses, time-consumption, and lower quality products created. This proposed framework allows the application of AI algorithms to enable ML and make predictions in large scale additive manufacturing. This not only optimizes the process in 3D printing but also encourages truly intelligent decision making to revolutionize the future of 3D printing.

The manufacturing industry, more specifically, the packaging sector is continuously affected by trends of mass customization and thus, the effort required to keep up with logistics and planning is ever increasing. Knoll et al (2019) propose an approach to use machine learning to automate the development of packaging for an individual packaging part through the overall characteristics available. Historical data of product parts and previous packaging details allow the training of a two-step machine learning model that is able to propose prototypes with an accuracy of 84% (Knoll et al., 2019). This model would aid companies in maximizing their efficiency allowing technologies to take on machine-dependent tasks focusing on quality control and encouraging process optimization. This not only saves time, but allows employees to focus on complex problem solving and direct consumer communication increasing customer satisfaction and user experience.

The impact, both positive and negative, of integrating automation technology in the graphic communications industry has long been discussed. However, it appears that there is a consensus when it comes to filling in the experience gap of skilled press operators. A completely automated offset package printing process allows for a multitude of benefits that are unable to be achieved by untrained employees. Although some may argue that the substitution of machinery takes away from a human's potential career opportunities, the increasing shortage of experienced press operators in the graphic communication industry would argue otherwise. With high image quality, production efficiency accurate predictions of delivery times, a fully automated package printing process would save time, resources and money. This directly translates into lower production costs with less human involvement, thereby allowing packaging manufacturers to decrease prices which leads to higher customer satisfaction and improved profitability.

**b) Quality Control**

Supervised learning is recognized as a subcategory of Machine Learning (ML) and Artificial Intelligence (AI) that uses large data sets to develop and enhance algorithms to predict outcomes (Cloud Education, 2020). Delli and Chang (2018) propose an automated process monitoring system in 3D Printing using Supervised Machine Learning (ML) to keep track of and oversee the printing process (Delli et al., 2018). The suggested technique successfully fulfils the real-time monitoring of a 3D printing process by combining the efficacy of image processing and supervised machine learning. As further advancements were investigated, the research showed that the Supervised ML method was also applicable to monitor quality control and assess the final product. The ML used two data sets to determine whether the printed product fit the pass or fail criteria, optimizing the decision-making process. Previously, this job would've been done through human labor, however, through the use of integrated ML, the back-end procedures of production facilities can rely on integrated technologies to automate the 3D printing process. It's important to note that although workflow efficiencies and quality control are streamlined in this scenario, there are still various drawbacks in the supervised ML method such as having to regularly stop the 3D Printing machine to take images of the process.

Moreover, 3D Printing is unique in its ability to not only advance the Graphic Communications Industry, but also utilize cutting-edge printing technology in various applications throughout different industries. From the biomedical sector (SITU 3D Printing) to manufacturing (Goh et al., 2020), the integration of machine learning techniques at the various phases of the printing process, from design to process optimization to quality control, can help improve the product's overall quality, no matter the end-use as it relates to different industries. As Goh, Sing, & Yeong (2020) state, "ML has been demonstrated to be a powerful tool to perform data-driven numerical simulation, design features recommendation, real-time anomaly detection, and cybersecurity" (Goh et al., 2020). The ability of ML to be implemented in a wide range of applications within the printing process allows the technology to truly streamline and automate mundane back-end tasks that normally require the attention of human labour. As Industry 5.0 continues to take a leading role in the future, appropriately implementing machine learning within 3D printing has the rare potential to optimize processes for all sorts of businesses.

Another example of not only Quality Control in emerging technologies, but also the importance of Process Optimization is shown through Inkjet printing being used to create anti-counterfeit structure color labels that cannot be physically cloned, with a reliable random photonic structure and convenient AI certification (Li, 2021). The ability of the researchers to use both machine learning and validation methodology techniques to develop a training set and authentication methods that can differentiate fake labels from genuine ones is an attestation to the deep learning methods that allow for powerful and accurate pattern recognition through AI, and serves both quality control and process optimization efficiencies in modern-day inkjet printing.

