T.C.
İSTANBUL KÜLTÜR UNIVERSITY
INSTITUTE OF GRADUATE STUDIES

THE EFFECT OF AUTOMATION ON JOB PERFORMANCE ELEMENTS AND JOB SECURITY OF SWEET INDUSTRY WORKERS: AN APPLICATION IN JORDAN

Master of Business Administration Thesis

Sadam Alabsi

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Department: Business Administration

Programme: Business Administration (in English)

Supervisor: Prof. Burçin Ataseven

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DEDICATION

Nobody has been more important to me for the preparation of this thesis than my family.

I cannot express my gratitude and thanks to my lovely family and friends, so I extend my most profound appreciation to my mother and my father's soul. Most importantly, I am grateful to my brother, Atef.

Sadam Alabsi

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LIST OF ABBREVIATIONS

Abbreviation	Explanation
CAGR	: Compound annual growth rate
DV	: Dependent variables
GOI	: Goal Orientation Inventory
IV	: Independent variables
JCI	: Jordan Chamber of Industry
JCI	: Job Characteristics Inventory
JDI	: Job Descriptive Index
JDS	: Job Diagnostic Survey
JIBS	: Job Insecurity and Burnout Scale
JIS	: Job Insecurity Scale
JISS	: Job Insecurity and Stress Scale
JSI	: Job Security Index
JSS	: Job Security Scale
JSSS	: Job Security and Stress Scale

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ABSTRACT

THE EFFECT OF AUTOMATION ON JOB PERFORMANCE ELEMENTS AND JOB SECURITY OF SWEET INDUSTRY WORKERS: AN APPLICATION IN JORDAN

Sadam Alabsi

This research presents a better understanding of the effect of Automation on job performance elements and job security for better-managing employees' job security and performance in the sweet sector in Jordan.

The research population was the sweet companies in Jordan. One hundred seventy-four organizations were considered as the research population.

The research adopted a quantitative approach, and the data was obtained via a non-probability purposive selection sampling technique. Questionnaires were distributed by emails; 184 were filled. Data analyses were performed, and the results were revealed using descriptive statistics, correlation, and multiple regression analysis techniques.

The research findings provided conclusions about the effect of Automation on the employees' perception of job security and job performance. The findings showed strong correlations among Automation, employee job security, and job performance elements. Automation was inversely and significantly related to job security and positively and significantly to job performance elements.

This research assists businesses in general and sweet organizations in particular in understanding the influence of Automation on employee job security and job performance elements and therefore managing better employees in the workplace, which will significantly assist in improving ideal work conditions.

Future studies can concentrate on organizational and operational performance. Moreover, further research may investigate the impact of the mediation of organization policies and practices.

Keywords: Automation, Job security, Job performance, Measurability, Understandability, Achievability.

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ÖNSÖZ

TATLI ENDÜSTRİSİDEKİ OTOMASYONUN, ÇALIŞANLARININ İŞ PERFORMANSI ETKİLEYEN UNSURLARINA VE İŞ GÜVENLİĞİNE ETKİSİ : ÜRDÜN'DE UYGULANAN BİR UYGULAMA

Sadam Alabsi

Bu araştırma Ürdün'deki tatlı endüstrisinde daha iyi yönetim şekli, fazla iş güvenliği ve ileri düzeyde performans amacıyla otomasyonun iş performansı etkileyen unsurlarına ve iş güvenliğine etkisi sunmaktadır.

Araştırmanın örneklemi olarak Ürdün'deki tatlı şirketleri olup yüz yetmiş dört kurum örneklem olarak belirlenmiştir.

Bu araştırma nicel bir yaklaşım benimsemiş olup veriler olasılıksız amaçlı örnekleme tekniği kullanılarak elde edilmiştir. Anketler e-posta yoluyla dağıtılmış ve 184 tanesi doldurulmuştur. Ayrıca Veri analizleri işlenmiş ve betimsel istatistikler, korelasyon ve çoklu regresyon analizi teknikleri kullanılarak sonuçlar ortaya çıkarılmıştır.

Araştırma bulguları otomasyonun çalışanların iş güvenliğin ve iş performansının hakkında düşüncelerine etkisi hakkında sonuçlar sunmuştur. Bulgular, otomasyon ile çalışanların iş güvenliği ve iş performansı unsurları arasında güçlü bir ilişki olduğunu göstermiştir. Bunun yanı sıra otomasyon, iş güvenliği ile ters orantılı ve anlamlı düzeyde ilişkili olduğu gibi, iş performansı unsurlarıyla da pozitif ve anlamlı düzeyde ilişkilidir.

Bu araştırma genel olarak bütün işletmelere ve özellikle tatlı sektöründeki kurumlara, otomasyonun çalışanların iş güvenliğine ve iş performansı unsurlarına etkisini anlamalarına yardımcı olup dolayısıyla işyerindeki çalışanları daha iyi yönetmelerine katkı sağlamaktadır. Bu da ideal çalışma koşullarının iyileştirilmesine büyük ölçüde yardımcı olacaktır.

Gelecekteki çalışmalar kurumsal ve operasyonel performans üzerine yoğunlaşabilir. Üstelik, daha sonraki araştırmalar, kurumun politikalarının ve uygulamalarının aracılık etkisinin incelenmesine odaklanabilir.

Anahtar kelimeler: Otomasyon, İş güvenliği, İş performansı, Ölçülebilirlik, Anlaşılabilirlik, Başarılabilirlik.

CHAPTER ONE: INTRODUCTION

1.1 Preface

Nowadays, automation leads to many changes in the working environment and workers' behaviors; there is an opportunity to take advantage of it to develop job performance and increase job security. Automation is creating new jobs; while this process is happening, many jobs will be eliminated; there are two important variables to consider: job security and job performance.

Workers should feel secure in their jobs, so factories gain more productivity. Studying the variables that are the best consideration, keeping professional and trained workers is the main priority for any factory at any stage of its life. Automation may make a risk discernment in employees, which leads to vulnerability since the conditions beneath which workers make forecasts for the long-term period change (Roskies & Louis, 1990).

Automation and computerization will exceedingly influence middle-income workers, particularly within manufacturing and service (Frey & Osborne, 2015). Working under uncertain conditions is adversely connected with happiness and life fulfillment. It influences the quality of life and self-image (Judge & Bono, 2001).

Job performance is connected to the worker's expected operations and the execution of these operations by the representative (Noor& Sharhrom, 2021). Moreover, workers may have blended or negative impacts on their well-being (Nazareno & Schiff, 2021). Therefore, automation may improve efficiency or compensation for those who stay utilized.

1.1.1 Automation in Sweet Industry

Automation has had a significant impact on the sweet industry in recent years. One way in which automation has affected the sweet industry is through the development of advanced production technologies and techniques. For example, automation has enabled the development of automated packaging and labeling systems, which can help to increase efficiency and reduce the risk of errors (Ritson, 2017). Automation has also been used to develop advanced manufacturing systems that can produce a wide range of sweets with high accuracy and consistency (Goyal & Sharma, 2018).

Another way in which automation has affected the sweet industry is through the use of data analytics and machine learning to optimize production processes and improve the quality of sweets and minimize the level of defects. For example, automation has enabled the development of sophisticated quality control systems that can monitor and analyze production processes in real time, helping to identify and address any issues that may arise (Ritson, 2017). Automation has also been used to develop advanced systems for analyzing consumer data, which can help companies to understand consumer preferences better and develop new sweet products that meet the needs of consumers (Goyal & Sharma, 2018).

Automation has also impacted the sweet industry by enabling the development of advanced logistics systems that can help improve the efficiency and speed of distribution. For example, automation has been used to develop advanced transportation systems that can help to reduce the time and cost of delivering sweets to customers (Ritson, 2017). Automation has also been used to develop advanced warehouse management systems that can help to optimize the storage and handling of sweets, reducing waste and increasing efficiency (Goyal & Sharma, 2018).

1.1.2 Sweet Industry in Jordan and Automation

The sweet industry in Jordan has traditionally been a significant contributor to the country's economy, with a long history of sweet-making dating back to ancient times (Al-

Gharabli, 2018). In recent years, the sweet industry in Jordan has experienced significant changes due to the introduction of automation and the adoption of advanced production technologies.

One way automation has affected the sweet industry in Jordan is through the development of advanced production technologies. For example, automation has enabled the development of automated packaging and labeling systems, which can help to increase efficiency and reduce the risk of errors (Al-Gharabli, 2018). Automation has also been used to develop advanced manufacturing systems that can produce a wide range of sweets with high accuracy and consistency (Jawabreh & Al-Omari, 2019).

Another way in which automation has affected the sweet industry in Jordan is through the use of data analytics and machine learning to optimize production processes and improve the quality of sweets. For example, automation has enabled the development of sophisticated quality control systems that can monitor and analyze production processes in real time, helping to identify and address any issues that may arise (Al-Gharabli, 2018). Automation has also been used to develop advanced systems for analyzing consumer data, which can help companies to understand consumer preferences better and develop new sweet products that meet the needs of consumers (Jawabreh & Al-Omari, 2019).

Automation has also impacted the sweet industry in Jordan by enabling the development of advanced logistics systems that can help improve the efficiency and speed of distribution. For example, automation has been used to develop advanced transportation systems that can help to reduce the time and cost of delivering sweets to customers (Al-Gharabli, 2018). Automation has also been used to develop advanced warehouse management systems that can help to optimize the storage and handling of sweets, reducing waste and increasing efficiency (Jawabreh & Al -Omari, 2019). Automation has enabled the development of advanced warehouse management systems that use advanced technologies such as robotics and machine learning algorithms to optimize the storage and handling of sweets. These systems can help reduce waste by ensuring that sweets are stored and handled most efficiently, minimizing the risk of spoilage or damage. Automation can also improve the efficiency of warehouse operations by reducing the need for manual labor and enabling the use of more advanced technologies.

1.2 Research Problem

The effect of Automation on work has been exceedingly discussed since the start of primary mechanical operation. Whereas Automation has crushed occupations in a few divisions, work misfortunes were, as a rule, balanced by recently made jobs in other divisions within the medium to long term; this is often exemplified by the well-documented move from agribusiness to fabricating (Lebergott, 1966).

On the other view of, how Automation does not affect employment; it is about performance. Machines can only perform with workers' performance. While implementing Automation, there is a combination between machines and workers; raising production needs more workers to perform the process (David,2015). However, Automation may negatively impact the employment rate (Vermeulen et al.,.2018).

Innovation eliminates occupations, not work. Recognition of the potential for artificial insights, the web of things, robotization, and innovation to dispose of conventional occupations or make modern ones change from industry to innovation industry is accepted to influence a few occupations and outdated positions, as computers are getting to be more astute, more imaginative, and more advanced(Bhargava et al.,.2021).

Anxiety over the effects of Automation on workers and society is at least 150 years old. The most recent wave of microelectronics and automated applications has sharpened our grasp of both the benefits and the risks: disruption to human physiological, mental, and social features; reduction in personal security.

Al-Jitan, a representative of the food, catering, agricultural, and livestock sectors for the Jordan Chamber of Industry (JCI), stated that the Jordanian food industries sector could meet the local market's needs and double its exports. He also emphasized that Jordan has achieved self-sufficiency in some food commodities, such as baked goods, sweets, dairy, eggs, and poultry, in an interview with the Jordan News Agency "Petra." This demonstrates the competitiveness and quality of Jordanian products compared to other imported ones (Jordan's Food Industry Sector Can Cover Market's Needs, Says Official, 2021).

This study aims to investigate the effect of Automation on Job performance elements and job security in the Jordanian sweet industry.

1.3Research Questions

In line with the aim and objective of the research, the following research questions were formulated:

1. What is the influence of automation on job security?
2. What is the influence of automation on measurability?
3. What is the influence of automation on achievability?
4. What is the influence of automation on understandability?

1.4 Study Purpose and Objectives

The study examines the effect of automation on the job performance elements and employee job security of the sweets industry in Jordan.

