



## Research note

## Robotics and AI automation in hospitality and tourism: An ability-based approach

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## ABSTRACT

There is currently debate about whether digital technologies, such as robotics and AI, will be able to automate jobs in the service sector. An analysis based on the abilities required in each job could be a useful method for addressing this question. In this research, we analyze the probability of automation for four hospitality occupations (i.e., chambermaids, chefs/cooks, receptionists, and waiters/waitresses) based on the abilities required in each. We assessed the probability of automation for each of the required abilities by asking 43 computer science academics with AI and robotics experience. We asked the academics about the capacity of robotics and AI to perform the abilities in three time periods: the present, in the medium-term, and in the long-term. Using this ability-based approach, our results indicate that the probability of automation of these jobs is .72, .83 and .91 in the short, medium, and long term, respectively.

## 1. Introduction

There is currently debate about whether digital technologies, and more specifically AI, robotics, and AI-powered robots, will be able to replace workers in the service sector or even cause the creation a new type of hotel based on robots. Recent research has identified factors that will promote and inhibit the adoption in hospitality (Shin et al., 2025). Analyses of the probability of automation of jobs are commonly performed at a broad scale, for example, at the occupational level, under the assumption that technologies will likely advance in the next few years to a point where they can perform almost any task. However, authors such as Lee (2020) warn against this type of reasoning, which has been compared to trying to reach the moon by building a longer ladder. In fact, recent research has identified that factors such as job tenure can be relevant when trying to predict automation (Yuan and Liu, 2025). There is also an ongoing, large-scale debate about whether technology will substitute or enhance human labor (Ivanov and Webster, 2020; Tuomi, Tussyadiah and Stienmetz, 2021). Extensive research has been conducted on the factors that influence the adoption of automated devices in service industries (e.g., Tuomi, Tussyadiah, and Hanna, 2021).

Current employment figures suggest that more precise analyses of the automation process are needed (Autor, 2015). In this sense, a

common argument is that researchers should focus on the potential automation of tasks rather than occupations (Ivanov and Webster, 2020; Melián-González and Bulchand-Gidumal, 2025). Tasks refer to specific job-related behaviors that workers must perform in their jobs. As automation technologies are usually created to automate activities, it has been suggested that technology automates tasks rather than jobs themselves (Bessen, 2016).

An alternative approach to exploring automation involves considering the worker characteristics (i.e., abilities or skills) that are needed in certain occupations (MacCrory et al., 2014). For example, Felten et al. (2021) used worker abilities to analyze the effect of automating technologies. According to the Occupational Information Network (O\*Net, n.d.), abilities are “[...] enduring attributes of the individual that influence performance.” Occupations can be characterized by a common set of abilities based on the importance of each of these abilities for the occupation. Ultimately, the extent to which these abilities can be replaced by technology could provide an index that reflects the probability of an occupation being automated. The main value of this abilities-based approach is that a common set of work descriptors can be used to analyze to what extent different occupations could be replaced by technology. In this research, we apply this approach to the case of four of the most common occupations in hospitality: chambermaids,

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chefs/cooks, receptionists, and waiters.

## 2. Methodology

O\*Net is the main database on the content of occupations. It has been used extensively in academic research. O\*Net uses a set of 52 abilities and provides the importance of each of these abilities for each occupation on a scale of 0–100. Out of the 52 abilities, 4 (i.e., sound localization, glare sensitivity, night vision, and peripheral vision) had a very low level of importance for the four occupations analyzed in this research and, thus, were excluded. Therefore, our final database included 48 abilities across the four following occupations: maids and housekeeping cleaners; waiters and waitresses; chefs/cooks; and hotel, motel, and resort desk clerks.

As an example, Table 1 presents the importance scores of two abilities for each of the four occupations considered based on the O\*Net database. The ability of time sharing shows differences in importance across the four occupations, while the ability information ordering shows similar importance in all of them. Time sharing is defined by O\*Net as “the ability to shift back and forth between two or more activities or sources of information (such as speech, sounds, touch, or other sources),” while information ordering is defined as “the ability to arrange things or actions in a certain order or pattern according to a specific rule or set of rules (e.g., patterns of numbers, letters, words, pictures, mathematical operations).” In the Appendix we provide an example of tasks in which these two abilities are used in the four occupations analyzed.

In May 2024, we asked 43 computer science academics with experience in the fields of robotics and AI about the capacity of robotics and AI to perform each of the included O\*Net abilities across three time periods: the present, in the medium-term (in 3–5 years), and in the long-term (in 10 years or more). The experts were selected using a convenience sample and snowballing procedure. The initial group consisted of computer science academics from the authors’ institutions and other institutions with which the authors had direct contact. These individuals were then asked to suggest other experts who could participate. The academics were asked to assess the possibility of automation of the ability on a scale of 1–7, where 1 meant that robotics and AI did not have the capacity to perform the ability and 7 meant that robotics and AI already had or would have the full capacity to perform the ability.

Since we believed that asking the respondents to answer these questions for 48 abilities across three timeframes would be excessive as each respondent would have to make 144 evaluations, each respondent was presented with 10 abilities randomly chosen. After evaluating these 10 abilities, the respondents were asked if they were willing to assess 10 more. For any ability and for any of the three timeframes, respondents were given the option not to answer if they felt that they were not able to provide an adequate answer. Thus, the number of answers received for each ability and timeframe was different.

