THE USE OF ROBOTS FOR DELIVERY OF PACKAGES IN FOOD INDUSTRIES AND ITS IMPACT ON JOB LOSS

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ABSTRACT: Artificial intelligence (AI) and robotics have developed rapidly in the last few years, both in terms of the resources and outputs they produce. The robots that work in the food industry contribute significantly to the transportation of food packages from one location to another. The main task of the robots in the food industry on which this research focuses is delivery of packages. Before the implementation of robots in food industries and in delivery packages, it was done by human beings. Now that the robots are utilised, human beings will lose their jobs. This might not necessarily be the case or there might be some unforeseen issues. That is why this research aims to investigate the influence of system quality, information quality, and business value on the delivery of packages by robots in replacing people's jobs. This study applied a quantitative research method in order to achieve all of the research objectives. A total of 310 participants took part in the survey. Based on PLS-SEM analysis, the path coefficient of system quality to business value was examined by hypothesis one (H1), and it was shown to be supported. It is clear that the relationship between system quality and business value is significant because there is a strong link between system quality and business value. Furthermore, the path coefficient of information quality to business value was investigated in hypothesis two (H2). Our second hypothesis is supported by the p-value being significant and positive. Hypothesis three (H3) is significant, as evidenced by the fact that it is supported. As a result, there are important connections between the use of robots and business value. Finally, the business value, which is a dependent variable, has a positive and significant relationship with all independent variables of this research. There is a strong path coefficient link from business value to system quality, information quality, and the use of robots. In the measurement model, there are substantial disparities between the industries with high levels of working experience and those with less working experience of robots. Information quality, use of robots, and business value all have positive and significant influences on the use of robots in the food industry (delivery of packages by robots). Furthermore, the analyses of PLS-SEM also show that system quality has a positive relationship but not a significant impact. Technological skills are highly important in order to improve and adopt delivery of packages by robots in the food industry. In addition, the findings of this research contribute to the literature on robots' implementation in the food industry and also contribute to limited empirical research on assessing the delivery packages by robots in food industries on replacing people's jobs.

KEY WORDS: *Artificial intelligence, robotics, delivery of packages, food industries, job loss*

1. INTRODUCTION

Artificial intelligence (AI) and robotics have been developed rapidly in the last few years, both in terms of the resources and outputs they produce (Shabbir & Anwer, 2018). In 1930, John Maynard Keynes famously predicted the rapid technological progress of the next 90 years but also conjectured that "We are being afflicted with a new disease of which some readers may not have heard the name, but of which they will hear a great deal in the years to come, namely, technological unemployment" (Davidson, 2017). The impact of robotic and artificial intelligence has been seen in different industries. Certain human powers have already been exceeded by AI. Deep Blue, IBM's computer, stunned world chess champion Garry Kasparov in 1997 (Newborn, 2012). With its triumph against two of Jeopardy's best champions in 2011, IBM's Watson startled the technology sector. In 2016, Google's DeepMind AlphaGo defeated the number one ranked human Go player, Lee Se-dol (Byford, 2016). It has acquired some cognitive characteristics of the human brain that could also learn and produce its own answers without explicit programming, and it is no longer just a science fiction fantasy or a simple computer programme that plays games. As a result, with continuous investment, AI has expanded rapidly and altered society significantly. Automation is becoming the norm in a variety of sectors. After steam power, electricity, and electronics, some have labelled AI the fourth industrial revolution (Schwab, 2017). Unlike previous revolutions, according to an Oxford University study, this revolution may put up to 35% of all employees in the UK and 47% of those in the US at risk of being displaced by technology over the next 20 years (Stewart, 2015). Many jobs have been lost in the past as a result of technological improvements, and huge levels of societal disruption have occurred. The Industrial Revolution in England in the nineteenth century provided a typical illustration of this. Workers and manufacturing workers in the United Kingdom were worried that less trained employees were depriving them of their livelihoods as the use of automated looms and knitting frames increased. The government did not help the weavers, so some of them broke into businesses and destroyed textile machinery (Su, 2018).

The number of robots in factories has been rising quickly, and robotics technologies have been introduced into many sectors beyond manufacturing, e.g., surgical or rehabilitation robots in hospitals, service robots, self-driving cars, and so on. However, from a roboticist's perspective, there is still a very long way to go before robots can totally replace humans (Pham et al., 2018; Abdullad et al., 2020; Ali et al., 2021).

Moreover, dairy and food industries have lagged behind other industries in the implementation of robots because of the fact that food products are very variable in shape, sizes, and structure, which poses a major problem for the development of manipulators to handle them. On the other hand, grading of food products, pick and place operations, packaging and palletizing, meat processing, milk and milk product production and processing are a wide range of potential applications for robotics in the dairy and food industries. Although robots have many advantages, such as safety, consistency, and efficiency, they also have some disadvantages, such as high costs and requirements for skilled engineers (Prasad, 2017).

2. RELATED WORK

Artificial intelligence (AI) is a kind of technology that makes devices smart like human beings to develop human life by using these devices in all aspects of life, such as service robots, healthcare, education, including electronics, software, medicine, entertainment (games), engineering, communications, and manufacturing (Ahmed, 2018). Robots have been used in different industries. Dairy and food industries have lagged behind other industries in the implementation of robots because of the fact that food products vary in shape, sizes, and structure, which poses a major problem for the development of manipulators to handle them. On the other hand, grading of food products, pick and place operations, packaging and palletizing, meat processing, milk and milk product production and processing are a wide range of potential applications for robotics in the dairy and food industries. Although robots have many advantages, such as safety, consistency, and efficiency, they also have some disadvantages, such as high costs and requirements for skilled engineers (Prasad, 2017).