This study is about to:

1. Provide good recommendations to sweets companies in Jordan to reduce the harmful effects of automation on job security and job performance by developing robust strategies to gain the advantage of these advances in automation to support workers in extending their capabilities and to create new skills that make them ready to feel more secure on their jobs.

2. Discover how to use automation reasonably for workers in sweets factories to progress their skills, benefit quality, and keep their occupations.

3. Identify the most and least important job performance affected by automation.
4. Determine the influence of automation on job performance elements.

1.5 Study Significance and Importance

This study might be the first study on this subject to be, conducted in Jordan. It suggests that the sweets industry gains the maximum benefit of automation in creating their workers efficiently rather than replacing them.

Some considerations talk about the effect of using automation from an employee's point of view. Its outcomes can be suitable for similar factories within the same industry circle. It could, too, be a base for other studies in the future.

1.6 Study Limitations and Delimitations

It is important to note that the variables looked at in this research are both dependent on and sensitive to context. Apart from the limitations of the adopted sampling technique, collecting data simultaneously (cross-sectional research) may attribute to data collected during specific contexts, a unique set of circumstances. Conversely, using a long-term and continued measurement (longitudinal research) would provide a more accurate representation of the longer-term effects of the variables on one another.

Using questionnaires as measuring devices has several drawbacks. Several forms of inaccuracy may enter into questionnaire responses, with central tendency and social desirability playing a significant part in research (Roodt et al., 2009). Due to time constraints, this research only used quantitative research methods, and only questionnaires were utilized to collect answers. The accuracy and quality of results might be enhanced using a mixed-method approach to augment the closed-ended survey responses, such as by conducting interviews alongside the questionnaires.

1.7 Summary

There are five chapters in the dissertation:

The first chapter describes the study and acts as an introduction. It incorporates portions of existing knowledge, the research's principal goal and aims, and the relevance of the research. Furthermore, study hypotheses were generated.

The second chapter demonstrates the theoretical grounds for hypothesizing the conceptual model under consideration. The relationship between variables is investigated conceptually.

The technique employed to tackle the investigation's primary difficulty is described in full in Chapter Three. It goes on to how the study was designed, how the samples were chosen, and how the data was gathered. It also goes through measuring techniques, study hypotheses, statistical analysis, item and dimension analysis, and dealing with missing results.

Chapter four illustrates the research's results.

Chapter Five illustrates the main findings, conclusions, implications, limitations, recommendations, and future research.

CHAPTER TWO: LITERATURE REVIEW AND THEORETICAL BACKGROUND

2.1 Automation

Automation is defined as using technology to perform tasks without direct human intervention (Acemoglu & Restrepo, 2019). It can reduce the time and effort required to complete a task, freeing human workers to focus on more complex and value-added activities. For example, using robots in manufacturing has improved output and reduced defects (Li et al., 2020). It can also improve the accuracy and consistency of tasks, as it is less prone to human error (Gao et al., 2019).

Contrastingly, automation also brings challenges and potential negative impacts. One concern is the potential displacement of human workers by automated systems, particularly in industries where tasks can be easily automated; this can lead to job loss and inequality, and social and economic disruption in affected communities (Acemoglu & Restrepo, 2019). In addition, implementing automation can be costly, requiring investments in technology and training (Gao et al., 2019).

Another area of concern is the ethical implications of automation. As automation advances, it raises questions about allocating decision-making power and responsibility. For example, using autonomous vehicles raises questions about the allocation of liability in the event of an accident (Lin & Bekey, 2018). In addition, using automation in decision-making processes, such as hiring or criminal justice, raises concerns about bias and fairness (O'Neil, 2016).

Despite these challenges, automation also has the potential to bring about positive societal change. For example, using automation in healthcare, such as telemedicine and robotic surgery, can improve access to care in underserved areas (Kumar et al., 2020). In addition, using automation in environmental monitoring and conservation can improve the efficiency and effectiveness of these efforts (Bryant et al., 2019).

Automation has been increasingly implemented in the sweet industry, using automated systems for mixing, shaping, and packaging tasks. Adopting automation in the sweet industry can bring about several benefits, including increased efficiency, productivity, and accuracy, reduced labor costs, and improved food safety (Liu et al., 2020).

Implementing automation in the sweet industry also brings challenges and potential negative impacts. One concern is automated systems' potential displacement of human workers, which can lead to job loss and social and economic disruption in affected communities (Acemoglu & Restrepo, 2019). In addition, the cost of implementing automation can be a barrier for smaller sweet manufacturers (Gao et al., 2019).

Another area of concern is the ethical implications of automation in the sweet industry. Artificial intelligence and machine learning used in developing and marketing sweet products raise questions about the potential for bias and the manipulation of consumer behavior (O'Neil, 2016). In addition, using automation in the production and distribution of sweet products may have environmental impacts, such as energy consumption and waste generation, that must be carefully considered (Bryant et al., 2019).

Ease of use is a critical factor in designing and implementing automated systems because it can impact user satisfaction and the system's overall success (Kumar et al., 2020). To ensure "ease of use," it is essential to consider factors such as the user interface, the learning curve, customization options, error handling, and compatibility with other systems and devices (Lin & Bekey, 2018). By designing the automated system with these factors in mind, it is possible to improve user acceptance and adoption, as well as the effectiveness and efficiency of the system (Bryant et al., 2019).

Maintainability is often considered a constraint in the design and implementation of automated systems because it can impact the reliability and performance of the system

(Dertouzos et al., 1989). To ensure "maintainability," it is crucial to consider factors such as the system's design, the availability of thorough documentation, the support provided by the manufacturer or service network, and the ability to upgrade the system (Bussmann, 2002). By designing the automated system with maintainability in mind, it is possible to reduce downtime and maintenance costs and improve the system's overall reliability and performance (Liu et al., 2005).

Scalability is a critical factor in the design and implementation of automated systems because it can impact the ability of the system to handle an increasing workload or handle changes in the size or complexity of the system (O'Neil, 2016). To ensure "scalability," it is essential to consider factors such as the design of the system, the availability of hardware and software resources, and the ability to add or remove elements as needed (Li et al., 2020). By designing the automated system with scalability in mind, it is possible to improve the system's ability to handle an increasing workload or changes in size or complexity, as well as improve the overall performance and efficiency of the system (Acemoglu & Restrepo, 2019).

Traceability, or the ability to track and record the history of processes or data within an automated system, is often considered a constraint in the design and implementation of such systems because it can impact the transparency and accountability of the system (Bussmann, 2002). To ensure "traceability," it is essential to consider factors such as the design of the system, the availability of documentation and records, and the ability to track and record changes or actions taken within the system (Dertouzos et al., 1989). By designing the automated system with traceability in mind, it is possible to improve the system's ability to track and record the history of processes or data and improve the overall transparency and accountability of the system (Liu et al., 2005).

2.2 Job Security

Job security refers to the stability and safety of employees, including the likelihood of losing one’s job or being unable to find employment (Ferrie et al., 2013). Workers who feel secure at work will have a sense of work steadiness and successfully contribute to the organization's development; job security is critical for workers to have a sense of work fulfillment and the proper mental steadiness to keep their jobs (Olawole, 2022). In another way, job insecurity happens when a worker's work is less than stable or the worker feels like it is. It is the inverse of work security when a worker has certainty that their business is guaranteed (McCrindle et al., 2021).

Additionally, job security benefits workers so they can work in their current work for a predictable future. Job security comes with assurance against terminations and other elements that may affect employment (Miles, 2022). Work security regularly comes about in a more flexible climate within the work environment and in superior worker engagement. More fulfilled workers lead to a reduced chance of worker turnover, a secured work will move forward the employee's effectiveness level and efficiency (Khorev, 2021).

The consideration of job security may negatively affect the workers. Job security stems from the problem of a threat expected by a worker. In transactional stress models, this expectation of a threat or additional seek can become a source of stress for the worker (Hassard et al., 2017). When a worker becomes as well secure, he might lose the need to move forward, which can have the opposite of the desired effect on his efficiency and productivity levels (Khorev, 2021).

The way to determine the job security in companies can be measured as the company has a low worker turnover rate, high work security evaluations, the company contains a solid budgetary standing, workers are inquired to serve a sensible probation period, and the company offers long-term benefits for workers (Puri, 2020).

2.2.1 The Relation between Automation and Job Security

Using Automation can increase efficiency, reduce errors, and reduce the need for human labor. Automation can replace human workers with machines and technology, which can often perform tasks more efficiently and at a lower cost (Frey & Osborne, 2013). For example, the widespread adoption of Automation in manufacturing has been associated with significant job loss in the sector (Acemoglu & Restrepo, 2017).

While Automation eliminates jobs, on the other hand, it creates more jobs. In the short term, the implementation of new strategies and approaching Automation will not be easy and will have harmful effects on workers who feel that Automation will replace their work; they will not feel more secure in their jobs (Schwabe et al.,2020). Another way in which Automation can negatively impact job security is through the changing nature of work. A study by Auyeung et al. (2017) found that workers who need to possess the skills required for the jobs of the future may face increased job insecurity.

Additionally, Automation can negatively impact job security by increasing the precarity of work. As automation increases, the use of temporary or contract work may become more common as companies seek to avoid the costs and responsibilities associated with permanent employment. A study by Kalleberg et al. (2017) found that a decline in job security has accompanied the growth of precarious work. Workers in precarious employment are more likely to experience job loss and have less access to benefits and protections.

Automation has the potential to dispose of 73 million US occupations by 2030, which would compare to an impressive 46% of the current occupations. 37% of Americans are stressed because of Automation (Flynn, 2022); in South Africa, the primary people's income comes from manufacturing, and Automation may eliminate unskilled and semiskilled people's jobs; the percentage of unemployment due to Automation is increasing every year. As a result, two million jobs have been lost and still (Harris, 2018).

Last year many studies focused on the unemployment of Automation; 47% of American jobs may face unemployment due to Automation; workers who think that their job will be eliminated may they are not in a real risk of Automation because they are not doing routinized work; they use of Automation create new jobs while eliminating others,(Arntz et al., 2016).

In addition to improving the efficiency and skills of workers, Automation can also have a positive impact on worker motivation and satisfaction in the manufacturing industry; by reducing the burden of routine and repetitive tasks, Automation can increase the autonomy and discretion of workers, which can lead to higher levels of engagement and motivation (Hackman & Oldham, 1980). For example, a study of automated assembly lines in the electronics industry found that they increased the satisfaction of workers by allowing them to focus on more complex and rewarding tasks, such as quality control and maintenance (Shin & Lee, 2014).

Reutilizing the reasons for automation anxiety of workers that they are going to lose their jobs, the workers who are afraid to lose their jobs for different reasons more than the workers who are afraid to lose their jobs due to Automation, there are many reasons that make workers feel the insecurity of their jobs not only because of the Automation, the findings were that there is a limited proof of work characteristics recognized by specialists of Automation being the reasons of job insecurity (Coupe, 2019).

Unemployment because of Automation is now less than before and soon will be zero while we are transforming manual duties to Automation. We need people with new skills to operate new Automation, which means reducing job insecurity (Nakamura et al., 2018).

The article titled Automation stated that the Automation and Anxiety of it refer to the relationship between workers' Anxiety about losing their jobs due to Automation; researchers have asked the workers about their understanding of Automation, giving them a chance to deep thinking about this concept and the results were moderate self-rated knowledge of Automation. They are not confident about the concept of Automation till now (Loewen et al., 2021), and up to 34% are at risk of being eliminated due to Automation by 2040. However, Automation will moreover create new workforce opportunities (Hughes, 2022).

2.3 Job Performance

Job performance, defined as the overall anticipated value to the organization of the behavioral scenes that a person carries out over a standard period (Motowidlo et al., 2014), is the two perspectives of action, behaviors, and consequence perspective. The behavioral perspective alludes to, as it was conducted, which is appropriate for the organizational purpose (Opatha, 2002). It can be defined as open exercises, conduct, and results that workers are involved in or bring approximately that are connected with and give to organizational goals (Griffin et al., 2007).