Iuganson (Iuganson, 2018) discusses the interaction between artificial intelligence and additive manufacturing to enhance quality control in stereolithography (SLA) in 3D printing. Based on literature and practical experience, Iuganson studies the future possibilities of SLA to provide a further understanding of the importance of AI in 3D printing. A variety of projects related to real-time 3D print control optimization processes are highlighted to showcase how the implementation of these monitoring methods will enhance Industry 4.0 and work towards the emergence of Industry 5.0. On the other hand, Khan et. al (2021) studies the use of machine learning and Convolutional Neural Network (CNN)-Deep learning models in providing an automation tool to check the quality and provide real-time defect detection of 3D printing products that are generated using Fused Filament Fabrication (FFF) method, an Additive Manufacturing (AM) method that is mainly used in commercial applications.

**<u>Customer Satisfaction:</u>** The second category of Customer Satisfaction specifically discusses how integrated technologies impact the customer satisfaction of companies who've implemented these technologies within the last 10 years through the automation of the Decision Making process itself, and the successful analysis of User Experience.

**a) Decision Making**

Big Data can be used alongside Deep Learning methods to optimize the selection of ideal packaging for different consumer food products. By classifying a variety of food under specific packaging and food characteristics such as type of food recognized, nonperishable vs. perishable and maximum shelf-life, Big Data is able to configure an ideal matching system between food packaging and food characteristics. Implementing Big Data categorization modules like this can help the food packaging sector make better decisions by streamlining the process of selecting appropriate packaging options for various foods (Wei, 2020). The integration of Big Data enhances the capacity to classify and recognize food packaging, consequently encouraging intelligent food packaging development.

Artificial intelligence (AI) can radically change both marketing strategies and customer behaviors, but the lack of information about Industry 4. 0 within marketing creates room for significant uncertainties. Authors such as Davenport et. al (Davenport, et al., 2019) suggest a multi-dimensional framework that not only deals with how marketing strategies and customer behavior will change in the future, but also highlights key policy issues regarding bias and ethics. The authors suggest that AI will be more effective when it complements (rather than replaces) human administrators, thereby predicting customer behavior and aiding in making more informed decisions to assist human managers. This mechanical intelligence enhances the overall consumer experience as the combined decision making of technology and human interaction allows for a statistically sound user experience, therefore increasing customer satisfaction.

Researchers have long since discovered the benefits of automating the selection of graphic design elements as a significant time-saving and effective tool in the design process. However, Wang et al (2020) developed a deep element selection network (DESN) to facilitate designers in selecting elements that appeal to the layout and aesthetic of the overall design, thereby easing time-consumption inefficiencies in the decision making process in design. The machine learning used within this tool allows for the balancing of cost as well as promotes the quality of the design itself through the automated tool that continuously learns the elements that are best suited, and then selected, for the anticipated product (Wang et al., 2020).

Machine learning (ML) and advanced analytics are being used to implement accurate real-time data in the manufacturing process to improve the quality of finished packaging products. Not only is this prediction model being used to provide quality measurements that maintain accurate conditions in the face of changing machine circumstances as the world transforms into a digital era, but also enhances the quality of the finished product as it measures process changes with pre-set packaging standards. In accordance with Industry 4.0, this reduces the need for human disruption as the need for an employee to single handedly dedicate their role to continuously predictive model tuning is alleviated (Rechtin et al., 2019). This allows the packaging critical quality parameter tool to focus on quality control and decision making as it reduces inconsistencies within packaging standards released into the market thereby positively impacting a consumer's perception toward a brand that implements these machine learning algorithms. In addition, Knoll et. al. (2019) demonstrate another initial approach of using machine learning in providing automated solutions in packaging planning and decision-making process in the automotive industry which would influenced by other related information such as logistics functions, suppliers and legal conditions. The approach would contribute to determining the best package and fill rate calculation.

**a) User Experience**

IoT tools such as smart sensor technologies like Near-Field Communication (NFC) tags can be used in customer settings to increase digital consumer engagement, and provide companies with unique marketing and analytics capabilities. Tambo and Lydekaityte (2019) discuss the benefits of implementing NFCs in consumer packaging to collect advanced patterns of objective data during the interaction of consumer consumption. The retrieval of this data allows for advanced analytical processing as well as better performance measurement and management in regard to the effectiveness of marketing efforts. The potential benefits of enhanced insight into consumer consumption and customer experience are advantageous to brand owners and enable IoT integration to improve the packaging sector (Tambo et al., n.d.).

