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# Future of smart greenhouses in Almería: Farmers' perspectives and fuzzy logic-based evaluation

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ABSTRACT

The adoption of automation technologies in intensive greenhouse agriculture is a key challenge for achieving greater efficiency and sustainability. This study explores the perceptions of farmers in Almería (Spain), Europe's most prominent greenhouse region, regarding automation and robotics, identifying the main socioeconomic and technical barriers to implementation. A structured survey was conducted among greenhouse operators, and the data were analyzed using descriptive statistics and multiple linear regression to examine correlations between automation levels and farmer characteristics. From this, a fuzzy logic decision-support system was developed to evaluate the feasibility of different automation technologies, based on three key factors: implementation cost, perceived safety risk, and expected efficiency. The model was applied to five real-world configurations, ranging from simple mechanized tools to advanced robotic systems. Results show that semi-automated, low-cost solutions with minimal risk are more likely to be adopted than high-end technologies, even when the latter offer greater functional capabilities. The study demonstrates the value of combining technical assessment with local knowledge to identify realistic and scalable pathways for agricultural innovation in greenhouse systems.

## 1. Introduction

The province of Almería, located in southeastern Spain, is one of the most important agricultural regions in the country and in Europe, particularly notable for its intensive greenhouse farming model. With >30,000 hectares of covered land, it constitutes the largest enclave of greenhouse horticultural production in Europe, supplying >40 % of the fresh vegetables consumed on the continent during the autumn and winter months [1]. This agricultural model has not only transformed a historically impoverished region like Campo de Dalías into a socioeconomic powerhouse but has also generated a productive ecosystem that integrates small farmers, auxiliary industries, technology companies, and logistics networks [2]. Almería's agricultural sector, therefore, represents a fundamental pillar of the regional economy, generating thousands of direct and indirect jobs and articulating a highly specialized and competitive territorial structure [3,4].

The current global situation demands a profound transformation of the agricultural model. Global population growth, estimated at >9 billion people by 2050 [5], will require a 60 % to 100 % increase in food production, posing unprecedented challenges in terms of environmental sustainability, efficient use of resources, and resilience to climate change [6]. Added to this are emerging problems such as soil degradation, water scarcity, and pressure on biodiversity [7,8]. In this scenario, agriculture must move toward a more sustainable, resilient, and technologically advanced model, as reflected in the United Nation Sustainable Development Goals, particularly Goal 2 [9].

Sustainable agricultural intensification is positioned as a key strategy for responding to these challenges [10]. It is based on significantly increasing agricultural productivity while protecting the natural environment, reducing emissions, and optimizing the use of resources such as water and energy [11,12]. To achieve this, it is essential to incorporate digital tools and new technologies such as automation, the Internet of Things (IoT), Big Data, and Artificial Intelligence (AI), which enable more precise, efficient, and controlled agriculture [13–16]. In this sense, the digitalization of the agricultural sector is emerging as one of the main drivers of change, especially in systems such as intensive

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greenhouse agriculture, where pilot implementations of advanced technologies are already being observed [17].

In recent years, greenhouse design has evolved significantly, moving from simple plastic-covered structures to complex automated systems known as smart greenhouses [18–20]. These new models allow for management of the internal climate environment using sensors, communication networks, predictive algorithms, and AI-based optimization techniques [21]. However, despite the transformative potential of these technologies, their adoption in intensive agriculture in Almería is still limited. Economic, technical, and social barriers persist that hinder their large-scale implementation, creating a significant gap between the scientific knowledge developed in universities and research centers and its practical application in the field [22]. Thus, many greenhouses continue to operate with low levels of automation and robotization, which limits the efficiency and sustainability of the system.

This article addresses the role of digitalization and automation in the context of intensive greenhouse agriculture in southern Spain, analyzing the current state of technological adoption, existing barriers, and opportunities for transformation toward a smarter, more efficient, and sustainable agricultural model. This study aims to analyze the current situation and future prospects of farmers in the province of Almería in relation to greenhouse automation and robotization, addressing both the technical factors and the economic and social barriers that determine its adoption. The aim is to characterize the sociodemographic and productive profile of farmers, assess the current level of automation on their farms, and understand their perceptions of the main obstacles to automating their greenhouses, such as cost, technical complexity, training requirements, and comparisons with the efficiency of human labor. The relationship between farmers' characteristics and their willingness to adopt advanced technologies is explored through statistical analysis. A fuzzy logic system is also developed to estimate the feasibility of different technological configurations. This system is applied to validate specific automation designs, thus providing a flexible decision-making support tool that combines empirical evidence and local perception, and can contribute to guiding realistic and sustainable technological transition strategies in intensive agriculture in southern Spain, specifically in the region of Almería. The main objective of this study is to evaluate the current state and future potential for automation in intensive greenhouse agriculture in Almería by integrating farmers' perceptions with technical analysis. The novelty of this work lies in the application of a fuzzy logic model informed by empirical data from local farmers, allowing for a simulation-based assessment of automation strategies that reflects both technological feasibility and user acceptance. This combined methodological approach provides a practical decision-support tool grounded in the specific socioeconomic context of one of Europe's most important agricultural regions, bridging the gap between academic innovation and real-world implementation.

This article is structured as follows. Section 2 presents the materials and methods, including the survey design, statistical analyses, and the development of the fuzzy logic system. Section 3 details the results of the descriptive statistics and correlation analyses, followed by the simulation outcomes generated by the fuzzy model. Section 4 discusses the implications of the findings in light of existing literature, and Section 5 summarizes the main conclusions and outlines future research directions.

## 2. Materials and methods

### 2.1. Description of the study area

This research is based on the application of a structured questionnaire to farmers in the province of Almería, with the aim of exploring their perceptions of technological transition and robotization in greenhouses. The questionnaire includes nine key questions addressing demographic aspects, the current degree of farm automation, perceived barriers to its implementation, and expectations about its future development. Data collection was carried out through in-person surveys in three representative areas of the intensive agricultural model in Almería: Campo de Dalías, Bajo Andarax, and the Níjar region. Fig. 1 shows the geographical distribution of the respondents participating in the study.