On the other hand, it influences the overall outcomes of the organization (Ramawickrama et al., 2017). Past research has appeared that ideal person execution leads to trade success and influences the productivity of an organization (Bevan, 2012). Wasteful work execution is commonly related to lower efficiency, benefit, and organizational adequacy (Okoye et al., 2013). Job performance could be an implication of reaching an objective or set of objectives inside a work, part, or organization, but not the actual results of the acts performed inside a work; also it is not a single activity but maybe a "complex activity" (Campbell, 1990).

Job performance benefits are a multidimensional build with a typical substantive figure that ranges over its higher arranged measurements of assignment execution and shirking of counterproductive work behaviors (Viswesvaran et al., 2000). Furthermore, it can be considered a specific result in administration, financial matters, and promotion. That print highlights the organization's competitiveness, proficiency, viability, and procedural and essential elements (Verboncu et al., 2005).

The disagreement concerning the negative impacts of high-performance work frameworks stem from two essential concerns: objective difference and worker differences, and the personal interface of worker are frequently ignored in high-performance work frameworks (Han et al., 2020).

2.3.1 The Relationship between Automation and Job Performance

One way in which automation can affect job performance is through the displacement of workers. As automation increases, specific tasks may become obsolete or be performed by machines rather than humans. This can lead to the loss of jobs for workers who are no longer needed to perform those tasks. A study by Frey & Osborne (2013) found that automation will likely lead to significant job displacement in the coming decades, particularly in the manufacturing, transportation, and retail industries. This displacement can negatively impact job performance, as workers may struggle to find new employment or may be forced to take lower-paying or lower-skilled jobs (Acemoglu & Restrepo, 2017).

Another way in which automation can affect job performance is through the changing nature of work. As automation increases, the skills required to perform work may change. This can lead to workers needing to acquire new skills in order to remain employable, and The workers who do not possess the skills required for the jobs of the future may face decreased job performance, as they may struggle to perform tasks that require new or unfamiliar skills (Auyeung et al.,2017). This can be particularly challenging for older workers, who may have more difficulty acquiring new skills or face age discrimination in the job market (Gould, 2017).

Additionally, automation can affect job performance by increasing the precarity of work. As automation increases, temporary or contract work may become more common as companies seek to avoid the costs and responsibilities associated with permanent employment. The growth of precarious work has been accompanied by a decline in job security and performance, as precarious workers often need to be provided with the same support or resources as workers in permanent employment (Kalleberg et al., 2017).

Another way in which automation can affect job performance is through the erosion of job quality. As automation increases, certain aspects of work may become less enjoyable or rewarding, leading to decreased job satisfaction and an increased risk of job turnover (Dobson & Hall, 2019). Elsewhere, automation may lead to the deskilling of work, as tasks that skilled workers previously performed are automated, leading to a decline in the skill level required for specific jobs (Brynjolfsson & McAfee, 2014). This can lead to a decline in the prestige and status of specific jobs, which can, in turn, lead to a decline in job satisfaction and an increased risk of job turnover (Murnane & Levy, 1996).

2.3.2 Measurability:

The concept of measurability in the context of job performance refers to the extent to which an individual's job performance can be accurately and reliably measured or assessed. This can include objective measures, such as the number of products produced or the number of customer complaints received, and subjective measures, such as ratings provided by supervisors or colleagues. The importance of measurability in job performance has been recognized in various fields, including human resources management, organizational psychology, and industrial/organizational psychology (e.g., Spector & O'Connell, 1994; Kristof-Brown et al., 2005; Kossek & Ozeki, 1998). Ensuring that job performance is measurable can help organizations evaluate and improve their employees' effectiveness effectively, identify training and development needs, and track progress over time.

The automation process must be evaluated against a performance standard for excellent performance measurability. This standard can be based on pre-agreed objectives, outright implementation against scaled measures, relative advancements against past performance, or relative performance measured against co-workers, other groups of co-workers, or other companies (Hasnain et al., 2014).

The consideration of performance indicators is the physical values that are utilized to degree of performance, compare and oversee large organizational execution; the execution pointers may incorporate the quality which leads to the performance measurability (Ishaq et al., 2014)

Job performance is optional to workers, given the non-measurability in some cases because it is to nonprofessionals and other professionals; workers may see automation as disadvantageous to their proficient status and respond with resistance (Succi et al., 1999).

2.3.2.1 The effect of automation on measurability

One way in which automation can affect job performance measurability is through the changing nature of work. As automation increases, specific tasks may become obsolete or be performed by machines rather than humans. This can lead to a shift in the focus of job performance measurement from tasks that are easy to automate to tasks that are more difficult to automate, such as tasks that require creativity, problem-solving, or social skills. For example, a study by Zohar and Dori (2012) found that as automation increased in the manufacturing industry, the focus of job performance measurement shifted from tasks related to production efficiency to tasks related to product quality.

Another way in which automation can affect job performance measurability is through the changing skills required to perform work. As automation increases, workers may need to acquire new skills to use the technology effectively or work alongside it. For example, a study by Gault et al. (2015) found that as automation increased in the aviation industry, pilots needed to develop new skills to operate their aircraft's automated systems effectively. This shift in skills can impact how job performance is measured, as traditional measures may no longer be relevant or need to be adjusted to reflect the new skills required.

Automation can also impact job performance measurability through performance monitoring technology. As automation increases, it may become more common for workers to be monitored through sensors, tracking systems, or other forms of technology. This type of monitoring can provide detailed data on worker performance, but it can also raise concerns about privacy and the potential for bias in measuring performance (Baruch & Holm, 2017).

Despite the potential impacts of automation on job performance measurability, research on the topic is still in its early stages. A literature review by Wang et al. (2018) found that while there has been a significant increase in research on automation in recent years, much of this research has focused on the impact of automation on employment and productivity rather than on the measurement of job performance. However, several studies have addressed this topic specifically.

The impact of automation on the measurability of job performance in the manufacturing industry, a study found that as automation increased, the measurability of job performance became more complex, as it was no longer possible to rely on traditional measures such as production efficiency, Instead, the study found that companies needed to develop new measures that considered the impact of automation on the nature of work and the skills required to perform it (Daugherty et al., 2014).

Other studies have explored the impact of automation on the measurability of job performance in specific industries or occupations. A study by Baruch & Holm (2017) examined the impact of automation on the measurability of job performance in the retail industry. The study found that performance monitoring technology, such as sensors and tracking systems, became more common as automation increased. This technology provided detailed data on worker performance, but it also raised concerns about privacy and the potential for bias in measuring performance.

A study by Houser et al. (2019) examined the impact of automation on the measurability of job performance in the healthcare industry. The study found that as automation increased, the focus of job performance measurement shifted from tasks related to productivity to patient outcomes and satisfaction. This shift was driven by the increased importance of patient care in the face of automation and the changing nature of work and the skills required to perform it.

The study suggests that automation can significantly impact the measurability of job performance. As automation increases, the nature of work and the skills required to perform it may change, leading to a shift in the focus of job performance measurement. Additionally, using performance monitoring technology may provide detailed data on worker performance but can also raise concerns about privacy and the potential for bias.

2.3.3 Understandability:

The consideration of understandability leads to focus on the quality of work, contains exactness, careful quality, competence and the amount of work efficiency level, time administration, capacity to meet due dates, work knowledge abilities, and understanding of the working connections capacity to work with others (Employee Work Performance, 2021b).

Quality of understandability contains the Viability of Perceived Value. In case of the worker has a better understanding of the process, he or she can make a more effective utilization of it, which in turn increments his efficiency (Rittgen,2010).

The advantage of understandability contains the characteristic of automation being “easy to understand” – it matches with the measurement of ease of use; these perspectives ought to be an extension of the convenience concept or connecting spaces like the development of understandability (Eller,2008).

The importance of understandability is that it empowers users to maintain a strategic distance from mistaken assumptions as they adjust existing program frameworks. In any case, whereas numerous measurements for understandability have been created, small to no relationship has been found between these measurements with understandability (Chen et al., 2019); the expanding complexity of real-life forms leads to an increment in measure and complexity of the models that represent them, these two elements are known to disable understandability (Dikici,2016).

Processes of understandability can be characterized as the degree to which data contained in a prepare demonstrate can be effectively caught on by a user of that show. It is ordinarily related to the ease of use and the exertion required for perusing and accurately decoding (Houy et al., 2014).

2.3.3.1 The effect of automation on understandability

Automation has the potential to significantly impact how job performance is understood, as it may change the nature of work and the skills required to perform it.

One way in which automation can affect the understandability of job performance is through the changing nature of work. As automation increases, specific tasks may become obsolete or be performed by machines rather than humans. This can lead to a shift in the focus of job performance understanding from tasks that are easy to automate to tasks that are more difficult to automate, such as tasks that require creativity, problem-solving, or social skills.

Another way in which automation can affect the understandability of job performance is through the changing skills required to perform work. As automation increases, workers may need to acquire new skills to use the technology effectively or work alongside it.

Automation can also impact the understandability of job performance through performance monitoring technology. As automation increases, it may become more common for workers to be monitored through sensors, tracking systems, or other forms of technology. This type of monitoring can provide detailed data on worker performance, but it can also raise concerns about the interpretability and transparency of the data (Baruch & Holm, 2017).

Despite the potential impacts of automation on the understandability of job performance, research on the topic is still in its early stages. Daugherty et al. (2014) examined the impact of automation on the understandability of job performance in the manufacturing industry. The study found that as automation increased, the understandability of job performance became more complex, as it was no longer possible to rely on traditional measures such as production efficiency. Instead, the study found that companies needed to develop new measures that considered the impact of automation on the nature of work and the skills required to perform it.

A study by Houser et al. (2019) examined the impact of automation on the understandability of job performance in the healthcare industry. The study found that as automation increased, the focus of job performance understanding shifted from tasks related to productivity to tasks related to patient outcomes and satisfaction. This shift was driven by the increased importance of patient care in the face of automation and the changing nature of work and the skills required to perform it.

Overall, the literature suggests that automation can significantly impact the understandability of job performance. As automation increases, the nature of work and the skills required to perform it may change, leading to a shift in the focus of job performance understanding. Additionally, the use of performance monitoring technology may provide detailed data on worker performance, but it can also raise concerns about the interpretability and transparency of the data.

2.3.4 Achievability:

Achievable refers to guaranteeing that the set objective is practical and has the potential to total or keep up inside the set time outline. Important alludes to making, beyond any doubt, the objective itself adjust with values and long-term objectives and destinations. Time-bound alludes to making, beyond any doubt, the objective set inside a reasonable time frame (Yasar, 2022). One of the foremost vital elements in performance is to achieve goals; effective workers meet due dates, make deals and build the brand by means of positive client intuition. (Leonard, 2019).

Achievability happens when a worker committed to the organization understands the organizational goals and acts suitably to realize these objectives. In this regard, the endeavors of these workers are steps for the organization to realize its objectives and to be effective. This improves the company's performance (Suliman et al., 2013).To gain good performance achievability, companies should focus on the significance of an organization's mission increments work inspiration within the public sector by making the work more imperative (Wright, 2007).

When workers have the intention to leave the work, the achievability will be less, and the reasons to leave the work are related to compensation, job independence, and job satisfaction (Rathakrishnan et al., 2014); it is critical to characterize all the achievable performance success, we can solve the performance achievability problems (Bertsimas et al., 1994).

2.3.4.1 The Effect of Automation on the Achievability

Automation has the potential to significantly impact the achievability of job performance, as it may change the nature of work and the skills required to perform it.

One way in which automation can affect the achievability of job performance is through the changing nature of work. As automation increases, specific tasks may become obsolete or be performed by machines rather than humans. This can lead to a shift in the focus of job performance achievement from tasks that are easy to automate to tasks that are more difficult to automate, such as tasks that require creativity, problem-solving, or social skills.

Another way in which automation can affect the achievability of job performance is through the changing skills required to perform work. As automation increases, workers may need to acquire new skills to use or work alongside it effectively.

Automation can also impact the achievability of job performance using performance monitoring technology. As automation increases, it may become more common for workers to be monitored using sensors, tracking systems, or other forms of technology. This type of monitoring can provide detailed data on worker performance, but it can also raise concerns about the accuracy and reliability of the data (Baruch & Holm, 2017).