Besides that, today, many military organisations use the help of military robots for risky jobs. The robots used in the military are usually employed within integrated systems that include video screens, sensors, grippers, and cameras. Military robots also have different shapes and sizes according to their purposes, and they may be autonomous machines or remote-controlled devices (Simon, 2015). Since 1961, technology has improved significantly. Robots are now able to control soft, fragile, easily deformable products without damaging them. This issue of Robotica validates that new technology is at the stage where it is feasible for robots to control food industries. Robot applications can handle all three sectors of the traditional economic food industry, like food production, food processing, and food service (Kassler, 2020), from seeding, spraying water and harvesting to cutting, processing, and packaging of food products (Sun, 2016). All industries are now using robots in several applications; robots are even helping humans at home to perform daily chore activities, which are some of the novel applications (Fernando, Mathath, & Murshid, 2016). The largest manufacturers, like Apple, have planned to replace employees in recent years with about a million robots (Moran et al., 2011). Robots have several important features, including improved control systems, dependability, fast speed, high agility, many installation locations, cleaning, agility, vision, and conveyor monitoring (Nayik, Muzaffar, & Gull, 2015). Tesla motors can perform many tasks such as welding, riveting, bonding, and installing a component in its assembly line, where the usual robots can only do a single function (Markoff, 2012). BMW utilised it for its advanced machining in the axle design (Kochan, 2004).

Robots can produce more accurate and high-quality products (Singh et al., 2013). Collaborative Robots also incorporate one or more of these features, such as Safety-rated Stop Monitoring, Hand Guiding – Teaching by Demonstration, Speed and Separation Monitoring, and Power and Force Limiting. Additionally, operation in automatic mode with a person in the collaborative workspace means when the person acts, the robot reacts. A robot's behaviour can be easily programmed through software to incorporate specific safety design features to protect a person from injury. Agents and, specifically, robots, usually present various kinds of sensing and acting devices. The flow of data from the sensors to the actuators is processed by several different modules, and the description of the interaction among these modules defines the agent's architecture (Chella et al., 2006).

The first, purely deliberative, architecture views the robot as an agent embedding a high-level representation of the environment and of the actions that it can perform. Perceptual data are interpreted to create a world model; a planner generates the actions to be performed; and the execution module carries out the plans. In practice, a sense-plan-act cycle is repeatedly executed. Reactive architectures focus on the basic functionalities of the robot, such as navigation or sensor interpretation, and propose a direct connection between stimuli and response (Chella et al., 2006). Robotics are increasingly consumed in several operations, including welding, sealing, and painting; process control, assembling, and inspections; and non-automotive sectors including computers, consumer products, pharmaceuticals, and service (Hall, 2008).

2.1. Conceptual framework

This study conceptualized a research model for the evaluation of the use of robots for package delivery in food industries and its impact on job loss. This model is based on three independent variables and one dependent variable. The independent variables include system quality, information quality, and the use of robots. Business value is the dependent variable that depends on the other three independent variables. In this study, the relationships among the variables were examined. They are the effect of independent variables and business value (dependent variable) that can influence the use of robots for package delivery in food industries and their impact on job loss (Kim, Oh, Shin, & Chae, 2009). Hence, the conceptual framework is presented in Fig. 1, where three hypotheses are formulated as follows:

H1: System Quality has a significant and positive impact on the Business Value in the industry of Robots.

H2: Information Quality positively and significantly effects the Business Value in the industry of Food robots.

H3: The Use of Robots positively and significantly influences the Business Value in the food industries.

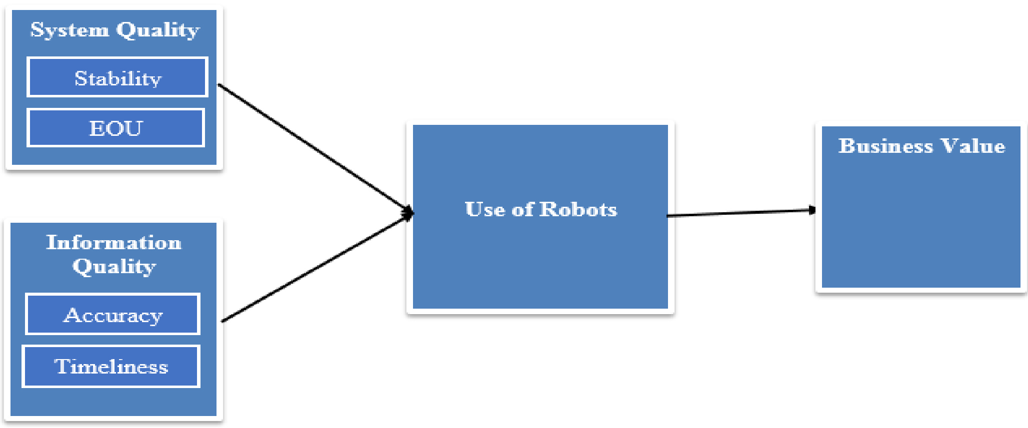

Fig. 1. Conceptual Framework

3. METHODOLOGY

This study adopted quantitative research methodology, which involves the use of statistical techniques to determine the relationship between variables and outcomes to evaluate the findings. It takes a subjective and descriptive approach to the subject matter. The quantitative research method has several significant advantages, the most notable is that it is extremely simple and quick to evaluate and administer. That is one of the reasons why this study adopted it. Moreover, it does not require a significant amount of time, and the data can be arranged in a short period of time (Choy, 2014).