According to data from the Ministry of Agriculture, the province of Almería has a total of 16,256 greenhouse farms [23]. To ensure that the study results are statistically representative of this population, the minimum sample size required was calculated using the formula for finite populations, assuming a 95 % confidence level and a 7,5 % margin of error [24]. The formula used is as follows:

$$n = \frac{N \cdot Z^2 \cdot p \cdot (1-p)}{\left(e^2 \cdot (N-1)\right) + \left(Z^2 \cdot p \cdot (1-p)\right)} \tag{1}$$

In this formula, n represents the required sample size, that is, the minimum number of surveys that must be conducted for the results obtained to be statistically representative of the total population. The variable N corresponds to the size of the population under study, which in this case is 16,256 greenhouse farms in the province of Almería, according to data from the Ministry of Agriculture. The parameter Z refers to the value associated with the desired confidence level; for a 95 % confidence level, the Z value used is 1.96, taken from the standard normal distribution. p is the expected proportion of individuals presenting a given characteristic within the population. Finally, e represents the margin of error tolerated in the study; in this case, it has been set at 0.075, which is equivalent to 7,5 %. Therefore, the minimum number of surveys to be conducted to obtain statistically representative results is 170.

### 2.2. Study variables and data analysis

To conduct the study, a questionnaire for data collection was designed to gather relevant information on farmers' characteristics, the level of automation on their farms, and their perceptions regarding the incorporation of new technologies. The questionnaire was structured into four thematic blocks:

- Block 1: Sociodemographic and productive characteristics, which collected information on age, educational level, predominant crop type, and farm area.
- Block 2: Level of automation, assessed on a scale of 1 to 10, where 1 indicates a complete absence of automation and 10 represents a fully automated system.
- Block 3: Technological perceptions, with questions about preference between simple tools or robotics, and expectations about future automation.
- Block 4: Perceived barriers to automation, in which various obstacles were assessed using a scale of importance from 1 to 10.

Various statistical techniques were used to process the data obtained from the questionnaire to further study farmers' perceptions of greenhouse automation and robotization. Statistical analyses were performed using IBM SPSS Statistics version 29.0.2.

First, a descriptive analysis was conducted on categorical variables, such as crop type, farmer age, farm size, and educational level. Absolute frequencies were calculated to characterize the sample. Likewise, measures of central tendency and dispersion were determined for scalar variables. Secondly, multiple linear regression to explain the level of greenhouse automation based on the sociodemographic characteristics of the farmer with the objective of comparing the current degree of automation of farmers based on the type of crop, the age of the farmer, the level of education and the size of the farm, looking for the current relationships that occur in agriculture.

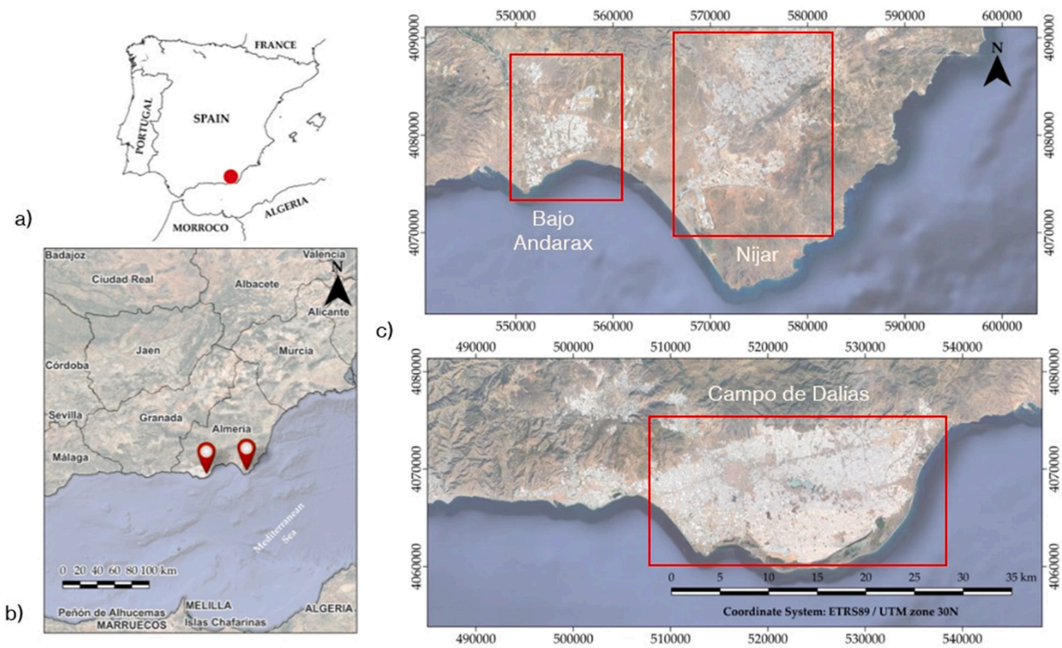


**Fig. 1.** Geographic areas of the farmers surveyed in the region of Almeria. a) Location of Almeria (Spain). b) Location of the zones in Almeria. c) Detail on the three representative areas of the intensive agricultural model in Almería.

### *2.3. Fuzzy logic system*

As part of the methodological approach, a fuzzy logic system was developed to model and validate the perceived feasibility of various levels of greenhouse automation, integrating both farmers' perceptions and technical criteria [25,26]. This tool enables the structured representation of human reasoning under uncertainty, which is particularly useful in contexts where decision variables such as cost, perceived risk, or expected efficiency cannot be precisely quantified or involve a high degree of subjectivity.

The system follows a Mamdani-type architecture, with three input variables: Implementation Cost, Perceived Risk Level, and Expected Efficiency.