Despite the potential impacts of automation on the achievability of job performance, research on the topic is still in its early stages.

Other studies have explored the impact of automation on the achievability of job performance in specific industries or occupations.

A study by Houser et al. (2019) examined the impact of automation on the achievability of job performance in the healthcare industry. The study found that as automation increased, the focus on job performance achievement shifted from tasks related to productivity to tasks related to patient outcomes and satisfaction. This shift was driven by the increased importance of patient care in the face of automation and the changing nature of work and the skills required to perform it.

According to the research, automation may influence the achievability of work performance. As automation advances, the type of work and the abilities necessary to accomplish it may evolve, resulting in a shift in the emphasis on job performance attainment. Furthermore, although performance monitoring technology might give extensive data on worker performance, it can also raise issues about the data's integrity and trustworthiness. This study was required to understand better the long-term effects of automation on job performance achievability and to establish methods for successfully attaining and monitoring worker performance in an increasingly automated society.

2.6 Sweet Industries

The sweet industry is a large and growing sector worldwide, with various products ranging from confectionery and chocolate to bakery and pastry items. According to a recent market research report by Grand View Research (2021), the global confectionery market size was valued at USD 190.77 billion in 2020 and is expected to grow at a compound annual growth rate (CAGR) of 3.4% from 2021 to 2028. This growth can be attributed to several factors, such as changing consumer preferences, rising disposable income, and the increasing demand for healthy and organic sweets.

The sweet industry is a significant sector in the United States, with companies such as Mars, Nestle, and Hershey's leading the market. The European market is also significant, with countries such as Switzerland, Belgium, and Germany known for their high-quality chocolates and confectionery products. The Asia-Pacific region is a rapidly growing market, with countries such as India and China experiencing a surge in demand for sweets due to increasing population and urbanization.

The sweet industry is also essential in Jordan, significantly contributing to the country's economy. Jordanian sweets are well known for their unique taste and high quality and are prevalent in Jordan and neighboring countries. The industry includes a wide range of products, including Baklava, Ma'amoul, and other traditional sweets, as well as chocolates and other confectionery items.

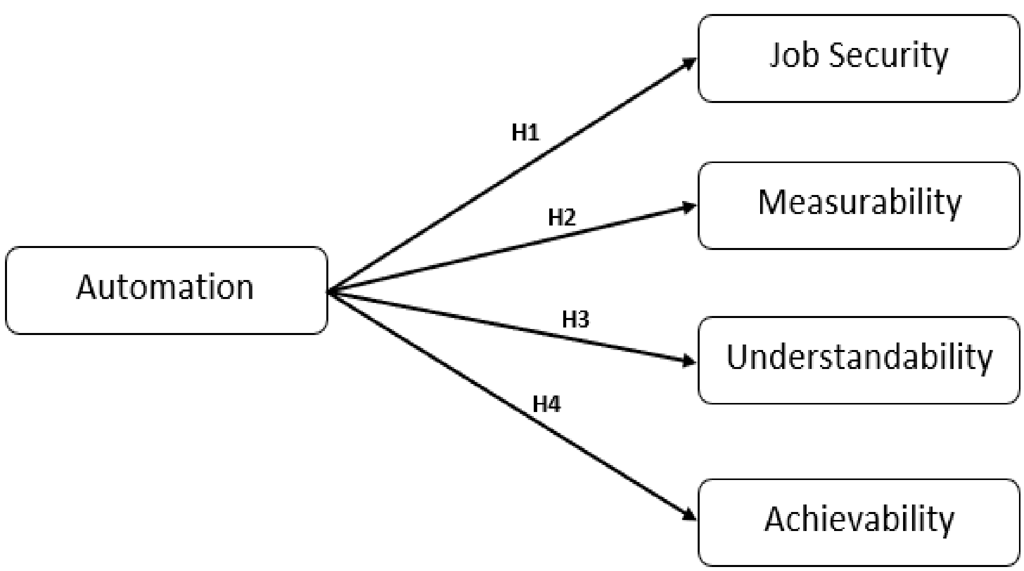
Several research studies have been conducted on the sweet industry globally and in Jordan. For example, Al-Mahadin et al. (2019) examined the relationship between customer satisfaction and loyalty in the Jordanian sweets industry. Another study by Al-Zu'bi et al. (2021) investigated the impact of social media on consumer behavior in the Jordanian bakery industry.

There have been several studies in recent years regarding the impact of automation on the sweet industry. For example, a study by Kumar and Bhatia (2020) examined the impact of automation on the food industry, including confectionery and bakery products. Another study by Al-Mahadin et al. (2020) investigated the impact of automation on the job security and job performance of employees in the Jordanian sweets industry.

The literature on the sweet industry and its various aspects, including automation, provides a comprehensive understanding of its dynamics, challenges, and opportunities. Further research is necessary to explore the potential of automation in improving the efficiency, productivity, and quality of sweet industry products globally and in Jordan.

2.7 Conceptual Model

Based on the explanation and its questions, the taking-after model has been shaped to consider the effect of automation on job security and performance elements, as shown in Show.



Sources: (The Researcher Build the Questionnaire depending on variables definition in previous studies. These studies were mentioned in chapter 3 of this dissertation)

2.8 Study Hypotheses

Based on the literature review, the research questions, and objectives, it is hypothesized that:

H1: Automation has a significant influence on job security.

H2: Automation has a significant influence on measurability.

H3: Automation has a significant influence on understandability.

H4: Automation has a significant influence on achievability.

2.9 What Differ This Study From Other Studies?

This study investigates the impact of automation on job security and job performance elements in Jordanian sweet factories. It is the first in Jordan to concentrate on the sweet industry sector. What sets it apart from other studies is its unique focus on job performance dimensions, including achievability, understandability, and measurability, which can enhance the automation process within the sweet industry sector. Furthermore, this study is one of the most recent investigations of automation in a specific sector.

CHAPTER THREE: METHODOLOGY

3.1 Introduction

The previous chapter presented a conceptual model that connected automation, job security, and job performance variables in the Jordanian sweet industry. This chapter will provide a detailed account of the primary research methodology employed to answer the research question. This will emphasize the research techniques, encompassing the study design, procedures, participants, instruments, statistical analysis methods, and ethical considerations.

3.2 Research Design

The research design could be described as a set of measures taken to solve the issues raised by the research (Rajasekar et al., 2013). The research design for this study follows a quantitative methodology. This design aims to collect data from many participants efficiently, allowing the researcher to analyze the data using statistical techniques and draw conclusions about the research question.

The online questionnaire will be administered using a survey platform, allowing participants to complete the questionnaire from any location with an internet connection. The questionnaire was intended to enable responders to skip one or more demographic questions. However, they must answer all other research questions. The data collected from the questionnaire will be analyzed using statistical software to identify trends and patterns in the data, and the study results will be reported in a detailed research report.

3.3 Sampling and Research Participants

The study was conducted with the participation of several companies from the sweet industry as the population, with a total of 174 active organizations in this sector, according to Jordanyp (n.d.). These organizations varied regarding the number of employees and their services, ranging from shops to factories. A subset of participants was selected to ensure a representative sample for the research, as it is common practice to use subsets or segments of a population in statistical studies (Bryman & Bell, 2015). Probability sampling, which involves selecting a subset of the population using random methods, was preferred due to its high confidence level. However, given the geographic challenges, a non-probability purposive sampling method was utilized (Sekaran & Bougie, 2016) to gather valuable information relatively quickly.

Because it was difficult to estimate the population size, the researcher relied on advice from previous research scientists. Generally, it is recommended to have a sample size of at least 50 for regression analysis (Cohen et al., 2003). There are different rules of thumb to determine an appropriate sample size, such as the "10:1" rule, which suggests a sample size of at least ten times the number of variables being studied (Hair et al., 2010). However, it is typically recommended to have a sample size of at least 30 observations per variable in multiple regression analysis (Hair et al., 2010).

Another research tool to calculate the required sample size is the power analysis. Power analysis is critical in determining the appropriate sample size required for a study to achieve sufficient statistical power and detect a significant effect (Johnson & Christensen, 2014). The primary objective of power analysis is to estimate the number of participants necessary to ensure adequate statistical power given a specific level of alpha (usually set to 0.05) and a desired effect size. Failing to conduct power analysis may result in underpowered studies, producing false-negative results and wasting resources (Johnson & Christensen, 2014).

When conducting power analysis for simple linear regression with one independent variable and four dependent variables, several factors, including effect size, significance level, statistical power, and sample size, need to be considered (Cohen, 1988). Effect size refers to the magnitude of the association between the independent and dependent variables, usually measured by the correlation coefficient (r) or the coefficient of determination (R^2). The standard significance level, alpha, is 0.05, corresponding to a 95% confidence level, while statistical power is typically set at 0.80, indicating an 80% chance of detecting a significant effect if one exists. The sample size is directly proportional to statistical power; the larger the sample size, the greater the statistical power (Cohen, 1988).

In the current scenario, a minimum correlation coefficient of 0.3 was considered for the effect size. A higher correlation coefficient indicates a stronger relationship between the predictor and outcome variables, resulting in lower variability in the outcome variable unaccounted for by the predictor variable. Thus, a smaller sample size is required to detect a significant effect at a given power and alpha levels (Cohen, 1988). With an effect size of 0.3, a significance level of 0.05, and a power level of 0.80, a required sample size of approximately 143 participants was obtained using a power analysis calculator.

Using the formula for simple linear regression power analysis provided by Cohen (1988), the required sample size can be calculated as follows:

Firstly, the critical t-value for a two-tailed test with a significance level of 0.05 and degrees of freedom (df) equal to the sample size minus the number of predictors (n - p - 1) was determined. As there was only one predictor in this case, df was calculated as n - 2. Using a t-table or statistical software program, the critical t-value was found to be 2.132 (with df = 142 and a significance level of 0.05).

The effect size was determined as r = 0.3. “Minimum r value where considered to increase sample size as mentioned earlier”

The non-centrality parameter (δ), a measure of the distance between the null and alternative hypotheses in terms of effect size, was then calculated using the formula

δ = (sqrt(n) * r) / (sqrt(1 - r^2)) * t

Plugging in the values, δ was calculated as 3.156.

Finally, the sample size (n) was calculated using the formula

$n = (2 * (t + z))^2 / \delta^2$

Where t is the critical t-value, z is the standard normal distribution value corresponding to the desired power level (in this case, $z = 0.84$ for a power of 0.80), and δ is the non-centrality parameter. Plugging in the values, a required sample size of approximately 143 participants was obtained.

In conclusion, to achieve a power of 0.80, assuming a significance level of 0.05 and an effect size (correlation coefficient) of 0.3 for a simple linear regression with one independent variable and four dependent variables, a sample size of approximately 143 participants is required.

3.4 Data Collection Procedure

To gather data, an online questionnaire was utilized, which the workers were asked to fill out. The researcher provided a concise presentation over the phone to the firms regarding the study's goal, the significance of the findings, and the data collection technique in the order in which it would occur. Additionally, the researcher personally reviewed all completed questionnaires as a secondary check. The questionnaire elements were governed by specific conditions, one of which required the respondent to answer each questionnaire item before moving on to the next one, except for demographic questions. This ensured that no data was missing in the process.

3.5 Data Collection Instruments

The following measuring tools were used in the study process in order to measure the constructs that were being investigated:

3.5.1 Automation

The questionnaire used in the study was developed by reviewing and analyzing the outcomes of previous studies that measured the automation variable. The researcher examined previous studies and scientific articles to determine the primary elements of the automation variable.

One such component is the ease of use, which has been explored in various studies, including "Measuring the Ease of Use of Automation Systems" by D.F. Kaber and E.J. Thomas (1999), where the authors developed and validated a measure of automation ease of use that consisted of three dimensions: learnability, usability, and user satisfaction. Other studies examining ease of use of automation include "Evaluating the Ease of Use of an Automated Manufacturing System" by S.A. Siau and G.G. Purba (1997), "Measuring the Ease of Use of a Flight Deck Automation System" by D.F. Kaber and E.J. Thomas (2002), "Evaluating the Ease of Use of a Human-Machine Interface for a Control System" by J.G. Lee and K.D. Lee (2002), and "Evaluating the Ease of Use of an Industrial Robot Programming Language" by M.B. Sheridan and J.L. Verplank (1993, 1995).