3.1 Research Design

The research design of the study specified the research population, sampling, instrumentation, and data collection strategies, as well as the analytical technique (or techniques) that were used. Using a quantitative research methodological design as the primary approach of this study, the target population was defined, a sampling technique was provided, research instrumentation was formulated, and data collection techniques were specified, as well as the analytical procedure. The target population comprised individuals working in the field of robotics, and the samples were drawn from among them.

3.2 Population, Sampling and Instrumentation for Data collection

A research population is a group of individuals, entities, objects, or items for which measurements are obtained (Amitav & Suprakash 2010; Abubakar et al., 2020; Manssoori et al., 2021; Rahmani et al., 2021; Abubakar et al., 2021; Faizi et al., 2021). Sampling is a small number of participants selected from a large number of population. The population of this research are stakeholders in the areas of robotics and its application.

This research employed random sampling in order to allow all stakeholders in robotics and its applications to participate in the study. This is an essential element for the research study, and it will avoid bias. The sample for this research was obtained from the overall population using a nonprobability sampling technique. The probability sampling technique uses a random method to ensure that everyone has an equal chance of being chosen as a sample. Hence, the sample size of this research was anticipated to be around 500. However, according to Louangrath (2018), the minimum sample size of a research should be 30 to 200 participants. Also, Hair (2010) stated that a minimum sample size of 200 is required for SEM (structural equation modeling). Comrey and Lee (1992) revealed that a sample size of 50 is very poor, whereas 100 is poor, 200 is reasonable, and 300 is good. Based on these references, this research has collected 310 responses from the targeted population.

The data collection instrument for this research is a questionnaire, from which the primary data will be collected by using a survey. The questionnaire design was adopted and modified from which they are categorised into two main sections, namely, the demographic information section and variable questions concerning robots and AI on a five-point likert scale.

4. DATA ANALYSIS AND PRESENTATION OF RESULTS

This research analysis process and the results of the analyzed data are presented in this section. The analyses include correlation, descriptive, and PLS_SEM model analysis. Data cleaning and screening were performed first to have pure and clean data, followed by the descriptive analysis, which provided an overview of the data, and finally, the PLS_SEM analysis. The results of the descriptive analysis are presented and discussed to give an overview of the demographic data and to better understand the characteristics of the respondents. The measurement model and the structural model for determining how well the theory or principle has been tested and proven are presented.

4.1. Data Cleaning and Screening

The treatment of missing data, unengaged responses, and outliers are the data cleaning and screening techniques used for this research. This involves measuring the skewness and kurtosis to determine whether the data contain some outliers. Crucial to this is the assessment of outliers. Any measurements that are numerically distant from the rest of the data set are considered outliers. Each research item has been analyzed. "System quality items" contained some outliers, but there were no extreme outliers. All the outliers have been removed from the dataset.

The data distribution for a specific variable is explained by normality. Non-standard data would have an effect on the interpretation and conclusions (Hair et al. 2017). Data normalization was carried out in this study because of its significance. Shape, skewness, and kurtosis (flat or peaked) are all indicators of data normality (Hair et al. 2017). Skewness is a term that refers to a symmetrical evaluation of data distribution. If the data is skewed to the right or left, it is called skewed (Hair et al. 2017). Skewness is governed by two principles: (1) positive (right) skewed if the skewness value is greater than 1, and (2) negative (left) skewed if it is less than -1. The number in the middle, on the other hand, is fine. Outliers in data distributions are known as kurtosis.

According to Hair (2017), when the case distribution is too skewed, there is a possibility that the kurtosis of data with outliers will also be high and the majority of answers will be in the middle. When it comes to Kurtosis, a rule of thumb is that if the number is greater than +1, the distribution is too peaked. It means that the distribution is too flat if it is less than -1 (Hair, 2017). Table 1 shows the values for skewness and kurtosis for each of the items in this study.

System quality was assessed based on nine items, with the mean ranging between 2.01 and 3.26. The mean is higher than the standard deviation for all items. The values of skewness and kurtosis of the system quality items are +1 to -1, which indicates that the values are within the normal range. Similarly, the evaluation for information quality was based on seven items. The mean of the items is 2.07 to 3.23. The values of 0.879 to 0.985 are the standard deviation range. The values of skewness and kurtosis of information quality items are between +1 and -1, which are within the normality range. Business value was assessed based on six items. The standard deviation value is within the range of 0.861 to 0.894. The mean value is between 1.97 and 3.21. The skewness and kurtosis of items of business value are within the range of +1 to -1, which indicates that the values are within the normal range.

