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Optimizing Manufacturing Efficiency using human-centered design and AI

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Abstract

This study explores the implementation of a new machine, in a ceramic industry's production process, that detects and categorizes plate defects using artificial vision and machine learning algorithms. Simultaneously, the novel UTAUT-for-Industry framework will be applied to assess worker acceptance of the new machine, aiming to ensure that worker feedback and acceptance are central to the implementation process, while enhancing product quality and production efficiency. This dual approach supports industries in advancing towards Industry 5.0, emphasizing human-centric smart manufacturing systems and promoting human-machine intelligent cooperation

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1. Introduction

As industries evolve towards increased automation and digitalization, the seamless adoption of New Technologies (NT) by shop floor workers becomes vital for enhancing productivity and efficiency across various sectors. Within the evolving landscape of Industry 5.0, which is reshaping the role of human workers from low-level tasks to high-expertise roles [1], addressing human factors through comprehensive workplace analyses is essential to achieve human-centered technology integration. To that end, multiple models have been proposed to assess how users respond to the implementation of NT, such as Technology Acceptance Model (TAM), Expectation-Confirmation Model (ECM), Self-Determination Theory (SDT) with the Unified Theory of Acceptance and Use of Technology (UTAUT) serving as a prime example [2-4]. Designed to identify the influence of four key constructs — performance expectancy, effort expectancy, social influence, and facilitating conditions — in technology acceptance [5], the UTAUT model unified eight theories and models, providing a comprehensive model for analyzing technology acceptance. The model was further developed, with UTAUT2 and UTAUT3 [6,7] adding important features to consider when accounting for the technological advances of the last decade, such as robots and automated vehicles.

In the context of NT implementation in industrial scenarios, multiple studies have identified the need of proper preparation of the users before the implementation itself, to prevent negative emotions, such as anxiety, from impacting the adoption rate of the technology [8,9]. Moreover, the application of human factor analysis was identified as a major requirement to understand how workers accept and adopt NT [10], with traditional models representing a guideline that should be adapted to consider industry-specific factors [11].

However, while the existing models offer valuable insights, their primary focus is on individual-level factors, which may not fully capture the complexities of technology acceptance in a dynamical environment, reducing the applicability in industrial settings, which involves multiple stakeholders and varying levels of expertise. Furthermore, these models often

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overlook important factors for industrial contexts, such as perceived safety [12, 13] and user satisfaction with the current system. Lastly, the development of multiple different models for assessing technology acceptance has resulted in a great number of scattered, and sometimes redundant, acceptance factors, highlighting the need for a more comprehensive approach to understanding technology acceptance.

With that, this research seeks to address the identified gaps by developing a novel model, termed UTAUT-for-industry, that incorporates factors specific to industrial settings, unifies the scattered acceptance factors into macro dimensions and integrates both individual and organizational factors into the assessment, providing a holistic understanding of technology acceptance. The model was then validated in an industrial case study, to ensure its applicability and define the next steps for improvement.

Nomenclature

IU	Intention to Use
HMI	Human-Machine Interaction
NT	New Technology
TAM	Technology Acceptance Model
UTAUT	Unified Theory of Acceptance and Use of Technology

2. UTAUT-for-industry: concept and description

The UTAUT-for-industry model was developed based on the UTAUT, and its updated versions, but integrating factors that the traditional models overlook, such as user satisfaction with the current system/technology and perceived safety. By including these factors into the analysis, the model provides a more nuanced understanding of technology acceptance, in industrial settings. The UTAUT-for-industry model is divided in three key groups, described below:

- Personal factors – representing the acceptance dimensions that are linked with the user's personal perceptions and characteristics;
- External factors – representing the acceptance dimensions that are linked with the organization and the use environment;
- Control variables – representing individual factors of the users, that may impact their intention to use (IU) the technology.

2.1. Personal Factors

The personal factors group is composed of four macro dimensions – perceived usefulness, perceived ease of use, perceived safety of use and satisfaction with the current technology – representing the aspects more related to the users and, therefore, not under direct control of the company.