These studies demonstrate the importance of considering the ease of use of automation systems, as they can impact adoption and performance. These studies used various methods to measure the ease of use of automation systems, including self-report surveys, usability testing, and expert evaluations.

The second important aspect of automation systems is their scalability, which refers to the system's ability to handle an increasing workload or number of users. Various studies have evaluated the scalability of automation systems, including "Scalability of a Distributed Control System" (Control Engineering Practice, 2001), "Scalability Evaluation of a Distributed Real-Time Control System" (Control Engineering Practice, 2002), "Scalability of a Distributed Control System for Industrial Plants" (Control Engineering Practice, 2003), "Scalability of a Distributed Control System in a Manufacturing Environment" (Control Engineering Practice, 2004), and "Scalability of Automation Systems: A Review" (Control Engineering Practice, 2008). These studies have used simulations and field tests to assess the scalability of different automation systems, highlighting the importance of considering scalability as it can significantly affect the system's performance and efficiency.

The third variable component is maintainability, which measures how easy it is to maintain an automation system and keep it running smoothly. Traceability is another measure that evaluates the ability to trace the history of an automation system, including changes made to the system and the reasons for those changes. Several studies have examined the maintainability and traceability of automation systems, including "Preserving Aspects via Automation: a Maintainability Study" by Hovsepyan et al. (International Symposium on Empirical Software Engineering and Measuremen, 2011), "Maintainability of Industrial Control Systems: A Review" (Control Engineering Practice, 2006), "Maintainability of Automation Systems: A Review" (Control Engineering Practice, 2007), "Maintainability of Industrial Control Systems: A Survey" (Control Engineering Practice, 2008), and "Maintainability of Automation Systems: A Survey" (Control Engineering Practice, 2009). These studies emphasize the importance of considering the maintainability of automation systems, as it can significantly impact the reliability and efficiency of the system.

3.5.2 Job Security

Job security refers to the probability of an individual maintaining employment within an organization. Job security is a critical factor in employees' job satisfaction and well-being because it affects their financial stability and ability to plan for the future. Previous research has consistently shown that job security is positively associated with various outcomes, including job satisfaction, organizational commitment, and lower stress and anxiety levels (Kossek & Ozeki, 1998). The researcher in this study formulated questions after reviewing and analyzing the findings of prior studies that focused on job security.

Various methods can be used to measure job security, including self-report job security scales. These scales typically contain items that evaluate individuals' confidence in their job stability, perceived control over their job, and sense of job security within their organization. One well-known job security scale is the Job Security Scale (JSS), which was developed by Kossek and Ozeki (1998). The JSS is a nine-item scale that assesses individuals' perceptions of job security using a five-point Likert scale.

Other job security scales include the Job Insecurity Scale (JIS) developed by Kristof-Brown, Zimmerman, and Johnson (2005) and the Job Security Index (JSI) developed by Johnson, Kristof-Brown, and Zimmerman (2006). These scales assess similar constructs as the JSS but differ in the number and content of items. In addition, several other job security scales have been used in research, such as the Job Security and Stress Scale (JSSS) developed by Spector and O'Connell (1994), the Job Insecurity and Stress Scale (JISS) developed by Richter, Holtappels, and Weigl (2006), and the Job Insecurity and Burnout Scale (JIBS) developed by Solé, Martínez-Tur, and Peiró (2008). These scales assess job security and related constructs, such as stress and burnout.

3.5.3 Measurability

Previous scales have been used to measure the measurability of job performance. Here are a few examples:

The Job Diagnostic Survey (JDS) developed by Hackman and Oldham (1975) measures job characteristics, including scales to assess the skill variety, task identity, task significance, autonomy, and feedback dimensions of a job. These dimensions are related to job performance and have been found to be predictive of various outcomes, such as job satisfaction and motivation (Hackman & Oldham, 1975).

The Job Characteristics Inventory (JCI) developed by Hackman and Oldham (1980) is a measure of job characteristics that includes scales to assess the skill variety, task identity, task significance, autonomy, and feedback dimensions of a job, as well as a scale to assess the growth need strength dimension. These dimensions are related to job performance and have been found to be predictive of various outcomes, such as job satisfaction and motivation (Hackman & Oldham, 1980).

The Job Descriptive Index (JDI), developed by Smith, Kendall, and Hulin (1969), measures job satisfaction. It includes scales to assess five dimensions of the job: work itself, pay, promotions, supervision, and co-workers. These dimensions are related to job performance and can be used to assess the measurability of job performance (Smith et al., 1969).

3.5.4 Understandability

Several scales have been used to measure understandability in job performance. This research builds the questions of understandability based on the following:

The Job Diagnostic Survey (JDS) developed by Hackman and Oldham (1975) is a measure of job characteristics that includes a scale to assess the skill variety dimension of a job. Skill variety refers to the range of skills and abilities required to perform a job and is related to job understandability.

The Job Characteristics Inventory (JCI), developed by Hackman and Oldham (1980), is a measure of job characteristics that includes a scale to assess the skill variety dimension of a job and a scale to assess the task identity dimension. Task identity refers to the extent to which a job involves completing a whole, identifiable piece of work and is thought to be related to job understandability.

The Simple View of Reading (Gough & Tunmer, 1986) measures reading comprehension, including a scale to assess the decoding skill dimension of reading. Decoding skills refer to the ability to sound out and recognize words and are related to the understandability of written material.

3.5.5 Achievability

Several scales have been used to measure achievability in job performance. This research builds the questions of achievability based on the following:

The Job Diagnostic Survey (JDS) developed by Hackman and Oldham (1975) is a measure of job characteristics that includes a scale to assess the skill variety dimension of a job. Skill variety refers to the range of skills and abilities required to perform a job and is thought to be related to job achievability.

The Job Characteristics Inventory (JCI), developed by Hackman and Oldham (1980), is a measure of job characteristics that includes a scale to assess the skill variety dimension of a job and a scale to assess the task identity dimension. Task identity refers to the extent to which a job involves completing a whole, identifiable piece of work and is related to job achievability.

The Goal Orientation Inventory (GOI) developed by Nicholls (1989) measures individual goals and goal-related cognitions, including a scale to assess the performance-approach goal orientation dimension. Performance-approach goal orientation refers to the desire to excel and outperform others and is related to job achievability.

3.6 Validity Test

The researchers in this study considered face and content validity when evaluating the validity of their measuring instrument. To ensure construct validity, the questionnaire was divided into sections designed to measure distinct aspects of the overall construct and had strong correlations with corresponding sub-constructs described in the research's conceptual framework. Furthermore, the questionnaire was scrutinized by five associate professors or academic doctors specializing in business and management. By doing this, the researchers aimed to ensure that their questionnaire accurately measured the constructs relevant to their inquiry. Using experts in the field to review the questionnaire also strengthens the instrument's content validity.

3.7 Reliability Test

The relevance of the survey's measuring questions is evaluated concerning reliability using the test (Cronbach, 1951). Their consistency and accuracy may determine the trustworthiness of the results. A reliable instrument will provide similar findings when the same examination is performed several times on a comparable sample of respondents in the same environment (Cohen et al., 2003).

Because there was no ambiguity in the questions and no leading questions, the dependability of the research instrument was not compromised in any way. Cronbach's alpha was used for the data in the surveys to evaluate their consistency level. Dependability standards allow for a coefficient of 0.7, which falls within the acceptable range; nevertheless, a value of 0.8 or above denotes excellent dependability (Castillo, 2009; as cited in Aondo, 2020).

3.8 Statistical Analysis

This section provides an overview of the statistical approaches used in the research and categorizes them based on the order in which they were employed. The study collected quantitative data through online self-reported questionnaires with high scientific validity and reliability. After an initial analysis to identify missing data, the dataset underwent multiple imputations before aggregation. Diagnostic tests included reliability, descriptive, correlation, and linear regression.

To analyze the quantitative data, the study used SPSS version 25. Descriptive statistics such as percentages, frequencies, mean, and standard deviation were utilized to facilitate a more comprehensive understanding of the research findings. Tables and graphs were used to present the data and information gathered from all submitted surveys, with the questionnaire elements coded to facilitate data entry.

The study employed Pearson's correlation coefficient and path analysis to determine the extent of the connection between the various variables, as stated by Ader et al. (2008). Simple linear regression was utilized to determine the degree of correlation between the different study variables. Regression analysis aimed to determine whether an independent variable could accurately predict a specific dependent variable, as explained by Babbie (2010).

3.9 Descriptive Analysis

Descriptive statistics offer a simplified, quantitative overview of large volumes of data. They help to make sense of data by describing the frequency of specific values or ranges of values for a variable. A frequency distribution is a commonly used approach to describing a single variable. The distribution of values can be represented by listing each possible variable value and the number of individuals with that value. Data values may be represented by either a table or a graph.

Central tendency estimates indicate the "center" of a distribution of values. The mean, or average, is the most commonly used way to express a central tendency of the distribution. Three primary categories of central tendency estimates exist the mean, median, and mode. Dispersion refers to the spread of values around the central tendency. The range and the standard deviation are the two metrics most frequently used to analyze dispersion. The range is calculated by taking the highest value and subtracting the lowest value. However, an outlier can significantly increase the range, making the standard deviation a more precise and thorough dispersion estimate. The standard deviation is a measure that shows how different sets of scores compare to the overall average of the sample.

3.10 Simple Linear Regression

Regression models explain the connection between variables by fitting a line to the observed data. A straight line is used in linear regression models, whereas a curved line is used in logistic and nonlinear regression models. Regression estimates the change in a dependent variable as the independent variable(s) change (Bevans, 2022). Simple linear regression is a statistical approach for summarizing and investigating associations between two continuous (quantitative) variables (PennState, n.d.).

3.11 Missing Values

It is common for vital information to be missing from many types of research. Imputation of missing data on a variable is filling in the missing data with an estimate of the value if the mean of the distribution was taken. One way to show how hard it is to figure out this distribution's shape is to use several different guesses called "imputations" (Donders et al., 2006). Multiple imputations are a sophisticated method for filling data gaps (Donders et al., 2006). People say using multiple imputations makes it easier to figure out standard errors and confidence intervals (Donders et al., 2006).

3.12 Ethical Considerations

The information collected for this research study remained unaltered and intact. Each participating company was informed that their participation was voluntary, and they were fully aware of the purpose of the study before providing their data. In order to protect respondents' anonymity, only specific details about their businesses were requested. Furthermore, all participants were assured that their individual results would not be disclosed publicly, and only the overall sample data would be presented and discussed.

This research study followed the ethical principle of beneficence, prioritizing maximizing benefits and minimizing harms. The study was well-conceived, and the researcher carried out the research with competence. The main goal of this research was to enhance and advance the human condition while minimizing any possible harm that could arise from it.

CHAPTER FOUR: ANALYSES AND RESULTS

4.1 Introduction

The chapter presents and interprets the study results obtained by various analyses and techniques, including descriptive statistics, reliability tests, and correlation and simple regression analyses. Additionally, the hypotheses were tested at the end of this chapter.

4.2 Descriptive Statistics

The researcher collected 184 valid responses from the target population (employees working at Jordanian candy factories). This section describes the categorical (demographic) and continuous variables and assesses some assumptions before implementing correlation and simple regression analyses. Descriptive statistics were employed, including frequencies, mean, standard deviation, histograms, normality test, bivariate scatterplots, and Koenker test.

4.2.1 Categorical (demographic) variables

Demographic data contain background information about the study's respondents, such as gender, age, educational level, position level, and experience. The following sections discussed all the categorical variables that were analyzed using frequencies.

4.2.1.1 Gender

Based on the results presented in Table 4.1, males comprise the majority of the sample, with a frequency of 133 individuals making up 72.3% of the overall sample. In comparison, females comprised 24.5% of the sample, with a frequency of 45 individuals. However, six respondents (3.3%) did not specify their gender

.