The three input variables were selected based on the most recurrent themes identified in the survey. Implementation Cost refers to the initial financial investment required to deploy automation or robotic systems within a greenhouse, including equipment acquisition, installation, and potential maintenance expenses. Perceived Risk Level relates specifically to safety concerns associated with the use of automated or robotic technologies. This includes the risk of accidents involving machinery, unintended harm to crops, or hazards for workers operating alongside these systems. Risk levels can be classified into three main categories: low, medium, and high, depending on the severity of the consequences they may cause to the worker. The low risk level is mainly associated with minor incidents or injuries that do not compromise the farmer's health nor require specialized medical attention. This type of risk includes small superficial cuts with pruning shears, scrapes with loading carts, temporary muscle discomfort from digging with the shovel, or situations that do not become accidents but do show the existence of unsafe conditions. The medium risk level refers to accidents that cause more significant injuries, although without being severe. Among them wounds can be found that require simple dressings, impacts from contact with tools or greenhouse structures, and falls from low height during trellising tasks that cause bruises or sprains. At this level, the damage is moderate for the farmer and, although it generally does not imply prolonged incapacity, it may require rest or basic medical treatment. Finally, the high risk level includes those accidents that can have serious consequences for the worker's health and safety. In this group are included falls from significant heights from lifting scaffolds, loss of consciousness due to high physical efforts or temperature, deep cuts with cutting tools or sharp elements, bone fractures, or injuries that may generate a temporary or permanent disability. These risks require urgent medical attention and even hospitalization, and their prevention is a priority in the management of occupational safety in greenhouses [27,28]. Expected Efficiency denotes the anticipated improvement in productivity, resource use optimization (such as energy or water), labor reduction, and crop quality resulting from the implementation of smart technologies. The output variable, Probability of Success, represents the overall viability of implementing automation under a given combination of these three conditions. It acts as a composite indicator that integrates economic feasibility, safety perception, and technological benefit, ultimately supporting informed decision-making about the likelihood of successful and sustainable adoption.

Each input variable was defined with three fuzzy membership functions (Low, Mid, High). The output variable is the Probability of Success, defined on a continuous scale from 0 to 1 and also divided into three linguistic levels: Low, Mid, and High. The rule base, was constructed based on the previous survey results. The rules were designed with explicit prioritization for instance, severely penalizing scenarios with high perceived risk, and favoring configurations with low cost and high efficiency.

Fig. 2 shows the architecture of the fuzzy inference system, including the input and output variables and the internal rule engine used to compute the final success. For the membership functions associated with each input and the output, gaussian membership functions were used to ensure smooth transitions and better modeling of intermediate values. The output variable, Probability of Success, was defined over a continuous scale from 0 to 1, corresponding to Low, Medium, and High success levels.

This fuzzy system not only allows for the analysis of current conditions for technology adoption but also enables the simulation of future scenarios and the validation of proposals from previous research. Therefore, it serves as a decision-support tool for designing automation strategies tailored to the agricultural context of Almería, combining empirical data with a flexible and interpretable expert model.

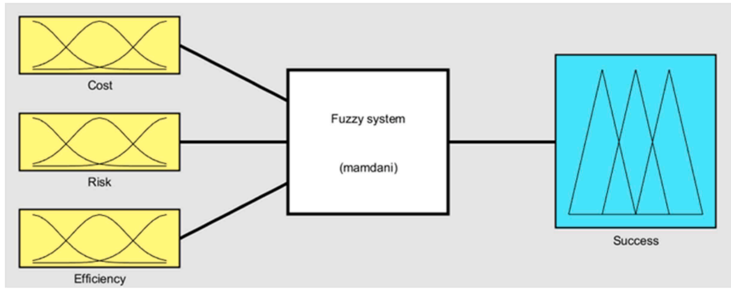


**Fig. 2.** Architecture of the designed fuzzy system.

## 3. Results

### 3.1. Sociodemographic profile of the farmers

The results obtained regarding the sociodemographic and productive characteristics of the farmers interviewed are presented in Fig. 3. Regarding the predominant type of crop, a clear concentration is observed around peppers and tomatoes, representing 37 % and 34 % of the cases, respectively. These two crops together exceed 70 % of the total, indicating significant specialization in these varieties. They are followed, to a lesser extent, by zucchini (12 %), cucumber (8 %), and other diverse crops (9 %).

Regarding the age of the farmers, the most represented group is those between 40 and 55 years old, making up 34 % of the sample. The 25–40 and over 55 age groups have a similar proportion, both at 30 %, while those under 25 barely reach 6 %, highlighting the limited presence of young people in the sector. Regarding farm area, the majority of farmers work between 1 and 3 hectares, accounting for 45 % of the total, followed by those managing between 3 and 5 hectares (31 %). Smaller farms, less than one hectare, and larger farms, over five hectares, are equally divided, each accounting for 12 %. This distribution shows a notable concentration among medium-sized farms.

Finally, regarding educational level, 45 % of farmers have secondary education, while 41 % have completed additional training, such as vocational training or technical courses. Only 4 % have university degrees, and 10 % have only primary education. This distribution suggests a medium-high educational profile, with a predominance of secondary and technical education, although with a limited presence of university graduates.

### 3.2. Degree of automation and perception of barriers

Fig. 4 shows the distribution of the current level of automation reported by farmers, measured on a scale of 1 to 10, where 1 represents no automation at all and 10 represents a fully automated level. Automation in agriculture refers to the use of tools that facilitate farmers' tasks through systems that reduce handling, intervention, presence, and effort. These automation systems, at their highest level, provide irrigation with automatic fertilization, smart climate control, robotic harvesting mechanisms, etc. [29–32]. Within the context of intensive agriculture in Almería, a high level of automation is classified for greenhouses that are fully domotized, which through sensors have parameters such as temperature or humidity and have intelligent systems to act according to the conditions, as well as autonomous robots that are capable of harvesting and classifying the fruits fully autonomously [33, 34]. The medium level incorporates simple mechanisms and semi-automatic equipment that allow reducing the physical load and the working time of the farmer, although constant supervision is still needed. This level in Almerian agriculture consists of having windows that can be opened and closed by crank systems, irrigation managed with controllers or timers, and fertilization carried out through automatic fertigation systems. In addition, semi-automatic tools are used to help with cultivation tasks, such as drills to make planting holes or electric shears to facilitate pruning. In this way, although there is no coordinated control of the greenhouse variables, it is possible to reduce the physical effort and increase the comfort of the farmer. At a low level,