The perceived usefulness and ease of use macro dimensions were formulated mainly from factors of UTAUT and the Technology Acceptance Model (TAM), pertaining to the users perceptions of the advantages offered by using the NT would be free of effort [14,15]. Meanwhile, perceived safety of use is a dimension not covered in the first versions of UTAUT and the TAM, being defined by [16] as the extent to which a user perceives that using a system will impact his well-being. Lastly, user satisfaction with the current system/technology was included in this study as an acceptance dimension, as it is a factor extensively analyzed in the consumer behavior literature, such as [17,18].

2.2. External Factors

The external factors group is composed of the remaining four macro dimensions – organizational support, implementation process, long-term consequences and social influence – representing the aspects more directly under control of the company, relating to the use environment.

Organizational support is a dimension developed by the incorporation of factors from traditional models, accounting for aspects such as the organization's readiness for innovation, the facilitating conditions provided to the users and the compatibility between the NT and the users' tasks. Similarly, implementation process relates to the manner in which the organization implemented the NT, encompassing the assimilation of the technology by the different teams/departments, the users' capacity to test the NT before the definite implementation, the voluntariness of use and the sense of involvement felt during the decision to implement the technology. As for social influence, it is a factor originally included in UTAUT2 and adapted to the industrial context by incorporating factors from other models, representing the user's perspectives regarding their peer's opinions on the usage of NT, the social status incurred by the use of the NT and their friends and coworkers' pressure to use the NT. Lastly, the long-term consequences dimension refers to the expected benefits/drawbacks that may arise when using NT, including fear of job loss, new skills/qualifications attained by the use of the NT and potential professional growth within the company.

2.3. Control Variables

In addition to the eight acceptance dimensions, such as Performance Expectancy, Effort Expectancy, Social Influence and Facilitating Conditions, aimed at explaining the IU of NT, the UTAUT-for-Industry model also presume the presence of two types of control variables, that are expected to moderate the relationships between the main dimensions and the IU of NT: socio-demographic factors and individual reaction to new technologies. Socio-demographic factors encompass the participant's characteristics, such as age, gender and educational level, which have been shown in studies to influence individual's inclination towards technology adoption [19-21]. Meanwhile, individual reaction to NT is related to the user's general attitude towards NT, including their perceived personal attitude towards technological innovations and their familiarity with the current technology employed

2.4. Implementation Steps

According to a review conducted by [1], the top four evaluation methods accounted by qualitative methods are as follows: questionnaires (49 %), interviews (26 %), scenario observation (16 %), and workshops. In this context, questionnaires were selected to collect the data. The step-by-step implementation of the methodology is presented below.

a. Objective definition: identification of the specific technology to evaluate acceptance;
b. Hypotheses definition: identification of the relevant factors for the technology acceptance;
c. Selection of factors: identification of the key factors that influence technology acceptance contextualizing with the environment and type of activities;
d. Surveys definition: development of questions that measure each factor, advisably using a Likert-type scale (1-5), as proposed by [7], to rate participant's agreement or disagreement with statements;
e. Analysis and data interpretation: analysis of the responses, using appropriate statistical methods to capture and understand the impact of each factor and establish correlations with the workers' IU.

3. Case Study

3.1. Process Overview

This study was conducted within a ceramic manufacturing company where plates are manually inspected and classified based on visible defects into four categories: C1, C2, second-rate, and unacceptable. Currently, the inspection and grading process takes approximately 11 seconds per plate, with an error rate close to 1.9 %, which points to potential improvements in precision and speed. Furthermore, the process poses ergonomic challenges for workers. The workstation environment exposes employees to loud noise and demands prolonged standing with limited foot support, causing poor posture and frequent repetitive movements. These factors not only affect worker comfort but also have implications for long-term health and efficiency. The introduction of an automated prototype for defect classification aims to address these issues by enhancing accuracy, reducing physical strain, and streamlining the workflow.

3.2. AI Model Overview

To build an AI model capable of accurately classifying the correct dishes, the first step is to understand the inspection process conducted by the workers. This process involves the workers picking up the dishes, rotating them, and inspecting them from different perspectives, with light reflecting off the dishes from different angles, both from the top and the bottom.