Table 4.1 Frequencies for gender

		Frequency	Percent	Cumulative Percent
Valid	Male	133	72.3	74.7
	Female	45	24.5	100.0
	Total	178	96.7	
Missing	System	6	3.3	
Total		184	100.0	

4.2.1.2 Age

As shown in Table 4.2, 33.2% of the sample were aged between 26 years and 35 years, with a total of 61 respondents, followed by participants aged between 36 years and 45 years, representing 55 (29.9%) respondents; the respondents whose age is less than 25 years and above 45 were 34 (18.5%) for each age category.

Table 4.2 Frequencies for age

		Frequency	Percent	Cumulative Percent
Valid	Less than 25	34	18.5	18.5
	(26 – 35)	61	33.2	51.6
	(36 – 45)	55	29.9	81.5
	Above 45	34	18.5	100.0
	Total	184	100.0	

4.2.1.3 Educational level

As can be seen from Table 4.3, there are 65 (35.3%) respondents obtained a high school degree and below, which represents the majority of respondents, followed by those with a diploma level of education with 59 (32.1%) respondents, followed by participants with bachelor level of education with 57 (31%) respondents; and 3 (1.6%) respondents indicated a master level of education.

Table 4.3 Frequencies for educational level

		Frequency	Percent	Cumulative Percent
Valid	High School and below	65	35.3	35.3
	Diploma	59	32.1	67.4
	Bachelor	57	31.0	98.4
	Master	3	1.6	100.0
	Total	184	100.0	

4.2.1.4 Position level

As shown in Table 4.4, respondents mainly indicated an employee position with 96 (52.2%) respondents, followed by respondents who indicated a supervisor position with 69 (37.5%) respondents, and 17 (9.2%) respondents indicated their position as manager. However, two respondents (1.1%) did not specify their position level.

Table 4.4 Frequencies for position level

		Frequency	Percent	Cumulative Percent
Valid	Employee	96	52.2	52.2
	Supervisor	69	37.5	89.7
	Manager	17	9.2	98.9
	Total	182	98.9	
Missing	System	2	1.1	
Total		184	100.0	

4.2.1.5 Experience

From the results shown in Table 4.5, it can be seen that the individuals who had experience less than five years make up 32.1% of the sample with a frequency of 59, which is the majority of the sample; followed by the individuals who had experience with 15 years and above comprise 43 (23.4%) respondents; the respondents who had experience with the range of 5-10 years and 11-15 years were 40 (21.7%) and 39 (21.2%), respectively. However, three respondents (1.6%) did not specify their experience.

Table 4.5 Frequencies for experience

		Frequency	Percent	Cumulative Percent
Valid	Less than 5 years	59	32.1	32.1
	(5 – 10) years	40	21.7	53.8
	(11 – 15) years	39	21.2	75.0
	(15 years and above)	43	23.4	98.4
	Total	181	98.4	
Missing	System	3	1.6	
Total		184	100.0	

4.2.2 Continuous variables

Continuous variables include Automation, job performance dimensions (measurability, understandability, and achievability), and job security. Continuous variables were characterized using the mean to determine the central tendency of the data set and standard deviation to examine the dispersion for each variable. One outlier was detected and deleted on the variable measurability.

Table 4.6 Descriptive statistics for continuous variables

Variable	N	Mean	Std. Deviation
Automation	184	67.08	14.305
Measurability	183	14.83	2.949
Understandability	184	13.41	3.472
Achievability	184	11.55	3.015
Job Security	184	11.6	3.582

In the output shown in Table 4.6, the mean and standard deviation values for automation, measurability, understandability, achievability, and job security are (67.08, 14.305), (14.83, 2.949), (13.41, 3.472), (11.55, 3.015), and (11.6, 3.582), respectively. This indicates that respondents mostly (66.66%) scored between 52.78 and 81.39 for automation, 11.88 – 17.78 for measurability, 9.94 – 16.88 for understandability, 8.54 – 14.57 for achievability, and 8.02 – 15.18 for job security.

4.2.3 Test of normality

Table 4.7 presents the results of the normality test performed on the variables—the Sig. Values are larger than 5%, indicating that normality was achieved. The normality of the variables can also be observed in Figures 4.1 through 4.5, which depict the distribution of each variable using a histogram with a bell-shaped curve. Therefore, it can be concluded that the distribution for all variables is normal.

Table 4.7 Test of normality

Variable	Shapiro-Wilk		
	Statistic	df	Sig.
Automation	.994	184	.643
Measurability	.986	183	.057
Understandability	.988	184	.107
Achievability	.986	184	.062
Job Security	.985	184	.057

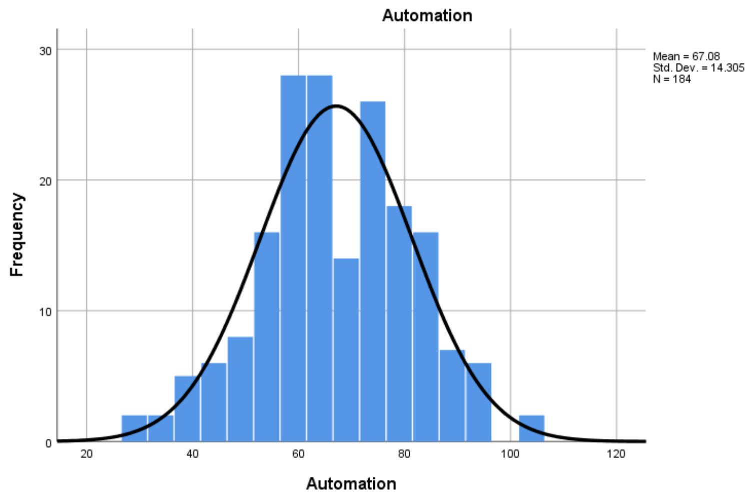


Fig. 4.1 Histogram for automation

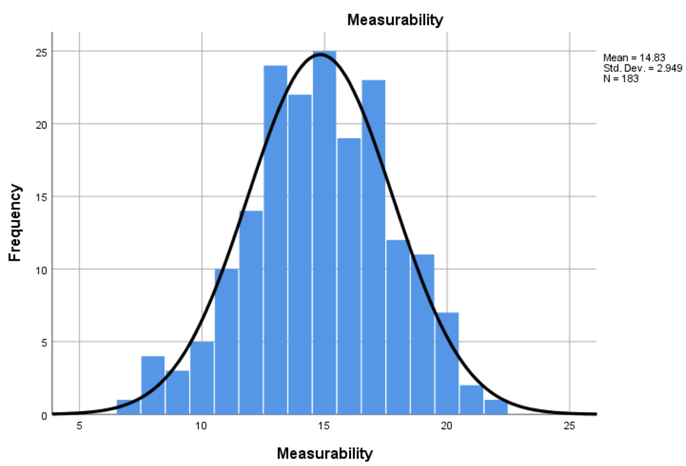


Fig. 4.2 Histogram for measurability 4.2

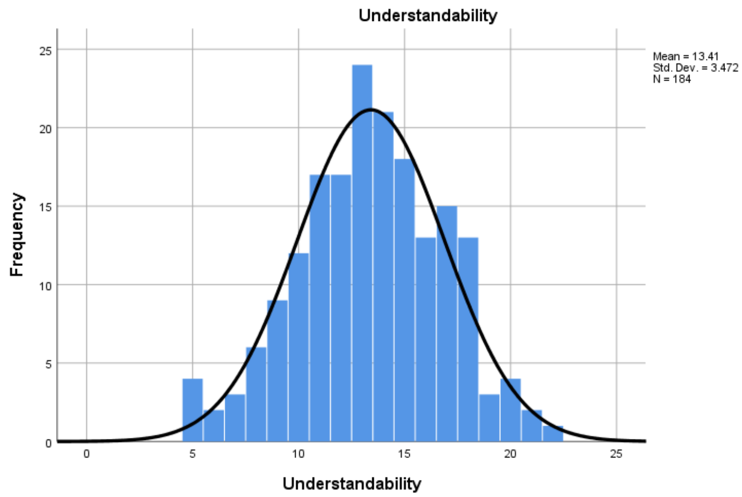


Fig 4.3 Histogram for understandability

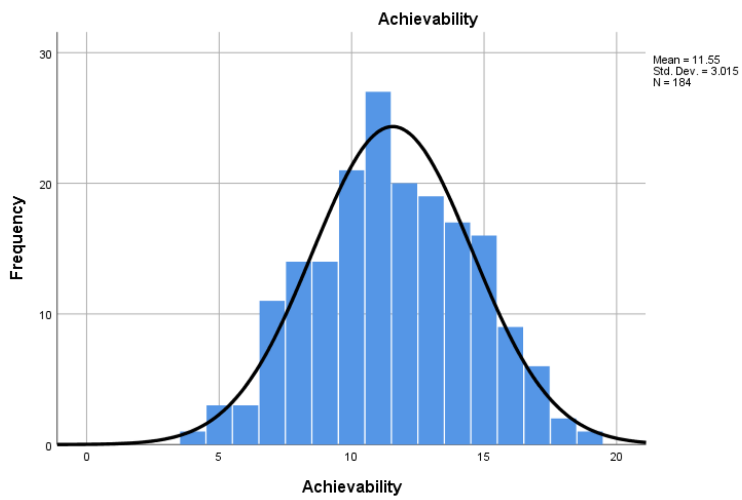


Fig. 4.4 Histogram for achievability

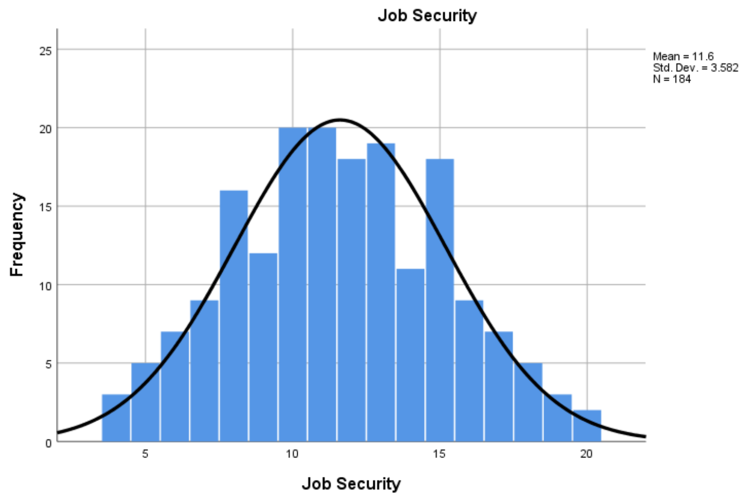


Fig. 4.5 Histogram for job security

4.2.4 Test of linearity

A linearity test is used in statistical analysis to determine whether there is a linear relationship between two variables. It is crucial to test for linearity because many statistical models, such as linear regression, assume that the relationship between the variables is linear. If the relationship is linear, the model may be appropriate and accurate (Hooper et al., 2008).

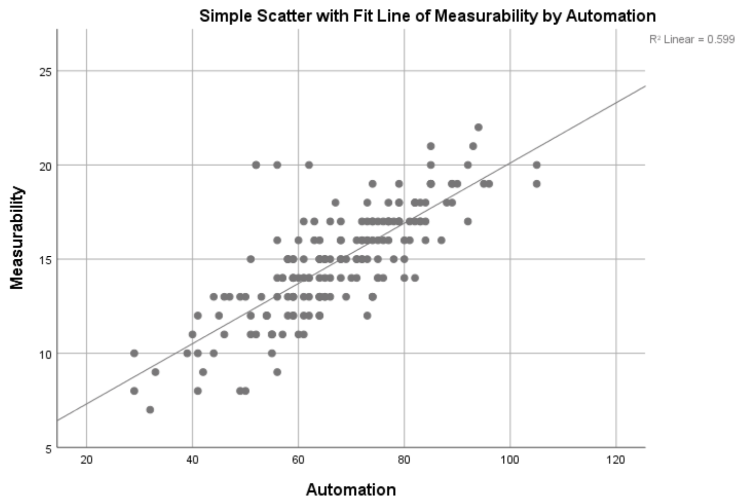
A test of linearity involves plotting the data points on a scatterplot and examining the pattern of the points. If the points form a linear pattern, then the variables may have a linear relationship. However, if the points form a non-linear pattern, a non-linear relationship may exist, and further analysis may be required.