Table 1: Normality Distribution Test

Items	Standard Deviation	Mean	Skewness	Kurtosis
System Quality				
System-QQ1	.732	3.23	.348	-1.072.
System-QQ2	.905	3.26	.257	-.718
System-QQ3	.863	2.01	.584	.020
System-QQ4	.967	2.23	.349	-.745
System-QQ5	.897	2.04	.622	.070
System-QQ6	1.164	2.62	.314	-.824
System-QQ7	.949	2.08	.737	.123
System-QQ8	.948	2.17	.660	.102
System-QQ9	.861	2.12	.413	-.455
Information-Quality				
Information-QQ1	.887	3.12	.571	-.064
Information-QQ2	.990	2.10	.940	.736
Information-QQ3	.973	3.23	.738	.370
Information-QQ4	.999	2.14	.724	.110
Information-QQ5	.889	2.99	.880	.672
Information-QQ6	.953	2.07	.953	.913
Information-QQ7	.975	3.14	.874	.570
Use of Robots				
Use-Robot-Q1	1.149	3.11	.195	-.772
Use-Robot-Q2	1.058	2.63	.053	-.794
Use-Robot-Q3	1.186	2.82	.103	-.8.48
Use-Robot-Q4	1.024	2.31	.495	-.303
Use-Robot-Q5	.981	2.30	.665	.251
Use-Robot-Q6	.976	2.13	.756	.273
Use-Robot-Q7	1.067	2.05	.774	.-.205
Use-Robot-Q8	1.02	1.97	.966	.444
Use-Robot-Q9	1.049	2.05	.901	.297
Use-Robot-Q10	.957	1.94	.777	-.070
Business Value				
Business-VQ1	.931	3.21	.566	-.055
Business-VQ2	.995	3.12	.546	-.142
Business-VQ3	.953	2.22	.572	.047
Business-VQ4	.962	2.21	.638	.165
Business-VQ5	.975	2.94	.924	.448
Business-VQ6	.988	1.97	.821	.091

4.2 Descriptive analysis

It is important to include a demographic analysis in the data collection process. This is because researchers need to know more about the population's specific characteristics, such as academic performance, age group, gender, socioeconomic status, and ethnic background. This segment discusses the demographic profile of the 310 respondents. The age group 25–34 years has the highest proportion of respondents (76.5%), followed by 15–24 years with 14.2%. While the age group 35–44 years accounted for 9% of the respondents in this survey. The next factor is gender, with males accounting for 83.5% of the total and females accounting for 16.5%. Male respondents made up 259 of the survey's 310 participants, accounting for 83.5% of the total, while female respondents made up 51 of the survey's 310 participants, accounting for 16.5%.

In terms of age, 237 participants are between the ages of 25 and 34, accounting for almost 76.5% of the total, which is the highest percentage in the entire dataset. In addition, 44 people, or 14.2% of the total survey population, were between the ages of 15 and 24. The survey included around 9% of people between the ages of 35 and 44, with a total number of 28 participants. It makes up the third highest percentage of data. Finally, only 3% of respondents were between the ages of 45 and 54, which is the very lowest percentage in the survey. It can be seen that this technology is more familiar to people from the ages of 24 to 34.

4.2.1 The Importance of Robots for the Delivery

According to the findings, most participants believed that robots are quite important for the delivery of packages in the food industry. It accounts for approximately 30.6 percent of total survey data. It is clear that robots are important for the delivery of packages, which are very heavy, and it is quite important to make the lives and work of humans easier and more comfortable. The second highest number of respondents in the survey pointed out that the delivery of packages by robots is very essential. It accounts for approximately 23.2 percent of all respondents. That means it is vital for industry to use and adopt the robot's technology for delivery of packages and heavy materials. In addition, 64 participants (20.6%), which is the third highest percentage of the total data, said that the delivery of packages by robots is very important. It is clear that they strongly preferred this technology to be used by the industry. They claimed that using robots for package delivery can make the work easier and can save time and money.

However, only 5.5% (17 participants) pointed out that it is "not at all important" to use robots for the delivery of packages in food industries. This is a very small number of people who disagreed with the use of robots compared to the participants who agreed and strongly agreed with the use of robots. As can be seen, just a small portion of the population believed that this technology is unimportant. In general, it can be seen that most participants agreed, and they wanted to use robots for the delivery of packages in the food industry to make work easier.

4.2.2 Effectiveness of Robots for the Delivery

As discussed above, on the importance of package delivery by robots in the food industry, most of the participants agreed that it is essential and important to use this technology. The majority of respondents (41.9%) indicated that the delivery of packages by robots is effective, according to the results of the effectiveness survey. Also, roughly 19.4% indicated that it is very effective to use this technology, which is a significant percentage of the total data.

Furthermore, 31% chose to be unconcerned (neutral) with the usefulness of package delivery by robots in the food industry. However, a very small percentage of the participants (1.90%) indicated that robots' delivery of packages is ineffective.

According to the survey results, delivery of packages by robots in the food industry is effective and very effective for the majority of the population.

4.3 PLS-SEM -measurement model

Generally, PLS-SEM is divided into two parts: the measurement model and the structural model. A measurement model is used to define the relationship between independent variables and their indicators (items). However, the second model is called the inner model, which is used to measure the relationships within observed and unobserved variables. In PLS-SEM, there are four procedures for reflective measurement assessment, such as assessment of internal consistency, indicator reliability, convergent validity, and discriminant validity. The result of the measurement model for this study is presented in Fig. 2.