With this in mind, a multi-modal neural network was developed to emulate this process. To achieve this, cameras placed at different positions capture multiple images of the dishes with fferent rotations, thus creating a comprehensive representation of the ceramic dish. The images are then

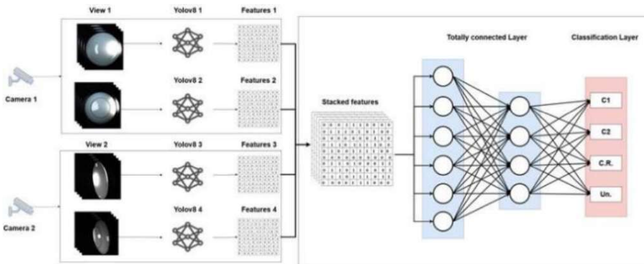

Figure 1. Machine Learning process.

grouped by the camera that captured them and by the side of the dish, resulting in four groups in total. For each group, a Yolov8 is embedded into the multi-modal neural network to act as a "specialist" for each view. The images are processed through their respective Yolov8 networks for feature extraction, leveraging the transfer learning capabilities of yolov8. Then, the fully connected layer aggregates the information from each "specialized" Yolov8 head, allowing the model to learn complex patterns across the different views of the dish. This enables it to make a more informed decision when classifying the dish. This process is represented in Figure 1.

This architecture was initially validated using a small dataset, and future results will be presented following the implementation of the prototype and the integration of a more robust and structured dataset.

3.3. Machine Overview

The primary objective of the prototype is to collect a dataset – composed by images of the top and bottom sides of ceramic plates and their respective classification in terms of quality assurance – to train an AI model for quality inspection. The prototype machine was developed for temporary deployment solely during the data acquisition phase, with manual

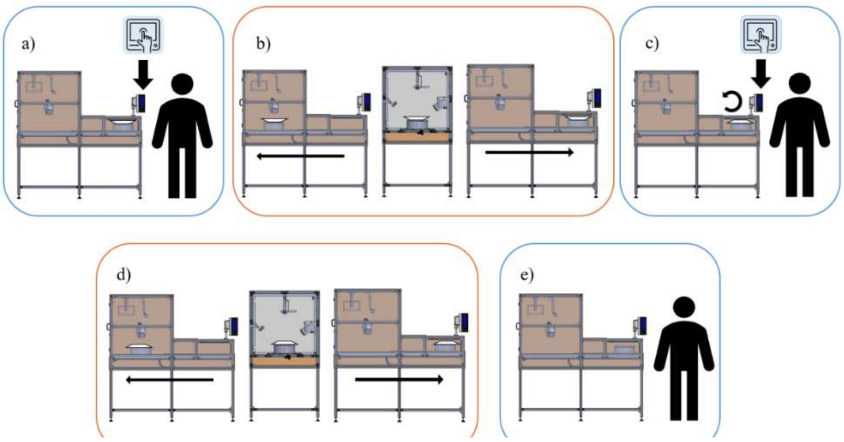

Figure 2. Working principle of the prototype. a) Plates placement and classification. b) Automatic acquisition of images. c) Plate flipping in the Feeding Area. d) Automatic acquisition of images. e) Plate removal.

interaction ensuring minimal disruption to the existing production line.

The equipment consists of a receptor on which plates are placed manually by the worker (Feeding Area). First, the plate is placed face up and, on a Human Machine Interface (HMI), the class and defects observed on the plate are introduced. Then, the receptor moves to a reserved Image Acquisition Area that automatically captures the images without any worker interference. Once the necessary images have been acquired, the receptor returns to the Feeding Area, where the worker flips the plate to expose the bottom side, and the process is repeated to acquire images for this side as well. A simplified overview of the working principle is shown on Figure 2 and the prototype can be observed in Figure 3.

Figure 3. Data acquisition prototype.

Within the Image Acquisition Area, a fully automated setup - comprising two cameras and two light sources - captures images of the plates. To ensure a uniform dataset, the receptor rotates the plate, guaranteeing the capture of all potential defects from different perspectives (which is very important due to the reflective surface of the plates).

During the design phase, significant attention was given to human-machine interaction, encompassing considerations from basic safety measures to ergonomic use of the equipment. The Feeding Area is restricted by safety barriers to guarantee that the worker only accesses it when it is safe to do so. The Image Acquisition area is also restricted during operation through a sensor that detects if the area is accessible. The prototype was designed as a standing workstation, with its height adjusted to suit the workers [22]. Concerning the receptor, several error-mitigation measures were implemented. A set of three sensors were incorporated detecting the presence, orientation and model of the plate. The system only accepts commands to move to the Image Acquisition Area if the correct plate model is detected and positioned accurately. To facilitate proper placement, the receptor includes cut-outs that align with the plate's shape, ensuring a secure fit.