Deniz E. Kurt's (2018) thesis discussed the impact of using artificial intelligence programs to generate visual art, architecture and design and investigated the question of "Can Machines Think", other similar research focused on the impact of using these technologies in arts and design classrooms and how it's important to stay ahead of changes whenever is possible and how that will improve the user experience and quality of performance for students in the classroom.

There seems to be a limited study on the user perspective in the current Internet of Things (IoT) research, and even less on how organizations in the sector address User Experience (UX) while creating for IoT. Bergman et al., (2017) discusses UX through specific methods and case studies, however, there is a lack of research from a broader perspective that focuses on the main challenges. Due to the limited research on the view of UX from a comprehensive approach, there is little discussion on the view of UX for IoT from an industry perspective. As it seems, further research must be conducted in order to investigate how the user experience should be taken into account during the development of IoT devices. Bergman el al.,

(2017) also explores to which extent this is done through a data-driven approach. With the prevalence of this research gap, more specifically, the absence of UX research from a holistic standpoint, the field of Graphic Communication's future progress is hindered due to the sheer lack of integration of such technologies within appropriate companies.

There are viable questions, concerns, and emerging issues that are pertinent to practices that remain undetected or mildly understood in regards to how modern technology has influenced arts and graphic design. Focusing on these underlying issues created by technological implementation in both Arts and Design, it is advisable to embrace the technology in the first place as the world moves towards Industry 5.0, rather than come up with the means to reject or outrun these dynamic changes. Staying ahead of the changes whenever possible is the surest way for businesses to survive in an industry that is so clearly defined by the latest tools and technologies constantly being implemented in a myriad of sectors within the Graphic Communications field. Although there might be some challenges and unfavorable changes that might come up with these implementations, staying ahead of the curve on all things technology allows for businesses to have an easier transition period through the learning curve of adapting to new tools, and therefore allows higher employee comfort and a better user experience (Poon, 2015).

Augmented Intelligent Reality (AIR) is viewed from a holistic perspective to recognize the combination of AR and AI, and how this can be used within packaging design to create engaging visual experiences and socially sustainable practices (Mariani, 2021). This is to say that AIR packaging, when combined with brand transparency and marketing strategies, can be used as a vessel to provide bilateral communication between consumers and companies. Whether that be to offer insight into supply chains or to inform users about the overall production process, this transparency can allow consumers the awareness of the environmental and social effects of the products they choose to consume, thereby reflecting positively on brands who choose to adopt this packaging design.

It's important to note that AI is present in many industry-standard design processes and software, although the designer may not be aware of it (Edberg et al,. 2020). From graphic design to web design, the effectiveness of AI has aided in daily tasks and workflow operations depending on the user's role and responsibilities. Due to natural skepticism and inaccessible information, many companies are hesitant to implement more AI, although it is undisputed that the adoption of AI has affected the essence of the digital design profession for decades prior. On the other hand, Doehling (2019) discusses the reluctance of companies who are predicting the end of graphic design through a deep dive with automation professional Peter O'Donovan (Doehling, 2019). The study encourages designers to adapt to the dynamic landscape of the career and emphasizes the need to pivot to supply what technology can't, which is truly thoughtful designs that cannot be replicated by machinery. Presently, more than ever before, the post-pandemic world is seeing a peak in content creation. That being said, the traditional designer as recognized today will likely become dispensable should they be defined only by their ability to manipulate software such as Canva, Photoshop, or Illustrator, while the truly thoughtful designer ready to adapt to the changing environment will potentially work with machinery to spearhead the beginning of Industry 5.0 as they shape the world of digital design. In the future, the ultimate goal of AI implementation would be the creation of perpetually complex designs that would confuse even humans, but would indeed persuade us to be valuable and add merit where a human brain lacks creativity (Boden, 1998).