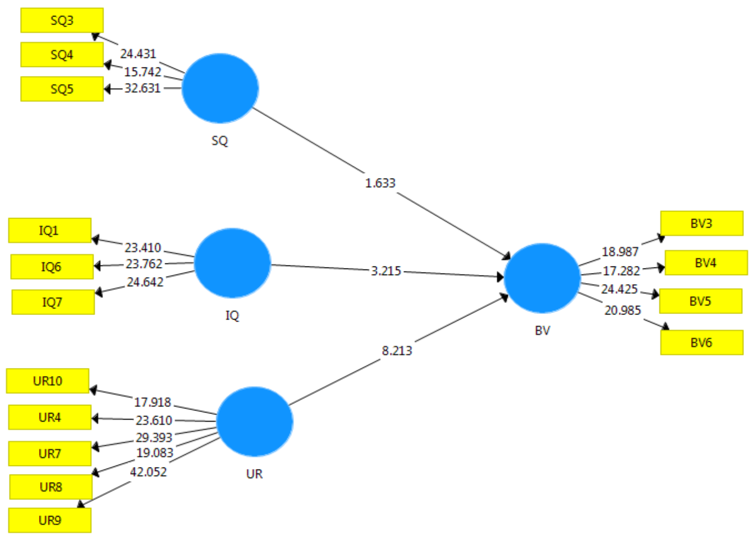

Fig. 2. Assessment of Reflective Measurement Model

4.3.1 Internal Consistency Reliability (ICR)

In this analysis, the Composite Reliability Index was used to assess the data's ICR and reliability. Table 2 indicates the analysis of CR, outer loadings, and Average Variance Extracted (AVE). Based on the result, the variables under investigation are consistent, with internal accuracy values changing from 0.844 to 0.884, and are considered satisfactory.

Table 2: Internal Consistency and Convergent Validity Analysis

Variable	**Items**	**loading**^{a}	**AVE**^{b}	**CR**^{c}
System Quality	SQ1	0.830	0.617	0.828
	SQ2	0.899		
	SQ3	0.924		
Information Quality	IQ1	0.797	0.646	0.846
	IQ2	0.812		
	IQ3	0.803		
Use of Robots	UR1	0.703	0.604	0.884
	UR2	0.740		
	UR3	0.814		
	UR4	0.785		
	UR5	0.835		
Business Values	BV1	0.748	0.575	0.844
	BV2	0.725		
	BV3	0.795		
	BV4	0.763		

4.3.2 Indicator Reliability (Outer Loadings)

The indicator reliability is defined as a test to see if the indicators are made in a way that measures the assigned items (Ramayah et al. 2018). When the dependability is not at an acceptable level, the PLS characteristic of consistency places a strong emphasis on the factors that researchers should evaluate when selecting whether to remove or keep current items (Lowry and Gaskin 2014). As shown in Table 2, all the items have loading values that exceed 0.70 to 0.80.

4.3.3 Convergent Validity (CV) of Measurement Model

The concept of convergent validity states that indicators of a variable should share a large proportion of their variance. There is proof of evidence on convergent when all the factor loadings for the items measuring the same construct are the same (Hair el al., 2017). The AVE values of all item variables can be used to test convergent validity. This study's AVE values (see Table 2) are all more than 0.5. As a result, Hair et al. (2017) suggested that the AVE values in this investigation meet the reliability standards.

4.3.4 Discriminant Validity (DV) of Measurement Model

The degree to which the measure is unique and not just a reflection of other variables is referred to as discriminant validity (Ramayah et. al 2018). The cross loading of discriminant validity will be achieved if all the indicators in the research model are higher loading on their corresponding variable (Lowry and Gaskin 2014). Discriminant validity in this analysis was assessed in three ways, as proposed by Hair et al. (2017): 1) Criterion for cross-loading, 2) The Criterion of Fornell and Larcker, and 3) Correlations Heterotrait-Monotrait ratio (HTMT).

According to Fornell and Larcker (1981), the diagonal value must be higher than the value of off-diagonal, this is due to the fact that the diagonal value is the square root of AVE, which is a specific variable. Meanwhile, all reflective constructs/variables are correlated in off-diagonal values (see Table 3).

Table 3: Discriminant Validity using Fornell and Larcker's Criterion

Variable	**1**	**2**	**3**	**4**
Business Value	0.758			
Information Quality	0.635	0.804		
System Quality	0.561	0.629	0.785	
Use of Robots	0.720	0.681	0.628	0.777

The latent variable loading is required to be less than the Item loadings and meet all the requirements (see Table 4). This indicates that the items of various latent variables are not interchangeable (Ramayah et. al 2018). Finally, the HTMT correlations were examined using a bootstrap with a 0.10 confidence interval and a two-tailed test form. The results in Table 5 show that all HTMT values are less than 0.90. This also clarified the existence of discriminant validity between two reflective constructs/variables.

Table 4: Cross Loadings Criterion

Variables	**1**	**2**	**3**	**4**
Business-ValueQ1	**0.748**	0.649	0.039	0.123
Business-ValueQ2	**0.725**	0.400	0.646	0.517
Business-ValueQ3	**0.795**	0.303	0.522	0.315
Business-ValueQ4	**0.763**	0.620	0.280	0.466

Information QualityQ1	0.359	**0.797**	0.328	0.484
Information QualityQ2	0.342	**0.812**	0.366	0.366
Information QualityQ3	0.516	**0.803**	0.413	0.450
System-QualityQ1	0.500	0.328	**0.789**	0.484
System-QualityQ2	0.522	0.371	**0.738**	0.532
System-QualityQ3	0.527	0.224	**0.827**	0.435
Use of RobotsQ1	0.511	0.310	0.420	**0.703**
Use of RobotsQ2	0.500	0.239	0.390	**0.740**
Use of RobotsQ3	0.326	0.399	0.466	**0.814**
Use of RobotsQ4	0.527	0.451	0.558	**0.785**
Use of RobotsQ5	0.351	0.327	0.321	**0.835**