The HMI for this equipment is a touchscreen located in the feeding area, designed to be simple and intuitive. At the beginning of the process, a prompt appears on the screen instructing the worker to place the plate facing up. Next, the worker must classify the plate according to its quality, selecting from five possible classes. Each class may contain different types of defects. When a class is selected, the interface displays all defects, but those that are not applicable to the chosen class are greyed out and cannot be selected. This feature ensures a uniform interface while helping the worker verify if the plate is correctly classified. Once the class of the plate and the defects present on the top side of the plate are selected, the worker can press a button to move the receptor forward. During data acquisition, to maintain image quality, live video feedback of the plate is displayed on the HMI. When the receptor returns to the Feeding Area, a prompt instructs the worker to flip the plate and re-enter the class and defects observed on the plate's underside. When the cycle is complete, the worker removes the plate from the receptor, allowing a new plate to be fed.

4. Results Discussion

The participants involved in the study were comprised of: 4 workers directly involved with the defect detection and classification task, 5 production supervisors and 1 quality control worker. As the participants perform different tasks in the process, the questionnaire was adapted to better apply to their respective contact levels with the new machine. The participant's characterization is presented below in Table 1.

Table 1. Participant's characterization

Profiles	N=10	Percentage (%)
Age		
20-30 years old	2	20
30-40 years old	1	10
40-50 years old	3	30
Over 50 years old	4	40
Gender		
Male	3	30
Female	7	70
Education Level		
Primary Level	2	20
Secondary Level	4	40
Higher Education Level	4	40
Job Role		
Shop Floor Worker	4	40
Supervisor	5	50
Quality Control	1	10
Time using the current system		
Less than 5 years	3	30
Between 5 and 10 years	4	40
Over 10 years	3	30

As presented below in Table 2, the questionnaire on technology acceptance revealed that IU the new machine is remarkably high, with an average rating of 93 % (equivalent to 4.66 on a scale from 1 to 5). This finding indicates a readiness for change among the workers, which may benefit the implementation of the machine in the shop floor. Analyzing the eight acceptance dimensions of UTAUT-for-industry, it can be noted that they received similar scores, with the lowest performance being of the long-term consequences dimension.

That result indicates a potential area of improvement for the company, regarding the adequate communication of long-term benefits that the workers may expect when implementing NT in their activities.

Table 2. Results for the technology acceptance questionnaire

Macro Dimension	Acceptance Score
Intention to use	4.66
Satisfaction with current system	4.09
Perceived usefulness	4.26

Perceived ease of use	4.00
Perceived safety of use	4.40
Organizational support	4.48
Implementation process	4.16
Long-term consequences	3.52
Social influence	4.20

Additionally, the results were converted from the 1-5 scale into percentages and were presented with an efficiency scorecard, as illustrated in Figure 4, segregated by the different job roles. The scorecard improves result analysis by offering a visually intuitive representation, with a color-coded scheme.

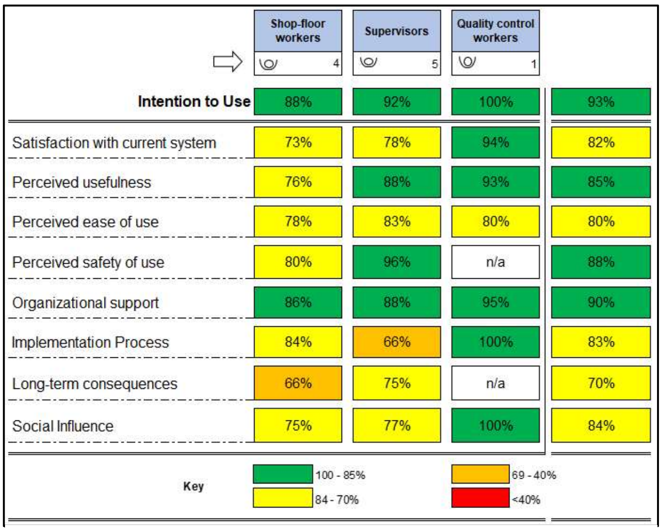

Figure 4. Efficiency scorecard.