Mazzone & Elgammal (2019) discuss the challenge of whether or not digital artists and historians will recognize AI-based creative pieces as an artistic work. They encourage the view of AI algorithms "as more than just tools and closer to a medium" to promote the evolution of AI and machine learning in the creative process (Mazzone, 2019). This would allow the intersection of human creative skills and AI tools to redefine digital art and user experience. Furthermore, as communicative data visualization matures, it has employed a variety of tactics to provide a set of controls helping designers improve the quality and performance of static and animated graphics, which will therefore reduce the need for expertise in graphic design allowing for the human mind and machine learning to work together and enhancing the user experience (Thompson, 2020).

## Analysis

Worries that emerged with Industry 4.0 and past industrial revolutions are embraced by the Industry 5.0 solutions. Unfortunately and inevitably, others remain and new ones appear. Industry 5.0 certainly has good premises, but it is important to understand its limitations and all the parts involved in the process to make it what it is expected to be in the future. Big tech companies, technology fair access, and ethical questions are examples of important subjects to be addressed in order to prepare a safe path to the next industrial revolution.

A question that was already brought up by the Fourth Industrial Revolution: who would benefit the most from industrial technology innovations? The answer seems easy: larger companies have always been ahead when it comes to new technologies employment. Even though these are expected to become more accessible through time and development, they must be guaranteed to keep a fair market share among different businesses. Industry tech owners must keep an effort in providing solutions for small firms. According to Significans (2020), there are already semi-automated systems (in contrast to the larger full ones) available in the market that could be adopted by small-scale businesses. According to Moore's Law, electronic devices tend to get smaller over time, which could contribute to the growth of new tech employment by small-scale firms.

Looking at the bigger picture, tech providers themselves, that is, the group of tech owners will also be largely benefited from the advancement of technology in the industry. Nowadays, big corporations such as Google, Amazon, Facebook, and Apple control most of the tech market share, with a huge influence on the directions taken by tech. As Stanford (2020) stated, "technology itself is neither exogenous nor neutral: the trajectories of innovation always reflect the priorities and interests of those who pay for it to happen". This tends to be a problem if concentrated only in the hands of a selected small group, resulting in monopolistic practices. Furthermore, many industries will be more dependent on tech providers in Industry 5.0, which could also enhance unfair practices such as vendor lock-in, among other ones caused by proprietary software. In this matter, open-source software plays a powerful role as an alternative and has been growing in popularity (Boulanger, 2005). They could fill a gap and contribute, for example, to the widespread adoption of Artificial Intelligence in automation by small companies. Open-source software focused on industrial tasks is already a reality in Industry 4.0 (Eclipse Foundation, 2017) and it is expected to provide an important contribution to 5.0 industries, keeping up with the industrial technology space.

Krafft et. al (2020) discussed the impact of the rapid evolution of these emerging technologies and that "the current disciplinary boundaries will blur at an accelerated pace" and thus, the demand for more interdisciplinary research that connects several stakeholders will also increase. " In this endeavor, there will be a need for significantly more interaction among scientists, technologists, policymakers, and other stakeholders, thus bringing many disciplines (e.g., engineering, computer science, biology, social science) to the table and creating a bridge between them."

New technologies should also be seen through the ethics lens, in order to identify the implications and dilemmas that come along. AI bias, for example, is one major problem that has been drawing a lot of attention recently, resulting in many studies by researchers and technologists. Therefore AI bias must be taken into consideration to ensure that algorithms work in favor of all humans in all conditions, promoting the harmonic collaborative workforce expected.

The most important question: would machine replace humans, would the increased adaptation and integration to those emerging technologies replace the human factor and expertise? Several studies were focused on exploring the human-machine interactions (Abbas, 2019; Albrecht, 2018; Nahavandi,2019), while others concluded that while using emerging technologies would provide real-time solutions and enhance the decision making process, the need to have human involvement and expertise is an asset (Verganti et. al, 2020; Doehling; 2019; Kraft, 2020 )

The other most important and final question is: will there be smart enough technologies available in the next future? Cobots and the idea of a perfect collaborative synergy between machines and humans will require a high level of automation and tech advancements never seen before. Industry 5.0 intentions are likely to be achieved, however, they rely on the technological progress that requires time and investment. At the present moment, technology has been providing incredible contributions to industrial automation, this ultra-connected environment is a significant step to integrate humans with machines. AI, ML, big data, IoT, and many others are the beginning of the future for the Next Industrial Revolution.