In addition, a linearity test can also help identify outliers or influential observations that significantly impact the relationship between the variables. These observations can be examined and, if necessary, removed from the analysis to improve the model's accuracy (Hooper et al., 2008).

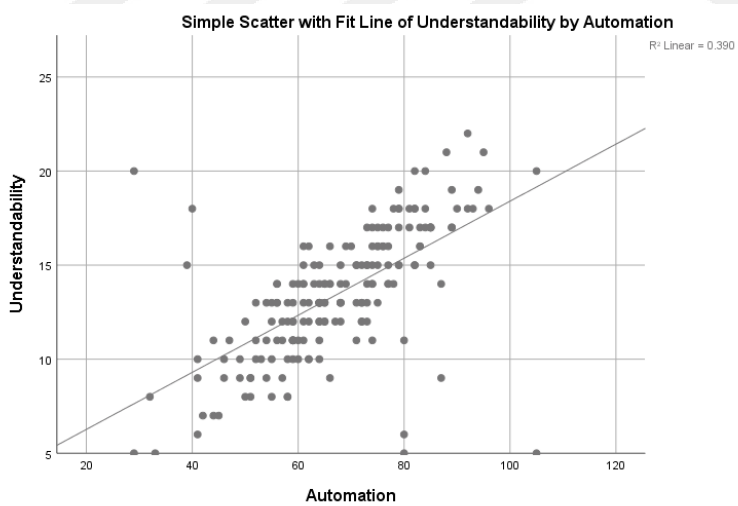
Overall, a linearity test is an essential step in statistical analysis to ensure that the appropriate model is used and that the results are accurate and reliable.

As shown in Fig. 4.6, Fig. 4.7, and Fig. 4.8, a positive and linear relationship exists between automation as IV and measurability, understandability, and achievability as DVs.

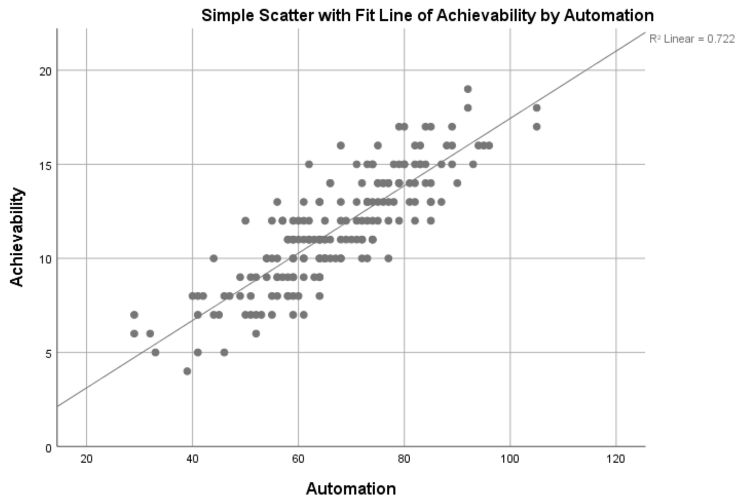
Also, Fig. 4.9 shows a negative and linear relationship between automation and measurability, understandability, and achievability. Thus, the linearity between the IV and the DVs was satisfied.



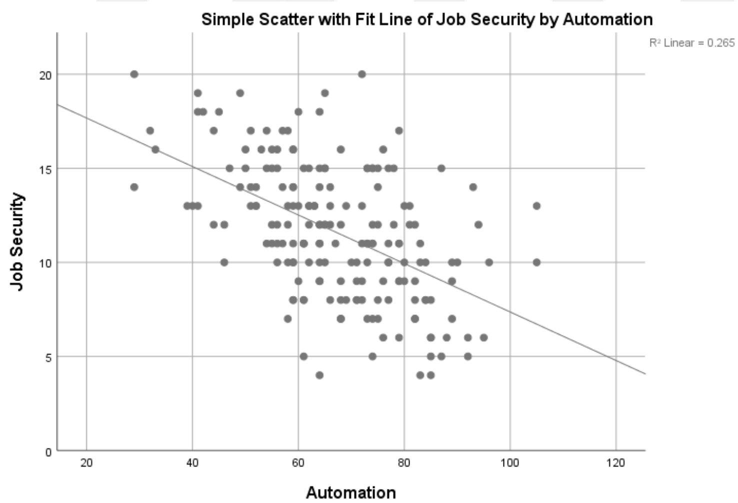
1- Fig. 4.6 Scatterplot for automation and measurability



2- Fig. 4.7 Scatterplot for automation and understandability



3- Fig. 4.8 Scatterplot for automation and achievability



4- Fig. 4.9 Scatterplot for automation and job security

4.2.5 Test of homoscedasticity

According to Johnson and Wichern (2007), testing for homoscedasticity is vital in statistical analysis to ensure the validity of models that assume a constant variance of the dependent variable across all independent variable levels. One way to test for homoscedasticity is to examine the residuals of the model, which are the differences between the observed values of the dependent variable and the predicted values based on the model. The Koenker test, also known as the Breusch-Pagan-Godfrey test, is a statistical test that can formally be used to test for heteroscedasticity (Fox, 2015). This test examines the relationship between the squared residuals and the model's predicted values and compares this relationship to what would be expected under the assumption of homoscedasticity. If the test statistic is significant, this suggests heteroscedasticity in the model.

Table 4.8 represents the homoscedasticity test for the variables, given that the Sig. Values are larger than 5%, and homoscedasticity was achieved.

Table 4.8 Test of homoscedasticity

Variable	Koenker	
	Statistic	Sig.
Measurability	3.7282	.054
Understandability	.4543	.500
Achievability	.3686	.544
Job Security	2.4837	.115

4.3 Reliability Test

Table 4.9 shows that Cronbach's alpha for all the scales was above 0.7, which is the acceptable limit for a scale to have good reliability. Automation and achievability had a Cronbach's alpha above 0.8, which indicates excellent reliability and measurability understandability. Job security had a Cronbach's alpha between 0.7 and 0.8, meaning the scales have good reliability (DeVellis, 2017).

Table 4.9 Reliability statistics

Variable	Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
Automation	.824	.824	21
Measurability	.750	.756	5
Understandability	.721	.721	5
Achievability	.805	.802	4
Job Security	.718	.720	4

4.4 Correlation Analysis

Table 4.10 presents the Pearson correlation between the study variables. There is a strong, positive, and significant correlation between automation and job performance dimensions – measurability, understandability, and achievability; ($r = 0.774$, Sig. value of $0.000 < 0.05$), ($r = 0.625$, Sig. value of $0.000 < 0.05$), and ($r = 0.849$, Sig. value of $0.000 < 0.05$), respectively. However, a high, negative, and significant association exists between automation and job security; $r = –0.515$, Sig. Value of $0.000 < 0.05$.

According to Dancey et al. (2017), Cutoff values for interpreting correlation coefficients are as follows:

- 0.00-0.25: little or no correlation
- 0.25-0.50: A fair degree of correlation
- 0.50-0.75: Moderate to the good correlation
- 0.75-1: Good to excellent correlation

Table 4.10 Pearson correlation between the study variables

Variable		Automation	Measur ability	Understand ability	Achiev ability	Job Security
Automation	Pearson Correlation	1	.774	.625	.849	-.515
	Sig. (2-tailed)		.000	.000	.000	.000
	N	184	183	184	184	184
Measurability	Pearson Correlation	.774	1	.554	.570	-.445
	Sig. (2-tailed)	.000		.000	.000	.000
	N	183	183	183	183	183
Understandability	Pearson Correlation	.625	.554	1	.533	-.469
	Sig. (2-tailed)	.000	.000		.000	.000
	N	184	183	184	184	184
Achievability	Pearson Correlation	.849	.570	.533	1	-.448
	Sig. (2-tailed)	.000	.000	.000		.000
	N	184	183	184	184	184
Job Security	Pearson Correlation	-.515	-.445	-.469	-.448	1
	Sig. (2-tailed)	.000	.000	.000	.000	
	N	184	183	184	184	184

Also, multicollinearity was checked using Pearson correlation for the dependent variables. The r – value of 0.7 and above is considered a sign of multicollinearity (Sekaran & Bougie, 2016). Job performance dimensions (measurability, understandability, and achievability) and job security had absolute correlation coefficients less than the cut-off value (0.7); r = 0.445, 0.469, and 0.448, respectively. In addition, the correlation coefficients between measurability, understandability, and achievability were r = 0.554, 0.57, 0.533, which also were less than the cut-off value. Thus, there is no collinearity between the dependent variables.

4.5 Simple Regression Analyses

Table 4.11 presents the R square values of 0.599, 0.39, 0.722, and 0.265. This indicates that automation explains 59.9% of the variance in measurability, 39% of the variance in understandability, 72.2% in achievability, and 26.5% in the variance in job security—moreover, the Sig. Value (0.000 < 0.05) confirms that automation significantly influences measurability, understandability, achievability, and job security.

Table 4.11 Simple Regression between the IV and the DVs

Automation- Measurability

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.774[a]	.599	.597	1.92520

a. Predictors: (Constant), Automation

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1007.259	1	1007.259	271.761	.000[b]
	Residual	674.567	182	3.706		
	Total	1681.826	183			

a. Dependent Variable: Measurability

b. Predictors: (Constant), Automation

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	3.890	.682		5.701	.000
	A	.164	.010	.774	16.485	.000

a. Dependent Variable: Measurability

Automation- Understandability

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.625[a]	.390	.387	2.71902

a. Predictors: (Constant), Automation

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	860.889	1	860.889	116.445	.000[b]
	Residual	1345.540	182	7.393		
	Total	2206.429	183			

a. Dependent Variable: Understandability

b. Predictors: (Constant), Automation

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	3.237	.964		3.359	.001
	A	.152	.014	.625	10.791	.000

a. Dependent Variable: Understandability

Automation- Achievability

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.849[a]	.722	.720	1.59518

a. Predictors: (Constant), Automation

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1200.442	1	1200.442	471.760	.000[b]
	Residual	463.118	182	2.545		
	Total	1663.560	183			

a. Dependent Variable: Achievability

b. Predictors: (Constant), Automation

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-.462	.565		-.816	.415
	A	.179	.008	.849	21.720	.000

a. Dependent Variable: Achievability

Automation- Job Security

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.513[a]	.264	.260	3.09177

a. Predictors: (Constant), Automation

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	622.684	1	622.684	65.141	.000[b]
	Residual	1739.745	182	9.559		
	Total	2362.429	183			

a. Dependent Variable: Job Security

b. Predictors: (Constant), Automation

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	20.243	1.096		18.474	.000
	A	-.129	.016	-.513	-8.071	.000

a. Dependent Variable: Job Security

4.6 Hypotheses Testing

Based on the results of the regression analyses, four hypotheses were developed to investigate the impact of automation on the dependent variables (DVs) of job security, measurability, understandability, and achievability.

H1: Automation has a significant influence on job security.

The regression analysis showed that automation significantly negatively affects job security (β = -.513, $p < .001$). This means that as automation increases, job security decreases.

H2: Automation has a significant influence on measurability.

The regression analysis revealed a significant positive effect of automation on measurability (β = .774, $p < .001$). This indicates that automation positively influences the ability to measure job performance.

H3: Automation has a significant influence on understandability.

The regression analysis results showed a significant positive effect of automation on understandability (β = .625, $p < .001$). This suggests that automation positively impacts the ease with which job duties can be understood.

H4: Automation has a significant influence on achievability.

The regression analysis demonstrated a significant positive effect of automation on achievability (β = .849, $p < .001$). This implies that automation positively influences the ability to achieve job objectives.