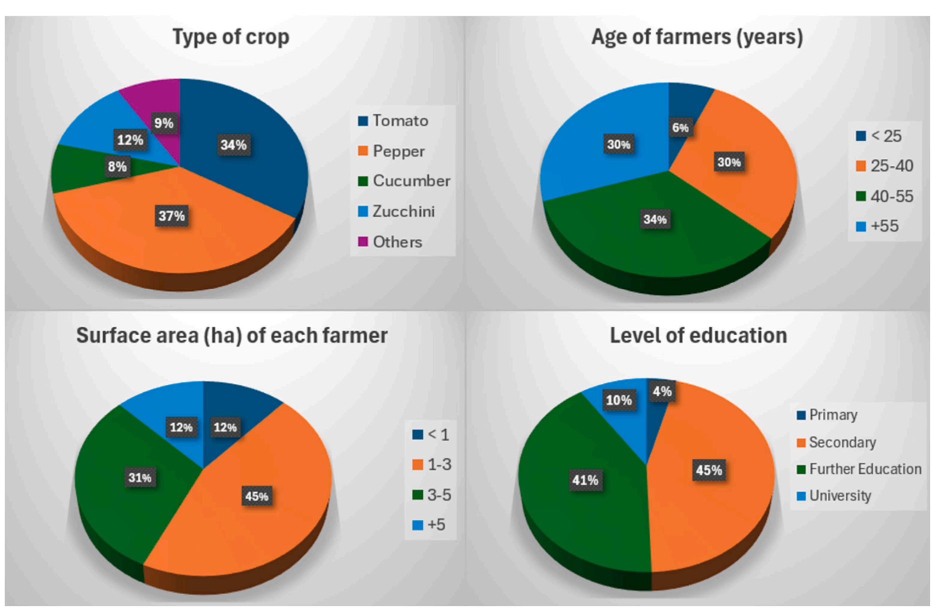


**Fig. 3.** Block 1 results. Sociodemographic and productive characteristics, which collected information on type of crop, age, farm area and educational level.

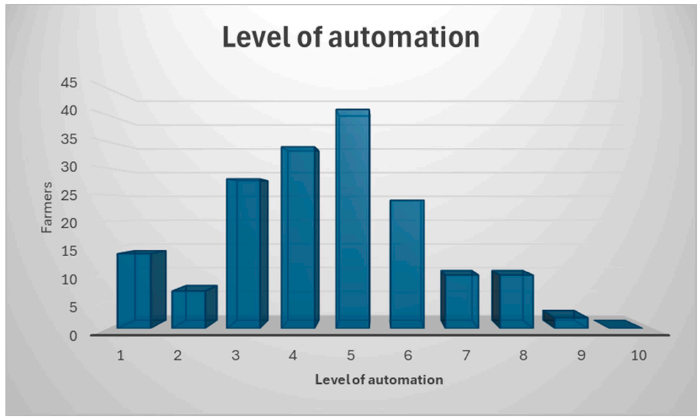


**Fig. 4.** Block 2 results. Level of automation, assessed on a scale of 1 to 10, where 1 indicates a complete absence of automation and 10 represents a fully automated system.

there are no automated control variables, since all operations depend directly on human intervention. This level is evident in Almerian agriculture in greenhouses where the farmer is responsible for manually opening and closing the greenhouse windows, controlling the switching on and off of the irrigation system, as well as carrying out harvesting and pruning with traditional tools such as manual shears. Planting, soil preparation and maintenance tasks are also carried out completely manually. This level is characterized by its low efficiency and by requiring a high consumption of time and labor [35,36]. The data reveal that most farmers fall within intermediate levels of automation, with level 5 being particularly notable, with over 40 responses, followed by level 4, with just over 30. This pattern indicates that, while there is a trend toward technology adoption, the overall level of implementation is still limited. Statistically, the average level of automation reported was 4.5 ± 1.85, which confirms the concentration of responses in the middle of the range. This data suggests that, while technological elements are being introduced on farms, there is still significant room for improvement to achieve higher levels of automation.

To understand farmers' technological perspectives, they were asked two key questions. The first investigated their preference for using simple tools versus robots. In the context of agriculture, simple tools are considered to be those mechanisms or systems through which farmers can reduce effort and improve efficiency in their agricultural tasks, such as electric shears, electric carts, brush cutters, etc. The results, Fig. 5, represented in the graph on the left, indicate a clear inclination toward simple tools, with more than twice as many responses in favor of robots. This data suggests that, today, the majority of farmers still rely on traditional methods, possibly for reasons of cost, ease of use, or maintenance.

The second question explored farmers' expectations regarding the future, specifically whether they believe greenhouses will be fully automated and robotized within the next 30 years. As the graph on the right shows, although a significant proportion responded affirmatively, the majority were skeptical. This reflects a certain degree of uncertainty or lack of confidence that full automation is achievable in the medium term, perhaps due to technological, economic, or sociocultural barriers that still need to be overcome.

A multivariate regression analysis was performed to analyze the categorical variables for each farmer and the level of automation on their farms, Fig. 6. It was found that crop type and age had a Student T-test of <1.96 and a significance level greater than 0.05, meaning that

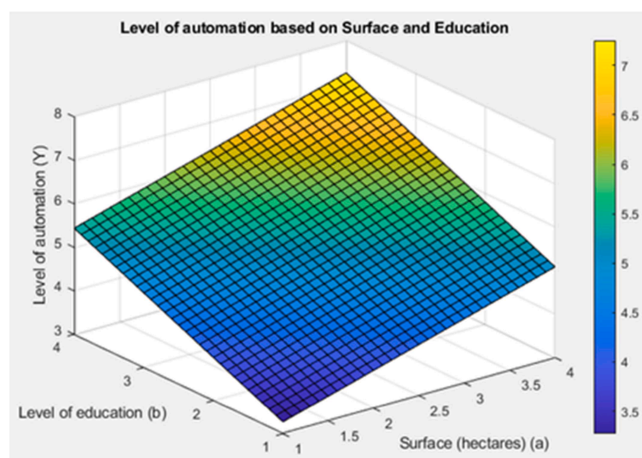


**Fig. 6.** Multivariate regression analysis results on level farm automation level based on surface area and farmers education.