## Conclusion

A systematic literature review was conducted based on PICO guidelines to showcase background information and current implementations of promising integrated technologies that are already taking place in the industry and discuss their use and challenges within Industry 5.0. The study aimed to address the research question *"In the Graphic Communications Industry, do the implementations of Integrated Technologies have an impact on the quality of performance and customer satisfaction of organizations who have adopted them in the previous 10 years?"* was considered to showcase the benefits and drawbacks of the implementation of relevant integrated technologies, such as Automation, AI, IoT, ML, Big Data, and Neural Networks. Current challenges, barriers, and the road to Industry 5.0 were also discussed.

While this approach is not a unique research method technique, the singularity of this study is that it was the only available study that covers the wide scope of sectors in the Graphic Communications field and hence bridges a research gap that was previously present. The findings that have been analyzed will benefit those within the Graphic Communications industries as well as those who may be thinking about integrating these technologies within their businesses, and are focused on performance quality and customer satisfaction. The exploration of the many benefits and drawbacks associated with the implementation of integrated technologies within a workplace setting allows a basis for professionals in the industry to consider the use of these promising technologies, and how it may impact their company's process optimization, quality control, decision making, and user experience.

As ongoing and current research at the Toronto Metropolitan University's (TMU) (formerly known as Ryerson), Creative School, 2022, this paper will serve as the basis on which further research will be conducted to cover more border sectors in the Graphic Communications and the Creative Industries that were not addressed in this current research, as well as contribute to providing clear and accessible evidence of a neglected research topic and one that is severely under-addressed within the field of Graphic Communications. In addition, advanced analytical methods will be implemented to provide comprehensive and organized research articles and introduce more focused knowledge clusters to accurately identify gaps in the available literature. In addition, this study would benefit from implementing

Keyword co-occurrence and cross-fertilization of selected fields analysis techniques similar to the techniques that were used in other systematic literature review studies such as by Marini et. al (2021), which would provide another in-depth examination method to better understand the broad implementation of the investigated technologies. For example, some machine learning technologies were used to enhance overall performance optimization which lead to better decision making. Analysis such as these would aid in the holistic approach considered in this paper to advance the Graphic Communications industry even further.

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## Literature Cited

Abbass, H. A. (2019). "Social integration of artificial intelligence: functions, automation allocation logic and human-autonomy trust". *Cognitive Computation, vol.11, no2*, pp.159-171.

Albrecht, A. (2018, April). "Printed Sensors for the Internet of Things", *Technische Universität München*. https://mediatum.ub.tum.de/doc/1437319/1437319.pdf

Bandyopadhyay, D., Sen, J. (2011) "Internet of Things: Applications and Challenges in Technology and Standardization". *Wireless Pers Commun vol (58)*, pp. 49–69 https://doi.org/10.1007/s11277-011-0288-5

Bergman, J., & Johansson, I. (2017, June 22). "Ergonomics and Aerosol Technology. The User Experience Perspective of Internet of Things Development". https://lup.lub.lu.se/student-papers/search/publication/8919050

Beyer, M.A. and Laney, D. (2012) The Importance of "Big Data": A Definition. Gartner. https://www.gartner.com/doc/2057415

Bi Z., Xu L. D. and Wang C., (2014, May) "Internet of Things for Enterprise Systems of Modern Manufacturing," in *IEEE Transactions on Industrial Informatics, vol. 10, no. 2*, pp. 1537-1546, doi: 10.1109/TII.2014.2300338.

Boulanger A. (2005) “Open-source versus proprietary software: Is one more reliable and secure than the other?,” in *IBM Systems Journal, vol. 44, no. 2*, pp. 239-248, , doi: 10.1147/sj.442.0239.

Cameron, L. (n.d.). “Deep Learning Meets the Internet of Things: How New Frameworks Will Drive the Next Generation of Mobile Apps”, IEEE Computer Society. https://www.computer.org/publications/tech-news/research/deep-learning-iot-frameworks-next-generation-mobile-apps

Chui, C., Bonilla-Brunner, A., Seifert, J., Contera, S., & Ye, H. (2019). “Atomic force microscopy-indentation demonstrates that alginate beads are mechanically stable under cell culture conditions”. *Journal of the Mechanical Behavior of Biomedical Materials, vol (93)*, pp. 61–69.