Presenting the results in this manner also promote greater comprehension of performance trends and areas for improvement, such as the Long-term consequences dimension. Overall, the machine was well rated among the different job roles, however, notable differences emerged in some dimensions. Implementation process, for example, presented the highest deviation, indicating that the company may have employed different approaches, among the different job roles, when communicating the adoption of the new machine. Meanwhile, organizational support received similar scores between the job roles, which is expected since all participants are affiliated with the same company. With that, a correlation analysis was performed to identify the dimensions most responsible for the worker's IU, as well as identify if any of the control variables is significantly impacting the acceptance of the new machine, as presented further below in Tables 3 and 4. It can be noted that *usefulness* and *social influence* are the most influential dimensions for worker's IU, indicating that the perceived benefits and social factors in the workspace play central roles in driving technology acceptance. In contrast, *implementation process* and *organizational support* show presented moderate correlations with IU, indicating a secondary, but relevant impact in technology acceptance for the company's context.

Table 3. Correlation between macro dimensions

	Satisfaction	Usefulness	Easy of Use	Safety of Use	Implementation Process	Organizational Support	Long-term Consequences	Social Influence	IU
Satisfaction	1								
Usefulness	0.4256	1							
Easy of Use	0.4764	0.3408	1						
Safety of Use	0.1807	0.6039	0.4631	1					
Implementation Process	0.0176	-0.1519	-0.3710	-0.1348	1				
Organizational Support	0.1397	0.0168	-0.1235	0.2172	0.6907	1			
Long-term Consequence	0.7669	0.4636	0.7957	0.5597	-0.3196	-0.2339	1		
Social Influence	0.3209	0.4927	-0.1256	0.1094	0.4893	0.5173	-0.1983	1	
IU	**0.4806**	**0.6406**	**0.5673**	**0.4666**	**-0.0835**	**0.0989**	**0.5105**	**0.6117**	**1**

Table 4. Correlation between the control variables and IU

	Intention to Use
Age	-0.3889
Gender	0.5777
Education Level	0.4476
Personal Innovativeness	0.5064
Time in the Company	-0.3475
Time using Current System	0.3120

As for the control variables, the results presented moderate positive correlations for *gender*, *education level*, and *personal innovativeness*, suggesting that male participants, those with higher education, and those more open to new technology may be more inclined to adopt NT. In contrast, *age* and *time in the company* have slight negative correlations, which may suggest some resistance to change among older and more tenured employees. Finally, *time using the current system* shows a weak positive correlation, indicating familiarity with the current setup has minimal impact on NT acceptance. These results highlight the potential of technology acceptance among workers and supervisors. However, to increase the satisfaction with the NT, more activities must be conducted between the design team, the workers that will operate the machine and the supervisors that are expected to integrate, with caution and attention, the NT in the process. In this context, the following step consists of prototyping evaluation by testing the HMI (human machine interface) and the plate position system. By implementing different methods on the product design development, starting with the presented model, UTAUT-for-Industry, to collect information from the user and prepare them prior the machine development and implementation, a human-centered design approach is promoted, being expected to increase acceptance and satisfaction, contributing to the success of the project.

5. Conclusions

This paper presents the application of the novel UTAUT-for-industry model in a real case study. The model was applied to evaluate the acceptance factors associated with the implementation of a new machine prototype in a ceramic industry. The results indicated high overall IU among the workers, with perceived usefulness and social influence emerging as the main factors impacting acceptance. This suggests that the workers are not only influenced by the perceived advantages of the new system, but also by their peers' perspectives, highlighting the importance of an innovative work environment for effective technology integration.

Moreover, control variables, such as gender, education level and personal innovativeness presented positive correlations with IU, with male and more educated participants showing higher willingness to accept the new machine. Meanwhile, age and tenure displayed negative correlations, suggesting a slight resistance to changes among older and more tenured employees. These findings provide a valuable guidance for the implementation of new technologies within the organization, indicating actions in which the company should focus on to improve acceptance, such as clearly communicating the usefulness of the new systems to the workers.

Lastly, the UTAUT-for-industry model has further potential capabilities to be explored in future works. Namely, the model should be applied in a post-implementation phase, to examine how accurately it can be used to predict the acceptance rate of NT.

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