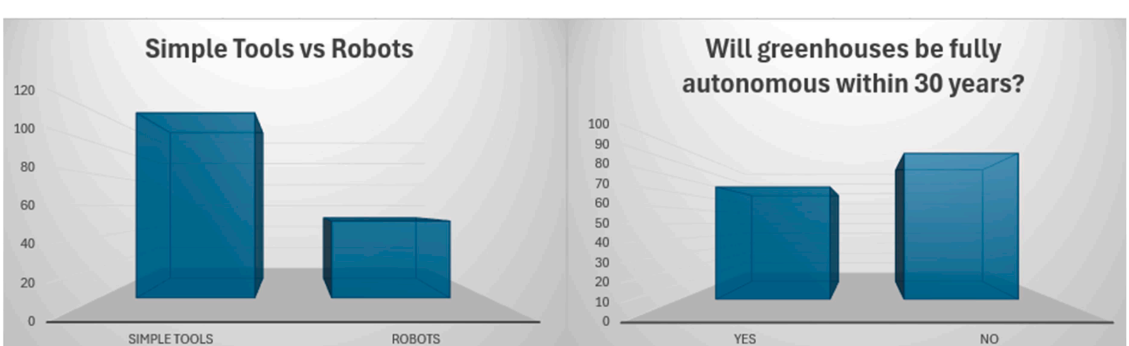


**Fig. 5.** Block 3 results. Technological perceptions, with questions about preference between simple tools or robotics, and expectations about future automation.

these two variables did not influence the level of greenhouse automation. The variables of surface area and educational level did influence the level of farm automation, both positively. This means that farms managed by more educated farmers and with more cultivated land tend to be more automated.

According to farmers, the main obstacles to automation and the incorporation of robots in greenhouses are:

- The high initial investment cost, which represents a difficult economic barrier to overcome, especially for small and medium-sized farms.
- The uncertainty surrounding potential breakdowns and configuration problems, which generates distrust in the reliability of these technologies.
- The perception that the human factor is still more efficient, particularly in tasks that require adaptability and real-time decision-making.
- The rejection or resistance to training in automation and robotics, due to both lack of time and low familiarity with new technologies.

These obstacles have been rated from 1 to 10 according to their level of importance, Fig. 7, where it has been obtained that the main problem is the initial investment, followed by the rejection of uncertainty in the face of possible breakdowns and configuration problems, then the perception that the human factor is still more efficient and finally the rejection or resistance to training in automation and robotics.

### 3.3. Results of the fuzzy logic system

The fuzzy logic system developed in this study was applied to evaluate the feasibility of automation implementation in greenhouses under varying conditions of cost, perceived safety risk, and expected efficiency. The system's structure and inference rules were based on the input from local farmers and previous technical considerations.

To visualize how the system responds to different combinations of inputs, a set of three-dimensional surface plots was generated. These plots depict how pairs of input variables influence the output, allowing for a deeper understanding of the system's behavior and its encoded decision logic.

Fig. 8 shows the output surface as a function of Cost and Perceived Risk, providing insight into how economic and safety-related concerns interact to shape the overall success probability of automation. The surface reveals a distinct plateau where success values are maximized, specifically under conditions of low perceived risk and moderate implementation cost. Conversely, scenarios with high risk levels, regardless of cost, consistently lead to low success scores. Likewise, extremely low or excessively high costs are also penalized, even when risk is minimal. This pattern confirms the strong influence of both variables in shaping farmer acceptance and feasibility evaluations. The sharp transitions between regions also highlight the sensitivity of the system to perceived safety concerns and investment thresholds.

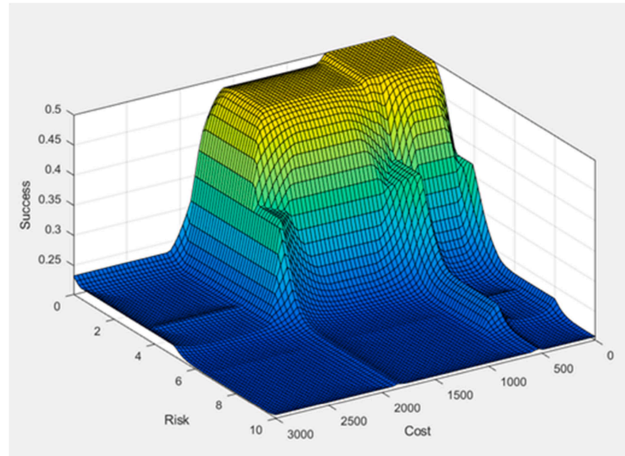


**Fig. 8.** Surface plot of Success probability as a function of cost and risk.

Fig. 9 presents the output surface as a function of Cost and Efficiency, illustrating how these two economic and performance-related variables interact in the evaluation process. The results show that the fuzzy model assigns the highest success scores to configurations that combine high expected efficiency with moderate implementation costs, forming a narrow optimal region. Notably, high efficiency alone does not compensate for excessive costs: success scores drop sharply when the investment surpasses certain thresholds, regardless of the potential gains. This suggests that farmers are particularly sensitive to financial viability, and that efficiency is only valued when it remains within economically acceptable bounds. The plot reinforces the importance of aligning performance expectations with cost realities to achieve feasible automation strategies.

Fig. 10 displays the output surface as a function of Risk and Efficiency, illustrating how these two factors jointly affect the success probability of automation adoption. The results confirm that low perceived risk is a prerequisite for achieving high success scores, even when expected efficiency is substantial. As risk increases, success scores decline sharply, highlighting the strong penalization implemented in the rule base for unsafe scenarios. The highest success values are confined to a specific zone where risk is minimal and efficiency is high, indicating

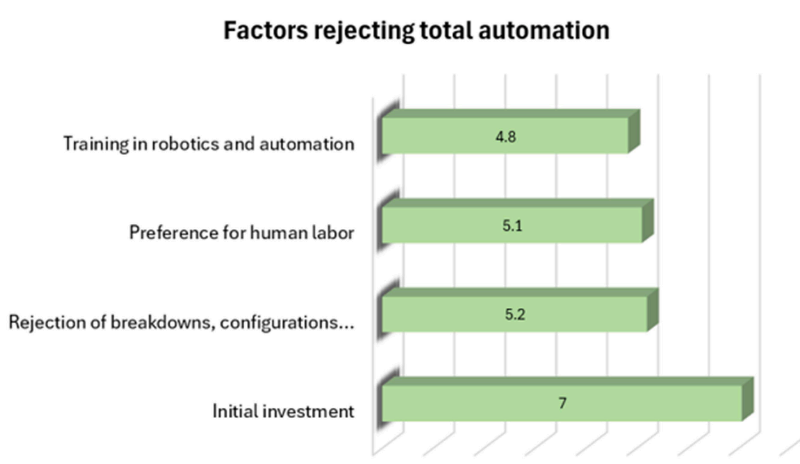


**Fig. 7.** Block 4 results. Perceived barriers to automation, in which various obstacles were assessed using a scale of importance from 1 to 10.