Cloud Education. (2020, August 19). “What is Supervised Learning?”, IBM Cloud Learn Hub. https://www.ibm.com/cloud/learn/supervised-learning

Davenport, T., Guha, A. and Grewal, D. (2019, October 10). “How artificial intelligence will change the future of marketing”. *J. of the Acad. Mark. Sci. vol (48)*, pp. 24–42. https://doi.org/10.1007/s11747-019-00696-0

Delli U., Chang S., (2018). “Automated Process Monitoring in 3D Printing Using Supervised Machine Learning”, *Procedia Manufacturing, Vol (26)*, pp. 865-870, https://doi.org/10.1016/j.promfg.2018.07.111.

Demir K., Döven G. and Sezen B., (2019 “Industry 5.0 and Human-Robot Co-working, *Procedia Computer Science, Vol (158)*, pp 688-695, https://doi.org/10.1016/j.procs.2019.09.104 .

Doehling R. M.,(2019) “Automation in Graphic Design” (2019). *Honors College Theses.* 400. https://digitalcommons.georgiasouthern.edu/honors-theses/400

Domingo M. D., (2012) “An overview of the Internet of Things for people with disabilities”, *Journal of Network and Computer Applications, vol (35), Issue no (2)*, pp 584-596, https://doi.org/10.1016/j.jnca.2011.10.015.

Drakontaeidis, G. (2019, November 7). “3Dprint.AI: Towards Open-Source”, Large-Scale 3Dprinting Beyond Intelligence. https://towardsdatascience.com/3dprint-ai-towards-open-source-large-scale-3dprinting-beyond-intelligence-1c692d0ac324

Edberg, E., & Beck, L. (2020, March). “Adoption of AI in Digital Design - A qualitative study about the effects on the profession”, Diva portal. https://www.diva-portal.org/smash/get/diva2:1333451/FULLTEXT01.pdf

El Naqa I., Murphy M.J. (2015) "What Is Machine Learning?". In: El Naqa I., Li R., Murphy M. (eds) Machine Learning in Radiation Oncology. Springer, Cham. https://doi.org/10.1007/978-3-319-18305-3_1

Goh, G.D., Sing, S.L. & Yeong, W.Y. (2021) "A review on machine learning in 3D printing: applications, potential, and challenges". *Artif Intell Rev 54*, pp. 63–94 https://doi-org.ezproxy.lib.ryerson.ca/10.1007/s10462-020-09876-9

International Society of Automation. (n.d.). "What is automation?" - ISA. isa.org. https://www.isa.org/about-isa/what-is-automation.

Iuganson, R. (2018). "ARCADA. Artificial Intelligence in 3D printing - Real-time 3D printing control.", Thesis https://www.theseus.fi/bitstream/handle/10024/155967/Iuganson_Thesis.pdf;sequence=1

Jara A. J., Zamora-Izquierdo M. & Skarmeta A. (2011). "An Internet of Things-Based Personal Device for Diabetes Therapy Management in Ambient Assisted Living (AAL)". *Personal and Ubiquitous Computing. Vol (15)*, pp. 431-440., doi:10.1007/s00779-010-0353-1.

Khan M. F., Alam A., Siddiqui M. A., Alam M. S., Rafat Y., Salik N. and Al-Saidan I., (2021) "Real-time defect detection in 3D printing using machine learning", *Materials Today: Proceedings, Vol (42), n (2)*, pp 521-528, https://doi.org/10.1016/j.matpr.2020.10.482.

Knoll D., Neumeier D., Prüglmeier M. and Reinhart G. (2019) "An automated packaging planning approach using machine learning", *Procedia CIRP, Vol (81)*, pp. 576-581, ISSN 2212-8271, https://doi.org/10.1016/j.procir.2019.03.158.