Table 5: Heterotrait-Monotrait (HTMT) criterion

Variables	**Acceptance**
Business Value	0.860
Information Quality	0.852
System Quality	0.769
Use of Robots	0.824

4.4 Analysis and Result of Structure Model (PLS Algorithm)

According to Hair et al. (2017), a structural model is utilized to describe the linear regression impact of the endogenous construct on one another. The structural model allows you to determine the pattern of relationships between variables (Lowry and Gaskin 2014). Five measures for measuring the structural model are presented. The following segment delves further into these systems.

4.4.1 Assessment of Collinearity

It is critical to recognize the collinearity problem in the reflective structural model, just as it is in the formative measurement model. The same hypothesized variables can measure the same constructs, resulting in erroneous results (Lowry and Gaskin 2014). Researchers can determine the degree of acceptance by analyzing the Variance Inflator Factor (VIF). The findings show that all the independent variables' inner VIF values are less than 5 (see Table 6), indicating that lateral multicollinearity is not an issue in this analysis. The VIF description result is shown in Table 6.

Table 6: Lateral Collinearity Assessment

Variables	**Acceptance**
Business Value	1.413
Information Quality	2.131
System Quality	1.886
Use of Robots	2.124

4.4.2 Path Coefficients

Bootstrapping and calculating t-values may be used to assess the importance and validity of structural model relationships (Lowry and Gaskin 2014). It is important for researchers to consider the following basic settings in order to conduct bootstrapping: 1) the number of bootstrap cases used to estimate the model must be the same to the number of observations used to estimate the model, 2) The number of bootstrap subsamples should be high, ranging from 500 to 5000, 3) Sign changes that occurred during the drawing of the subsamples, and 4) choose the outcome of the applicable confidence interval for discussion (Lowry and Gaskin 2014). The path coefficient values and t-value are used to investigate the hypothesized relationships. The path coefficient is considered important when the t-value is greater than the critical value (with certain error of significance level). As a result, all the hypotheses in this analysis are directional. Thus, the following requirements were established as the following: 1) 510 events, 2) 5000 subsamples with no sign shift, 3) two-tailed, bias corrected, accelerated confidence interval, and 0.05 significance level. Table 7 shows the path coefficient results.

The hypothesized correlations between the constructs can be measured using path coefficients and t-values. Its values are roughly between –1 and +1; however within this range, the value might be smaller or bigger. If the path coefficients are close to (+1), the association is strong and positive; otherwise, the association is weaker (near to zero or negative values). Relationships that are strong are usually significant, whereas those that are weak are not (Hair et al., 2017, pp. 206).

Table 7: Assessment of Structural Model

Tested Path	**Hypothesis**	**Path Coefficient**	**STD**	**T Value**	**P Value**	**R^2**	**Q2**	**f^2**	**Decision**
H1	System Quality ->Business Value	0.102	0.063	1.633	0.013	0.061	0.010	0.173	Supported
H2	Information Quality -> Business Value	0.232	0.072	3.215	0.001	0.012	0.231	0.154	Supported
H3	Use of Robots -> Business Value	0.498	0.061	8.213	0.000	0.231	0.114	0.268	Supported

The path coefficient of system quality to business value was examined by hypothesis one (H1), and it was shown to be true through the bootstrapping technique, with a path coefficient value of 0.102. The business value would rise to (0.102) or 10.2 percent if the system quality improved by one unit. It is clear that the relationship between system quality and business value is significant. The t-value is accepted at the level of 1.633, and the p-value is significant. As can be seen, the p-value is 0.013. In addition, the upper and lower bounds for the confidence interval of H1 were found to be 0.035 and 0.311, respectively. In conclusion, there is a strong link between system quality and business value and the first hypothesis is supported.

The path coefficient of information quality to business value was investigated in Hypothesis 2 (H2). The path coefficient value is 0.232, and the t-value computed using a bootstrapping approach with 5000 subsamples is 3.215 and the p-value is 0.001. H2 has a confidence interval of 0.33 for the lower bound and 0.457 for the upper bound. It can be seen that the p-value is significant and positive, thus our second hypothesis is supported. If the Information quality is increased by one unit, the business value will rise to (0.232) or to 23.2 percent.

Furthermore, there is a considerable association between the use of Robots and Business value, with a path coefficient of 0.498. When the value of the use of Robot is increased by one point, the Business value will rise to 49.8%, which is a very good figure. The t-value is also 8.213, which is higher than the crucial value. Additionally, the p-value is significant and positive at the 0.000 level. H3 has a confidence interval value of 0.515 with a lower bound value of 0.756 and an upper bound value of 0.749. The H3 hypothesis is supported. H3 is significant, as evidenced by the fact that it is supported. As a result, there are important connections between the use of Robots and Business value.

Finally, the business value which is a dependent variable has positive and significant relationship with all the independent variables of this research. There is a strong path coefficient link from business value to system quality, information quality and the use of robots.