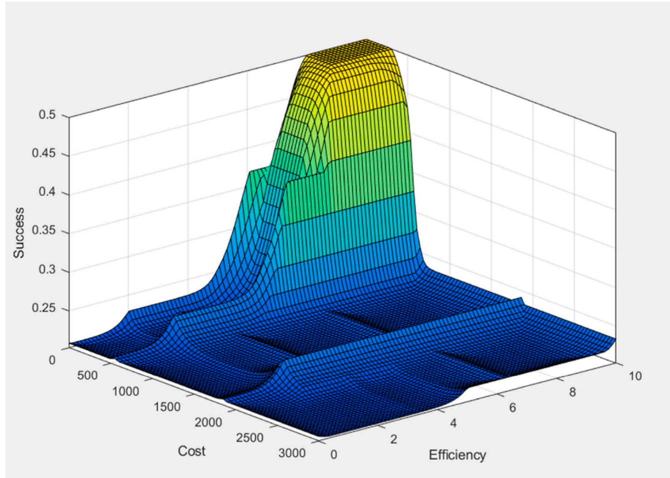


**Fig. 9.** Surface plot of success probability as a function of cost and efficiency.

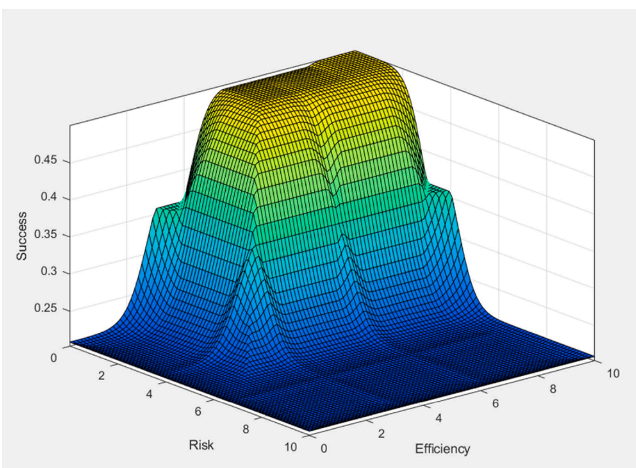


**Fig. 10.** Surface plot of success probability as a function of risk and efficiency.

the ideal conditions under which farmers are most likely to accept automation technologies. This plot underscores the central role of safety perception in the adoption process, validating the system's emphasis on risk minimization as a primary driver of feasibility.

The surface plots confirm the rule prioritization strategy implemented in the fuzzy system: scenarios involving high perceived risk consistently result in low success probabilities, regardless of the cost or efficiency levels. Conversely, the highest success scores are achieved when perceived risk is low, particularly in combination with moderate or low cost and high expected efficiency. These conditions define a narrow window of optimal configurations that align well with farmers' priorities and risk aversion. The results validate both the logical consistency of the model and its capacity to replicate expert reasoning and user expectations in real-world decision-making contexts.

### *3.4. Validation of automation designs*

To assess the practical applicability of the fuzzy logic system developed in this study, a set of automation configurations designs are evaluated using the fuzzy model. Each configuration is characterized by its implementation cost, perceived safety risk, and expected efficiency. These scenarios were selected to reflect a range of technological solutions, from basic automation tools to fully autonomous robotic systems, and to test their feasibility under the decision framework derived from the perceptions of farmers in Almería. Fig. 11 illustrates the five automation configurations evaluated through the fuzzy logic system, each representing a different technological approach to greenhouse operations:

a) Remotely operated robotic system with articulated arm (System-A) [37]: This configuration consists of a tracked mobile platform equipped with a multi-jointed robotic arm. It is designed to be remotely controlled by an operator and is intended for specific agricultural tasks such as making planting holes or manipulating stems and fruits. Its mechanical complexity and versatility suggest a high level of technical sophistication, with moderate autonomy and targeted functionality.
b) Autonomous robotic platform with computer vision (System-B) [38]: This fully autonomous system integrates an actuator arm and an embedded vision system. It is programmed to detect and locate ripe fruits using image processing algorithms, enabling selective and automated harvesting. This configuration exemplifies high-level automation, relying on advanced perception and decision-making capabilities to operate without human intervention.
c) Manual planting cart with pneumatic assistance (System-C) [39]: This semi-automated tool consists of a manually pulled cart fitted with a pneumatic mechanism for creating planting holes in the soil. While mobility and actuation are manually controlled, the pneumatic system reduces the physical effort required, enhancing ergonomics and efficiency in repetitive planting operations. It represents a low-cost, low-risk solution with moderate functional improvement.
d) Telescopic tool for crop trellising (System-D) [40]: This device is designed to perform vertical crop trellising in greenhouses with hanging plant systems. It consists of a telescopic mast that allows the operator to reach overhead wires or hooks to wind or unwind plants without using elevated platforms. By eliminating the need to work at height, it significantly improves worker safety and facilitates quick intervention in elevated greenhouse structures.
e) Electric scaffolding (System-E) [40]: This design corresponds to a mobile automatic scaffold intended for carrying out tomato plant trellising tasks. The system incorporates an elevated platform with safety railings, on which the operator can work in a stable and safe manner. The platform has an automatic movement system, allowing it to move along the greenhouse aisles without the need for manual pushing, which increases the safety and efficiency of the agricultural process.