Overall, the regression analyses indicate that automation significantly affects the DVs of job security, measurability, understandability, and achievability. These findings may interest organizations considering the implementation of automation in the workplace, as they highlight both the positive and negative impacts of automation on various aspects of job performance. Therefore alternative hypotheses H1, H2, H3, and H4 failed to reject.

Table 4.12 Summary of hypotheses testing

N	Hypothesis	Conclusion
H1	Automation has a substantial influence on job security.	Failed to reject
H2	Automation has a substantial influence on measurability.	Failed to reject
H3	Automation has a substantial influence on understandability.	Failed to reject
H4	Automation has a substantial influence on achievability.	Failed to reject

4.7 Summary

In this study, descriptive statistics were first used to provide an overview of the categorical (demographic) and continuous variables and to check the assumptions for the continuous variables before conducting correlation and simple regression analyses. Pearson correlation and simple regression analyses were then employed to examine the strength and direction of the relationships between the independent variable (Automation) and the dependent variables (job security, measurability, understandability, and achievability). Ultimately, the hypotheses were tested, and the results showed that the alternative hypothesis, which stated that automation substantially influences job security, measurability, understandability, and achievability, failed to be rejected. The reliability of all scales was also tested and found to be satisfactory.

CHAPTER FIVE: DISCUSSION AND CONCLUSION

5.1 Introduction:

This chapter introduces the discussion of the tables and data that were analyzed. The chapter considers the questionnaire's analysis following the literature review presented before, in addition to the discussion related to the acceptance or rejection of the hypothesis.

The current study tries to understand the effect of automation on job security and job performance within Jordanian sweets factories. The elements of job performance included: (achievability, understandability, and measurability).

5.2 Results discussion:

The following parts show the results and discussion of the study variables according to the statistical analysis, which was driven by the sample's answers on the study tool.

H1: Automation has a substantial influence on Job Security.

Upon analyzing the research findings, the researcher proposed an alternative hypothesis that automation affects the job security of the sweet industry. The study's results support the hypothesis, which agrees with several literature studies, including Acemoglu and Restrepo (2017) and Schwabe et al. (2020). The impact of automation on employment has been a topic of considerable interest in recent years, with several studies focusing on the potential for automation to displace human workers. For instance, it has been estimated that nearly 47% of American jobs are at risk of automation-induced unemployment (Frey & Osborne, 2017).

Automation creates new job opportunities while eliminating others (Arntz et al., 2016). Therefore, the impact of automation on job security may be complex and contingent on various factors, such as the nature of the work, the level of automation, and the availability of alternative employment opportunities. However, it is essential to note that workers who perceive their jobs as at risk of automation-induced displacement may not necessarily be at actual risk.

H2: Automation has substantial influence on Measurability.

The alternative hypothesis proposed in the research posits that there exists a correlation between automation and measurability. This hypothesis is supported by previous research, including a study conducted by Zohar and Dori (2012), which found that an increase in automation in the manufacturing industry led to a shift in the focus of job performance measurement from tasks related to production efficiency to tasks related to product quality. Although automation monitoring can provide detailed data on worker performance, it can also raise concerns regarding privacy and the potential for bias in measuring performance, as highlighted in a study by Baruch and Holm (2017).

Nonetheless, the findings of the study by Zohar and Dori (2012) provide initial support for the hypothesis that a correlation exists between automation and measurability. However, other studies have found a negative relationship between automation and measurability, as Daugherty et al. (2014) reported. This highlights the need for further research to understand better the complex relationship between automation and job performance measurement, considering the specific context in which it is being implemented.

H3: Automation has substantial influence on Understandability.

The above alternative hypothesis in the research suggests a relationship exists between automation and understandability. This hypothesis is supported by several studies, including a study by Houser et al. (2019) that examined the impact of automation on job performance understandability in the healthcare industry. The study found that as automation increased, the focus on job performance understanding shifted from productivity-related tasks to patient outcomes and satisfaction.

Similarly, Daugherty et al. (2014) investigated the impact of automation on job performance understandability in the manufacturing industry. The study found that job performance understandability became more complex as automation increased. These findings suggest that automation has the potential to impact how workers understand and perceive their job performance.

Further research is needed to fully understand the relationship between automation and understandability, considering the specific context in which it is being implemented. Nonetheless, the results of these studies provide preliminary support for the hypothesis that a relationship exists between automation and understandability of job performance.

H4: Automation Has Substantial Influence On Achievability.

The above alternative hypothesis was failed to reject. This came in line with a previous study conducted by Houser et al. (2019) to investigate the impact of automation on the achievability of job performance in the healthcare industry. Achievability refers to the ability of workers to understand organizational goals and act accordingly to achieve those objectives. This aligns with organizational commitment, where workers committed to the organization are more likely to act in ways that promote its goals and improve company performance (Suliman et al., 2013).

By examining the impact of automation on the achievability of job performance, the study aimed to understand how automation can affect worker commitment and organizational performance. The results of the study showed that as automation increased in the healthcare industry, the achievability of job performance was positively impacted. This suggests that automation can improve worker commitment to the organization and positively impact company performance.

Table (5-1) Hypothesis testing results summary

N	Hypothesis	Conclusion
H1	Automation has a substantial influence on job security.	Failed to reject
H2	Automation has a substantial influence on measurability.	Failed to reject
H3	Automation has a substantial influence on understandability.	Failed to reject
H4	Automation has a substantial influence on achievability.	Failed to reject

5.3 Recommendations

Based on the study's findings, several recommendations can be made to enhance automation in the Jordanian sweets industry:

Firstly, sweet industry factories should prioritize job security to improve job performance levels. This can be achieved by providing employees with more training and development opportunities and ensuring they feel secure.

Secondly, machine workers should be motivated to use automation to minimize adverse effects. This can be achieved by providing them with the tools and resources to use automation effectively and efficiently.

Thirdly, sweet factories should address any barriers that may hinder the adoption and effective use of automation. By doing so, workers will better understand the benefits of automation and its impact on job security and performance elements.

Overall, these recommendations help sweet factories maximize the benefits of automation while mitigating any potential negative impacts on job security and performance.

5.4 Future research

The study found that automation is widely used in sweet factories and has a positive influence on job security and job performance elements. Based on these findings, the researcher proposes several recommendations for future research. Firstly, it is recommended to conduct further research examining the effect of automation on job security and performance elements, specifically in sweet factories in Jordan. This will provide more in-depth insights into the impact of automation in this particular industry.

Secondly, it is crucial to examine the awareness among sweet factory workers in Jordan about the benefits of automation and the job performance elements affected by it. This will help determine the extent of their knowledge about job security concerning automation.

Thirdly, the study suggests exploring the effect of automation on business performance in different sectors individually, as each sector has unique characteristics that may influence the impact of automation.

Fourthly, it is recommended for future research to test this research model in other sectors to assess the generalizability of the findings beyond the sweet industry.

Finally, future research could explore the impact of automation on other aspects of organizational performance beyond job security and job performance elements, such as productivity or innovation. This could involve examining the role of specific types of automation or exploring the impact of automation in different organizational settings.

5.5 Conclusion

The primary objective of this study was to investigate the impact of automation on job security and job performance elements in the Jordanian sweets industry. Respondents from different sweet factories in Jordan randomly participated in an online survey, including employees, supervisors, and managers. The data collected from 184 respondents was analyzed using SPSS.

Most respondents demonstrated a good understanding of automation tools and their usage and recognized the potential impact of automation on job security and job performance. The study measured job performance using three dimensions: achievability, understandability, and measurability.

The statistical analysis of the hypothesis and related variables revealed a significant effect of automation on job security and performance. This study's findings indicate that automation significantly impacts job security, achievability, understandability, and measurability in the Jordanian sweets industry.

In conclusion, the study highlights the importance of understanding the impact of automation on job security and job performance in the context of the Jordanian sweets industry. The results suggest that automation can positively and negatively affect these factors, and organizations should carefully consider the potential impacts when implementing automation technologies.

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Appendix A: Panel of experts:

No.	Name	Qualification	Organization
1	Prof. Alhareth M. Abu Hussein	Associate Professor	Amman Arab university-Jordan
2	Prof. Murad Atiani	Associate Professor	Isra University- Jordan
3	Prof. Kamel Al hawajreh	Full Professor	Mutah University- Jordan
4	Prof. Husam Abu-Hamour	Associate Professor	Al- Balqa' Applied University- Jordan

Appendix B: Questionnaire of Respondents:

Dear Participant:

The purpose of this master research is to study “the effect of automation on job performance elements job security and on of sweet industry workers.”

This research contains 38 questions, which may take 10 minutes to answer it; therefore, I will be thankful to you for devoting your time to answer it.

Your answers will be top secret and will be used for research purposes only. I appreciate your participation in this research.

Please, if you have any questions or comments, please don’t hesitate to contact me at.

Thank you for your productive cooperation.

Study Questionnaire

First Part: Demographical Data

Gender: □ Male □ Female

Age: □ less than 25 □ 26-35 □ 36-45 □ 45 and above

Education: □ High School and below □ Diploma □ Bachelor □ Master

Position: □ Employee □ Supervisor □ Manager

Experience: □ Less than 5 years □ 5-10 years □ 11-15 years □ 15 years and Above

Please answer the following questions **(√)** based on your knowledge and experience about the statement taking into consideration that:

Second Part: **Independent Variable (Automation)**

A. Ease of Use

#	content	Strongly disagree	Disagree	undecided	Agree	Strongly agree.
1	The employees understand the functions easily.					
2	The employees use automation without much effort.					
3	The employees use automation to complete tasks with minimal supervision.					
4	The employees use automation to perform tasks easily.					
5	The employees use automation to simplify complex tasks.					

B. Scalability

#	content	Strongly disagree	Disagree	undecided	Agree	Strongly agree.
1	Machines are supporting future increases in throughput.					
2	Machines are maintaining the best possible user experience.					
3	Choosing the right machine that helps you to scale.					
4	Best design practices using the right tools and frameworks.					
5	We have growing in the product.					

C. Maintainability

#	content	Strongly disagree	Disagree	undecided	Agree	Strongly agree.
1	I know the test coverage for the machine that I am testing					
2	I know which tools I use for the machine that when I am testing					
3	The parts of machines are available					
4	Maintenance process is costly					
5	Maintenance tools available in my workplace					
6	The number of defects found by automation high					

D. Traceability.

#	content	Strongly disagree	Disagree	undecided	Agree	Strongly agree.
1	Very effective means to assure that the customer's requested product was built.					
2	Easy and quick navigation from machines requirements to the source code/hardware implementation.					
3	In case of changes, there is effective support of required analysis to avoid unintended side-effects.					
4	Support and simplification of completeness checking with respect to the product implementation.					

Third Part: **Dependent Variable (Job Performance)**

A. Measurability.

#	content	Strongly disagree	Disagree	undecided	Agree	Strongly agree.
1	I am moving quickly in my work					
2	I seem to be turning in tasks on time					
3	I do ask questions about tasks.					
4	I skipped out on work tasks.					
5	The employee uses artificial intelligence to simplify complex tasks.					

B. Understandability.

#	content	Strongly disagree	Disagree	undecided	Agree	Strongly agree.
1	I understand that why automation used.					
2	I understand the use of machines among workers.					
3	I understand that tools/ machines/ software that could assist me with tasks.					
4	I understand that tools/ machines/ software that is replaced my job.					
5	I understand that tool/ machines/ software able to reduce job risks.					

C. Achievability

#	content	Strongly disagree	Disagree	undecided	Agree	Strongly agree.
1	Automation helps of achieving work tasks in proper manner.					
2	Automation of achieving work productivity.					
3	Automation helps of achieving job perfection.					
4	Automation helps of achieving job goals without errors.					

Fourth Part: **Dependent Variable Job Security**

#	content	Strongly disagree	Disagree	undecided	Agree	Strongly agree.
1	You have misplaced your work due the usage of robotization innovations.					
2	You have any robotization (artificial intelligence) spare you from doing parts of your work last 2 years.					
3	You believe that within the next ten years, new automation technologies could potentially eliminate your job.					
4	You know people have lost their jobs as a result of new automation technologies being used at their place of employment.					