4.4.3 Coefficient of Determination (R2)

The R square or coefficient of determination is used to assess the model's predictive accuracy. It illustrates the regression's goodness-of-fit, which is extracted from the dataset's empirical results (Ramayah et al. 2018, Lowry and Gaskin 2014). Prior literature suggested that the R^2 value be large enough to determine the model's explanatory capacity. To properly describe the variance of a particular variable, this value should be equal to or greater than 0.10 (Lowry and Gaskin 2014). According to Hair et al. (2017)'s R2 parameters, a value of 0.75 indicates a high level of predictive accuracy, 0.50 indicates a moderate level, and 0.25 indicates a low level (Hair et al. 2017). Table 7 shows that the R2 values, according to the results for system quality, information quality, and the use of robots, predict business value to a degree of 56%. Finally, the findings show that business value has moderate R2 values. As a result, the model is adequate to reflect the collected data with moderate predictive accuracy.

4.4.4 Effect Size Assessment (f2)

Following the determination of R2, the effect size of the predictor construct is expected. By omitting and including a specific latent variable from the model, the effect size (f2) clarifies the shift in R2. The 0.35, 0.15, and 0.02 values suggested by Hair et al. (2017) can be interpreted as substantial, medium, and minimal effects, respectively. All supported hypotheses - H1, H2 and H3, with values of 0.173, 0.154, 0.268, have a medium impact in producing R2 to Business Value, as shown in Table 7.

5. DISCUSSION

The goal of this study is to examine and evaluate the overall use of delivery of packages by robots in the food industry, in terms of adopting them and their applications, and to find out the factors influencing the implementation of robots in the food industry. Additionally, this study identifies whether there will be job losses or not by the implementation of this technology. The acquired data from the target population was analysed using the Statistical Package of Social Science (SPSS) and PLSmart3 software to meet the research's goal and objectives. During the study, many statistical analyses were done to meet the research goals, including descriptive analysis, correlation analysis, and PLS-SEM.

One of the objectives of this research is to determine the influence of system quality on the delivery of packages by robots in the food industry. This has been achieved by testing hypothesis one using PLS-SEM analyses. It was used to meet the research's first goal and main objective. The first hypothesis is supported, which is "H1: System quality has a significant impact on the delivery of packages by robots in the food industry associated with business value". It has been discovered that the quality of the system has a favourable and significant impact on the use and adoption of robotic package delivery. This means that if one of these elements improves, the entire usability will improve as well. According to the results of the structural model analysis in the preceding section, a one-point increase in the system quality will increase the business value by 10% through the bootstrapping technique, with a path coefficient value of 0.102. The business value would rise by 0.102, or 10.2 percent, if the system quality improved by one unit. It is clear that the relationship between system quality and business value is significant. The t-value is accepted at a level of 1.633, and the p-value is significant. As can be seen, the p-value is 0.013.

Additionally, other studies that have been done in the context of evaluating the system quality for delivery of packages by robots in the food sector have produced similar results. The analysis found that most respondents were anxiously anticipating the services of this technology to improve the system and functionality. However, many participants claimed that most industries have yet to develop organisational policies and awareness programmes to make the process of implementing robot services simple and straightforward. In a separate analysis, these independent variables yielded different results. Two out of three of the independent variables appeared to be positive and significant. As a result of the different levels of PLS-SEM analysis, the level of system quality with the business value is significantly related, which can greatly impact the use of food robots. As a result, it is highly recommended that the robotics industry concentrates on system quality in order to have a ready framework for a successful and comprehensive implementation of the technology.

The next objective of this research is to examine the impact of information quality on the delivery of packages by robots in the food industry. This has been achieved by testing hypothesis two using PLS-SEM analysis. It was used to accomplish the research's second goal or objective. According to the PLS-SEM study, information quality has a positive link with the use of robotic delivery of packages, and the relationship is significant with business value. Based on the findings, business value will rise by 0.232 percent or 23.2 percent if the other independent variables remain constant and information technology increases by one unit. That means, there is a very strong and positive relationship between these two variables, which can greatly impact the implementation of delivery of packages by robot technology in the food industry. The second hypothesis of the study has been supported by this analysis: "H2: Information Quality positively and significantly effects the delivery of packages by robots in food industries associated with business value." In short, the second objective of the research has been achieved from the collected data by using PLS_SEM analysis, and the second hypothesis of the research has been supported.

The third objective of this research is to examine user awareness of the vulnerabilities of the use of robots in taking over their jobs in the food industry. This has been achieved by testing three hypotheses and using descriptive analysis. It was used to assess and comprehend the respondents' backgrounds. Various backgrounds of participation were explored and their rankings in terms of technological, social, and organisational terms in relation to the delivery of packages by robots' services were identified in this investigation. According to the findings, employees in the industrial sector and residents with more experience can easily adopt robotic services. However, according to the participants, the current usage and adoption are not responsive enough for all people and workers since there is a lack of awareness among people about the advantages and disadvantages of package delivery by robots in the food industry. Based on this, it will be difficult for the public to accept the concept or functionality of this technology. Most of them are afraid to lose their jobs, as they believe that such technology will replace human labour.