Following the definition of the fuzzy logic system and its input structure, five specific automation configurations, previously showed in

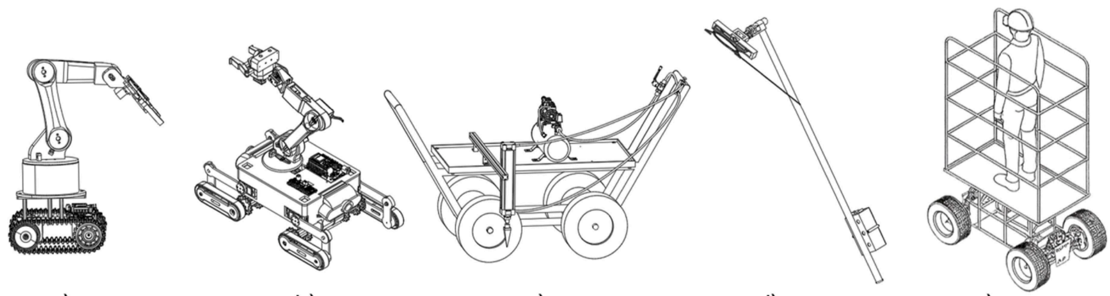


**Fig. 11.** Automation technologies analyzed in the fuzzy logic model.

Fig. 11, were analyzed in depth. Each system was characterized according to its technical functionality, degree of autonomy, safety implications, cost and implementation complexity. These qualitative assessments were then translated into the linguistic input values required by the fuzzy model. Table 1 presents the resulting input values for each system along with the corresponding success scores obtained by the fuzzy logic system. The outcomes reveal clear differences in feasibility: configurations with low perceived risk and moderate cost, such as System-C and System-D, obtained significantly higher scores than fully autonomous options like System-A, which, despite their technical potential, were penalized due to higher complexity and risk. These results confirm the model's ability to integrate technical and perceptual variables to support realistic decision-making in the context of greenhouse automation.

To visualize the internal reasoning of the fuzzy logic system and complement the success scores reported in Table 1, individual simulations were performed for each of the five automation configurations. These simulations display how the model processes the assigned input values, Cost, Risk, and Efficiency, by aggregating the contribution of activated fuzzy rules into a single output. Fig. 12 presents the inference outputs for the five evaluated systems, showing the aggregated activation patterns and the resulting success probability in each case. The final output value, displayed on the right column of each panel, reflects the combined influence of all activated rules for the given input scenario. These graphical results reinforce the interpretability of the fuzzy model, illustrating how variations in input levels, particularly perceived risk and cost, affect the feasibility score generated for each automation design. System-A (Fully autonomous robotic platform) was simulated using input values of high cost (2100), low risk (2), and low efficiency (2). Despite the safe profile, the high investment and limited benefit result in a low success score of 0.214. System-B (Autonomous platform with computer vision) received input values of high cost (3000), low risk (2), and medium efficiency (5). The success score (0.220) reflects the negative impact of the high cost, which is only partially offset by moderate performance. System-C (Manual planting cart with pneumatic mechanism) was assigned low cost (230), low risk (2), and high efficiency (8). This configuration achieved the highest success score (0.759), due to its low investment, minimal risk, and high functional gain. System-D (Telescopic crop trellising tool), with low cost (120), medium risk (6), and high efficiency (7), obtained a moderate success score (0.435). While the system is affordable and productive, the elevated risk perception reduces its overall feasibility. System-E (electric scaffolding), with high cost (2750), low risk (1), and high efficiency (7), obtained a moderate success score (0.396). In System-E the benefits of efficiency and safety are counterbalanced by the substantial investment required. These case-by-case simulations confirm the fuzzy model's capacity to distinguish between technological proposals based not only on their technical capabilities but also on their compatibility with local constraints and acceptance thresholds.

**Table 1**
Evaluated configurations using the designed fuzzy logic.

| System ID | Implementation Cost | Perceived Risk | Expected Efficiency | Success Score |
|---|---|---|---|---|
| A | High | Low | Low | 0.214 |
| B | High | Low | Medium | 0.220 |
| C | Low | Low | High | 0.759 |
| D | Low | Mid | High | 0.435 |
| E | High | Low | High | 0.396 |

## 4. Discussion

This study demonstrates that the adoption of automation technologies in greenhouses across Almería is primarily conditioned by three interrelated factors: perceived safety risk, implementation cost, and expected efficiency. These dimensions form the core of farmers' decision-making processes regarding technological transformation, and their interaction is effectively captured through the fuzzy logic model. Unlike traditional statistical approaches, fuzzy systems allow the incorporation of subjective perceptions and uncertainty into a structured decision-support framework.

The fuzzy system reveals that technologies with the highest adoption potential are not necessarily the most advanced, but rather those that offer a pragmatic balance, low perceived risk, affordable costs, and tangible functional gains. In this regard, semi-automated tools such as the pneumatic planting cart (System-C) and the telescopic trellising device (System-D) scored significantly higher than fully autonomous robotic systems (System-A and System-B), despite the latter's greater technical sophistication. The electric scaffolding (System-E) occupied an intermediate position, as it clearly improves safety and efficiency, but its high cost reduced the overall adoption score. This suggests that digital transformation in the greenhouse sector will likely occur through incremental, adaptive innovations rather than through the immediate implementation of high-end automation.

A central observation is the asymmetric influence of perceived safety risk over the other two variables. Across all configurations tested, scenarios involving high risk were consistently penalized, regardless of their potential efficiency or affordability. This aligns with earlier statistical findings in the study, where perceived risk, particularly in relation to unfamiliar or autonomous systems, was one of the most cited concerns among farmers. Even moderately priced and functionally effective tools, such as the telescopic crop trellising device (System-D), saw their success scores reduced when risk perception was not minimal. This reinforces the idea that automation strategies must not only demonstrate technical reliability but also actively address user apprehensions through training, safety protocols, or design features that promote trust. At the same time, the impact of implementation cost remains decisive, especially when not accompanied by a clear and measurable return in efficiency. This was evident in the low scores obtained by System-A and System-B, both high-cost configurations with either low or moderate expected performance. Despite their potential as advanced robotic systems, their feasibility was questioned by the model