Krafft M., Sajtos L. and Haenlein M. (2020) "Challenges and Opportunities for Marketing Scholars in Times of the Fourth Industrial Revolution.", *Journal of Interactive Marketing. Vol (51), n(1)*, pp.1-8. doi:10.1016/j.intmar.2020.06.001

Kurt, D. E. (2018, April). "Artistic Creativity in Artificial Intelligence". Thesis https://theses.ubn.ru.nl/bitstream/handle/123456789/5631/5ae1a7fabbba3-Deniz%20Ezgi%20Kurt%20Thesis%20-%20Artistic%20Creativity%20in%20Artificial%20Intelligence.pdf?sequence=1

Li, S., Xu, L.D. & Zhao, S. (2015) "The internet of things: a survey". Inf Syst Front 17, pp 243–259. https://doi.org/10.1007/s10796-014-9492-7

Li, Y. H., Liu, Z. W., Zhu, K., Ai, L. Q., Jia, P., Wu, N., Yu, H. T., Wang, J. Q., Yao, X., Zhou, J. M. and Song, Y. L., (2021) "Inkjet Printed Physically-Unclonable Structural-Color Anticounterfeiting Labels with Convenient Artificial Intelligence Authentication". *Adv. Mater. Interfaces vol (8)*, 2101281. https://doi-org.ezproxy.lib.ryerson.ca/10.1002/admi.202101281

Liu, C., Ren, Z., & Liu, S. (2021, September 16). "Using Design and Graphic Design with Color Research in AI Visual Media to Convey". https://www.hindawi.com/journals/js/2021/8153783/

Mariani, M. M., Perez-Vega, R., & Wirtz, J. (2022). "AI in marketing, consumer research and psychology: A systematic literature review and research agenda". Psychology & Marketing, vol (39), pp. 755– 776. https://doi.org/10.1002/mar.21619

Mariano, A. G. (2021, July 6). "AIR (Augmented Intelligent Reality) and packaging: Designing for Socially Sustainable Practices". https://yorkspace.library.yorku.ca/xmlui/handle/10315/38462

Martynov,V. V., Shavaleeva D. N. and Zaytseva A. A. (2019), "Information Technology as the Basis for Transformation into a Digital Society and Industry 5.0," 2019 International Conference "Quality Management, Transport and Information Security, Information Technologies" *(IT&QM&IS)*, pp. 539-543, doi: 10.1109/ITQMIS.2019.8928305.

Mazzone, M.; Elgammal, A. (2019). "Art, Creativity, and the Potential of Artificial Intelligence" *Arts vol (8), no. (1)*, pp 26. https://doi.org/10.3390/arts8010026

McKinsey & Company. (2019, February). "Driving impact at scale from automation and AI", (McKinseyDigital). https://www.mckinsey.com/business-functions/mckinsey-digital/our-insights/driving-im pact-at-scale-from-automation-and-ai.

Mokyr, J., & Strotz, R.H. (2000). "The Second Industrial Revolution 1870-1914", Northwestern University, https://faculty.wcas.northwestern.edu/~jmokyr/castronovo.pdf

Muro et. al, (2019, January), "Automation and Artificial Intelligence: How machines are affecting people and places", Metropolitan Policy Program at Bookings,

Nahavandi, S. (2019, August 13). Industry 5.0-a human-centric solution, Multidisciplinary Digital Publishing Institute (MDPI) https://www.mdpi.com/2071-1050/11/16/4371/htm.

Neil, S. (2019). “Delta Systems Pushes the Boundaries of Automation in Packaging”. Oem, http://ezproxy.lib.ryerson.ca/login?url=https://www.proquest.com/trade-journals/delta-systems-pushes-boundaries-automation/docview/2232207491/se-2?accountid=13631

Patel, K.K. and Patel, S.M. (2016) “Internet of Things-IOT: Definition, Characteristics, Architecture, Enabling Technologies”, Application & Future Challenges. *International Journal of Engineering Science and Computing, vol (6)*, pp.6122-6131.