Furthermore, the majority of participants claimed that robot technology will create some vital facilities for the industry, but it will take jobs. Also, this technology can provide reliable and responsive services for industries that need carrying very heavy items and materials, if the people are convinced of the usage and acceptance of this technology. Additionally, the findings revealed, based on the opinions of some individual respondents, that they have significant trust concerns when using this technology for robots. Based on the PLS-SEM measurement and structural analyses, there is a positive and significant relationship between business value and the use of robot technology. The related third hypothesis of the research has been supported, "H3: The use of robots for delivery of packages in food industries positively and significantly influences the business value." There is a very strong relationship between the use of robots and business value, with a path coefficient of 0.498. When the value of the use of robots is increased by one point, the business value will rise to 49.8%, which is a very good figure. The t-value is also 8.213, which is higher than the crucial value. Additionally, the p-value is significant and positive at the 0.000 level. The H3 hypothesis is supported. H3 is significant, as evidenced by the fact that it is supported. As a result, there are important connections between the use of robots and business value. In a nutshell, the third goal of the research has been met, and the hypothesis that goes with it is true.

The final objective of this research is to investigate the impact of business value on the use of robots in the delivery of packages in the food industry. This has been achieved by testing other three hypotheses of independent variables using PLS-SEM measurement and structural analyses. According to this analysis, business value has a significant and positive impact on the use of food robots, implying that a high level of business value promotes the use of robots in the food industry. Business value has a positive and significant relationship with all the independent variables of this research. There is a strong path coefficient link from business value to system quality, information quality, and the use of robots. The results showed that if all other independent variables remain constant and business value improves by one point, robot use will increase by (0.508) or 50.8 percent, indicating that business value has a significant impact on robot use. In contrast to other independent factors, business value had the greatest influence on the level of implementation of robots in food industries.

6. Implication of the Study and Recommendation

One of the main goals of this research project is to contribute to the literature on robotics implementation in the food industry. There has been a lot of research done on this topic, but there is still a lot of room for improvement when it comes to the use and adoption in any industry, worker willingness, and citizen desire to use robots to deliver packages. Furthermore, there is limited empirical research assessing the impact of robots on the delivery of packages in the food industry. As a result, the findings of this study may assist in package delivery by robot implementation for staff and robot companies. People will be convinced to use this technology in food industries and to believe that, by the implementation of this technology, people will not lose their all-job opportunities. Instead, it will create many new jobs for different levels of workers and staff. As a result, robot companies and the food industry will be able to make better decisions about how to use robotic development to deliver packages and make sure it works well.

The findings show that system quality, information quality, and business value have a great impact on the use of package delivery by robots. This section suggests several possible methods for robots' technology to improve their systems and awareness of the public and avoid some of the negative repercussions that might result from a lack of stability and ease of use, such as business failure and bankruptcy. First and foremost, it is suggested that the delivery of packages by robot companies must include some awareness programmes for general people and staff to be familiar with this technology. This technology should be somehow included in the education system's school and university curricula. This will assist businesses and users in understanding basic concepts of robots and AI functionality and the work process. They should hold workshops and programmes for people and staff to learn and get used to these high-tech services from robots and AI.

Additionally, it is suggested that robot owners and related companies should improve their degree of technological education, information abilities, and practical skills in order to raise work functionality and usability. Finally, it is recommended that robotics companies take major steps to improve the current state of robot-related jobs inside the industries to eliminate some of the jobs and make the work easier. There are a few limitations in this study that should be highlighted. The study's first limitation is the study's small sample size. Due to scheduling constraints, the study's sample size is only 310 people. A larger sample size is preferable for more trustworthy and accurate results. However, this sample size is sufficient to meet the research objectives. The second limitation of this research is based on the independent variables to be determined. The number of independent variables should be increased in order to acquire more information and data. Other demographic and socio-economic characteristics, such as parents' education level, age, gender, race, regional disparities, job place, and type of work, also affect the level of robot technology implementation and success. To be able to assess the level of adoption and usage, it would be ideal to include more demographic and socio-economic parameters to obtain more trustworthy results. Despite this, the research objectives can still be met with these constrained questions. Finally, the data were collected from only a few locations and limited robots' organisations due to time constraints, which is the third limitation. As a result, it is possible that it will not be appropriate in more areas and locations.

7. CONCLUSION

The key goal of this study is to find how system quality, information quality, business value, and the use of robots influence the level of jobs and jobs lost by the implementation of robot technology in the food industries. Nowadays, robot technology is a vital contributor to companies' economic growth and workforce reduction. There are some heavy items that humans cannot carry, or it will take a lot of time and budget to do so, and robots can do heavy and more work in a small amount of time (24 hours). Robot technology is one of the most effective strategies for reducing and simplifying the workforce. However, there will be some jobs replaced by this technology, but it will not take all jobs. It will create some new jobs that are not possible for robots and AI to do. As a result, robot technology and the ability to use robots for the delivery of packages are critical for companies and for the food industry. It can help companies stabilise for current and future growth and for their financial performance by focusing on system quality, information quality, and business value. Moreover, the data for this research were gathered through online surveys. The researcher used SPSS and PLSSmart3 software for analysing and getting the results from the collected data. To meet the research's goals, several statistical analyses were performed, including descriptive analysis, normality and reliability tests, and PLS-SEM. According to descriptive analysis and PLS-SEM, the degree of delivery of packages by robots in food industries is good and above average. Furthermore, according to the PLS-SEM measurement and structural analysis, all the independent variables, namely information quality and use of robots, have positive and significant effects on the implementation and usage of robotic package delivery. However, system quality is the only independent variable that has no positive impact but has a significant effect. In addition, the second goal of this study was to see how those three independent variables influence the usage of robotic technology for the delivery of packages.

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