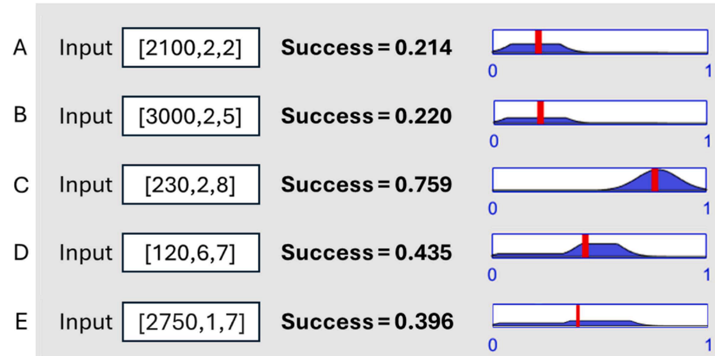


**Fig. 12.** Fuzzy simulation results for the evaluated automation systems.

due to unfavorable cost-benefit perceptions. A similar pattern was observed for the electric scaffolding (System-E), which, despite providing clear safety and efficiency benefits, received only a moderate score due to its substantial implementation cost. This finding reflects a broader truth in innovation diffusion: technological excellence alone is not sufficient for adoption unless matched by affordability and contextual relevance. The only configuration to achieve a high success score (System-C) was the one that combined low cost, minimal risk, and clear ergonomic benefit. This result illustrates how simpler, hybrid tools that enhance but do not replace human labor may currently represent the most viable entry point for technological transition in Almería's greenhouse sector. These tools match the existing operational habits of farmers while offering tangible improvements in efficiency and working conditions, with lower psychological and economic barriers to entry.

From a methodological perspective, the fuzzy logic approach has proven effective for integrating quantitative and qualitative inputs, especially in a context where decision variables are inherently vague, interdependent, and shaped by human judgment. By encoding expert reasoning and farmer perception into a structured, interpretable model, the system bridges the gap between experimental proposals and real-world constraints. Moreover, the graphical outputs provide an accessible way to visualize the trade-offs behind each configuration, supporting transparent, user-informed decision-making.

From a scalability standpoint, the findings indicate that the most feasible technological solutions for widespread adoption are those that align with existing workflows and investment capacities. By analyzing the questionnaires carried out by Almerian farmers, their interest in automation is evident. If the vision of these farmers is scaled up to the rest of the farmers in the province, the debate can be addressed that, by having intensive crops of larger areas such as fruit trees or cereals, it can be seen how farmers will be more interested in the automation of their crops, since this would considerably reduce the cost of labor and the risk for these workers [3,12,36]. The application of the fuzzy logic system designed in this broader context of the entire Almería region would facilitate the analysis and decision-making to implement new tools or systems in the crops, such as the manual planting cart with pneumatic assistance, robots for fruit harvesting, or semi-automatic pruning systems [33]. This insight is not only relevant for Almería, but also for other intensive agricultural regions with similar structural constraints, such as small farm sizes, moderate capital intensity, and reliance on family labor. The proposed model can thus serve as a transferable tool for assessing automation strategies in analogous agroecological and socio-economic contexts. The proposed roadmap to implement this methodology globally mainly consists of analyzing the activity that the farmer aims to automate or semi-automate. Then, assessing the level of risk and efficiency that this activity currently has and analyzing what level of automation they intend to reach, as well as the economic limitations. Once this situation has been fully studied and framed, next steps include determining which tools can be adopted and analyzing their new risks, efficiency, and economic investment, and evaluating them through the fuzzy logic system in comparison to the tools already in use. This allows the farmer to make a more precise and consensual decision when investing in the technological development of their agricultural exploitation.

In future developments of the model, expanding the set of evaluated scenarios to include additional systems with medium implementation costs would substantially improve its representativeness. While the current configurations capture two extremes, either low-cost, low-risk tools or high-cost robotic systems, the intermediate segment remains underexplored. This segment is especially relevant in real-world conditions, as many farms operate within moderate investment capacities and adopt partial automation strategies that do not fall clearly into either extreme. Importantly, the fuzzy logic tool developed in this study is fully capable of handling such intermediate configurations, as it allows for continuous input values and nuanced combinations of cost, risk, and efficiency. Including a wider variety of medium-cost cases in future simulations would therefore enhance the model's explanatory power and practical value, offering a more accurate reflection of the adoption scenarios faced by most greenhouse operators.

Nonetheless, some limitations should be acknowledged. Risk perception, although parametrized in the model, is a complex construct shaped by cultural, experiential, and informational factors that cannot be fully captured by a single input variable, and it's defined by several methods. Additionally, the model currently assumes a static framework. Dynamic elements, such as learning curves, maintenance costs, and long-term efficiency gains, remain outside the scope but are relevant for assessing sustained adoption over time.

Finally, this study highlights the importance of embedding sociocultural and psychological dimensions into technical assessments. Agricultural innovation is not solely determined by functional performance, but also by how technologies are perceived, trusted, and integrated into complex socioeconomic ecosystems.

## 5. Conclusions

This study has provided an integrated framework to evaluate the feasibility of greenhouse automation strategies in Almería, combining farmers' perceptions with a fuzzy logic-based decision model. The findings emphasize that the most promising technologies are not necessarily the most sophisticated, but those that effectively balance low perceived risk, reasonable implementation costs, and clear functional benefits. These results offer valuable guidance for designing and prioritizing automation solutions that are both technically sound and socially acceptable. The fuzzy logic system developed herein has proven to be a flexible and intuitive tool, capable of capturing the complexity of real-world decision-making under uncertainty. Its application has revealed key thresholds and trade-offs that can inform both technology developers and policy makers seeking to promote smart agriculture in intensive production systems. Future work may extend this framework by simulating adoption dynamics over time, exploring regional adaptations, or incorporating stakeholder feedback loops. The approach outlined in this study sets the foundation for user-centered innovation pathways that align with the operational and cultural realities of modern greenhouse agriculture.

## Ethics statement

Not applicable: This manuscript does not include human or animal research.

If this manuscript involves research on animals or humans, it is imperative to disclose all approval details.

## CRediT authorship contribution statement

**Antonio García-Chica:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Rosa María Chica:** Validation, Resources, Project administration, Methodology, Investigation, Formal analysis, Conceptualization. **Julio J. Caparros-Mancera:** Writing – review & editing, Writing – original draft, Visualization, Investigation, Data curation. **Antonio Giménez-Fernández:** Validation, Funding acquisition. **José L. Torres-Moreno:** Writing – review & editing, Writing – original draft, Validation, Resources, Investigation.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Data availability

Data will be made available on request.

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