Pfeiffer C., (2018). “The Internet of Things: A Marketing Tool for the Food Industry?”, Thesis, University Of Twente. https://essay.utwente.nl/75302/

Poon S. (2015). “Modernisation of Graphic Design: The Possibilities and Challenges of Digitalisation”. *Journal of Graphic Engineering and Design. Vol (06)*, pp. 05-09. https://www.researchgate.net/publication/305044156_Modernisation_of_Graphic_Design_The_Possibilities_and_Challenges_of_Digitalisation

Proquest (2019, Jul 02). “Print Equipment Market to Reach US$ 20.04 Billion by 2025, Introduction of Automation in Printing to Boost Marke”t, Says Fortune Business Insights. *PR Newswire Europe Including UK Disclose* http://ezproxy.lib.ryerson.ca/login?url=https://www.proquest.com/wire-feeds/print-equipment-market-reach-us-20-04-billion/docview/2250504896/se-2?accountid=13631

Rechtin, C., Ranjan, C., Lewis, A., & Zarko, B.A. (2019). “Creating adaptive predictions for packaging-critical quality parameters using advanced analytics and machine learning”, Solenis Chitta Rnjan, ProcessMiner. https://www.solenis.com/globalassets/resources/journal-articles/optix_papercon2019_rechtin.pdf

Schardt D. (2022, May 5). “INNOVATIONS IN PACKAGE PRINTING AUTOMATION: Newer technologies enable integration between press and post-press solutions to automate the entire package manufacturing process.” *Packaging Strategies June 2020: 20+. Business Insights: Global. Web.*

Tambo, T., & Lydekaityte, J. (n.d.). “Internet Of Packaging (IOP) For Consumer Experience: A Performance Management and Measurement Design Case”. https://pure.au.dk/portal/files/172000328/A18_Tambo_and_Lydekaityte.pdf

Tantawi K. H., Sokolov A. and Tantawi O. (2019) “Advances in Industrial Robotics: From Industry 3.0 Automation to Industry 4.0 Collaboration,” *2019 4th Technology Innovation Management and Engineering Science International Conference (TIMES-iCON)*, pp. 1-4, doi: 10.1109/TIMES-iCON47539.2019.9024658.

Thompson, J. (2020, December). "Augmenting Graphic Design Practices for Expressive Visualization Authoring", Smartech.gatech.edu, Thesis. https://smartech.gatech.edu/bitstream/handle/1853/64209/THOMPSON-DISSERTATION-2020.pdf

Verganti, R., Vendraminelli, L., & Iansiti, M. (2020, September). "Design in the Age of Artificial Intelligence". https://www.hbs.edu/ris/Publication%20Files/20-091_3889aa72-1853-42f8-8b17-5760c86f863e.pdf

Villalba-Diez, J. & Schmidt, D., Gevers, R. , Ordieres-Meré, J. , Buchwitz, M. & Wellbrock, W. (2019). "Deep Learning for Industrial Computer Vision Quality Control in the Printing Industry 4.0. Sensors". 19. 3987. 10.3390/s19183987.

Vincent Julian F. V, Bogatyreva Olga A, Bogatyrev Nikolaj R, Bowyer A. and Pahl A-K, (2006). "Biomimetics: its practice and theory". *J. R. Soc. Interface*. Pp. 3471–482 <http://doi.org/10.1098/rsif.2006.0127>

Wang, G., Qin, Z. and Yan, J. (2020). "Learning to Select Elements for Graphic Design". *Proceedings of the 2020 International Conference on Multimedia Retrieval. Association for Computing Machinery, New York, NY, USA*, pp. 91–99. https://doi.org/10.1145/3372278.3390678

Wei T. and Xiangbo S.,(2020) "Selection of Optimal Packaging Methods for Different Food Based on Big Data Analysis," *2020 IEEE International Conference on Power, Intelligent Computing and Systems (ICPICS)*, pp. 558-561, doi: 10.1109/ICPICS50287.2020.9202379.

Y. Junjun, (2021) "Research on product paper packaging container automation system based on computer big data," *2021 IEEE International Conference on Artificial Intelligence and Computer Applications (ICAICA)*, pp. 1084-1089, doi: 10.1109/ICAICA52286.2021.9498229.

Zheng Z., Zhu J. and Lyu M.r., (2013) "Service-Generated Big Data and Big Data-as-a-Service: An Overview," *2013 IEEE International Congress on Big Data*, pp. 403-410, doi: 10.1109/BigData.Congress.2013.60.