Once we had values for the short-, medium-, and long-term potential of robotics and AI to carry out each ability, we calculated the probability of automation for each occupation as follows:

$$ST_o = \frac{\sum_{a=1}^{48} (I_{oa} * st_a)}{\sum_{a=1}^{48} I_{oa}}$$

$$MT_o = \frac{\sum_{a=1}^{48} (I_{oa} * mt_a)}{\sum_{a=1}^{48} I_{oa}}$$

$$LT_o = \frac{\sum_{a=1}^{48} (I_{oa} * lt_a)}{\sum_{a=1}^{48} I_{oa}}$$

$o = 1..4$  (each occupation considered);  $a$

$= 1..48$  (each ability considered)

$ST = Short Term$ ;  $MT = Mid Term$ ;  $LT = Long Term$

$st_a$  = short term ability of robotics and AI to perform ability  $a$   
(normalized 0..1)

$mt_a$  = mid term ability of robotics and AI to perform ability  $a$   
(normalized 0..1)

$lt_a$  = long term ability of robotics and AI to perform ability  $a$   
(normalized 0..1)

$I_{oa}$  = importance of ability  $a$  for occupation  $o$

## 3. Results

We first analyzed the correlation between the importance of the 48 analyzed abilities for each occupation. The results are shown in Table 2. As shown, there was a significant correlation between the importance of each ability for the four occupations analyzed, with chambermaid and receptionist showing the lowest correlation and chambermaid and waiter/waitress showing the highest correlation.

For each ability, Table 3 shows the number of responses received and the mean and standard deviation of the respondents’ scores across each of the three time periods. The abilities are sorted based on the mean of the automation likelihood value for the current time period. The number of responses for each ability shown in Table 3 represents the minimum number of responses received across any of the three time periods for that ability. The lowest number of responses across all the abilities and time periods was 14.

Table 4 shows the automation probability for each occupation and each time period, calculated using the formula presented in the methodology section.

**Table 1**

Examples of the importance of selected abilities for the occupations analyzed.

|                                      | Ability      |                      |
|--------------------------------------|--------------|----------------------|
|                                      | Time sharing | Information ordering |
| Maids and Housekeeping Cleaners      | 25           | 47                   |
| Waiters and Waitresses               | 53           | 47                   |
| Chefs/cooks (Restaurant)             | 47           | 53                   |
| Hotel, Motel, and Resort Desk Clerks | 31           | 50                   |

Source: O\*net

**Table 2**

Correlation between the importance of the abilities for each occupation analyzed.

|                     | Chef/<br>cook | Waiter/<br>waitress | Chambermaid | Receptionist |
|---------------------|---------------|---------------------|-------------|--------------|
| Chef/cook           | 1.00          |                     |             |              |
| Waiter/<br>waitress | 0.64*         | 1.00                |             |              |
| Chambermaid         | 0.65*         | 0.81*               | 1.00        |              |
| Receptionist        | 0.70*         | 0.66*               | 0.48*       | 1.00         |

\* Significant at the  $p < 0.05$  level

**Table 3**  
Capacity of digital technologies to automate each ability.

| Abilities                   | Number of responses | Currently   | Mid-term    | Long-term   |
|-----------------------------|---------------------|-------------|-------------|-------------|
| Number Facility             | 18                  | 7.00 (0.00) | 7.00 (0.00) | 7.00 (0.00) |
| Memorization                | 19                  | 6.85 (0.38) | 6.85 (0.38) | 7.00 (0.00) |
| Stamina                     | 17                  | 6.41 (1.18) | 6.65 (0.70) | 6.81 (0.54) |
| Reaction Time               | 18                  | 6.33 (0.90) | 6.73 (0.46) | 6.87 (0.35) |
| Selective Attention         | 17                  | 6.27 (1.33) | 6.47 (1.19) | 6.60 (0.91) |
| Dynamic Strength            | 16                  | 6.17 (0.94) | 6.58 (0.67) | 6.88 (0.31) |
| Far Vision                  | 18                  | 6.10 (1.17) | 6.53 (0.83) | 6.87 (0.52) |
| Visual Color Discrimination | 16                  | 6.08 (1.50) | 6.54 (1.13) | 6.65 (1.11) |
| Control Precision           | 16                  | 6.07 (1.10) | 6.60 (0.74) | 6.87 (0.35) |
| Static Strength             | 15                  | 6.03 (1.19) | 6.47 (0.72) | 6.75 (0.58) |
| Information Ordering        | 16                  | 5.93 (1.54) | 6.46 (0.84) | 6.79 (0.43) |
| Near Vision                 | 18                  | 5.81 (1.71) | 6.31 (1.43) | 6.46 (1.37) |
| Spatial Orientation         | 16                  | 5.79 (1.19) | 6.43 (0.85) | 6.71 (0.61) |
| Perceptual Speed            | 17                  | 5.77 (1.18) | 6.75 (0.51) | 6.89 (0.29) |
| Time Sharing                | 17                  | 5.71 (1.45) | 6.47 (0.74) | 6.69 (0.60) |
| Category Flexibility        | 17                  | 5.68 (1.38) | 6.39 (0.92) | 6.82 (0.46) |
| Hearing Sensitivity         | 17                  | 5.58 (1.53) | 6.19 (1.18) | 6.54 (1.13) |
| Arm-Hand Steadiness         | 18                  | 5.57 (1.31) | 6.26 (0.74) | 6.83 (0.36) |
| Auditory Attention          | 16                  | 5.54 (1.20) | 6.46 (0.58) | 6.83 (0.39) |
| Response Orientation        | 18                  | 5.50 (1.26) | 6.21 (0.91) | 6.75 (0.45) |
| Mathematical Reasoning      | 18                  | 5.38 (1.26) | 6.06 (1.18) | 6.56 (0.96) |
| Trunk Strength              | 15                  | 5.36 (1.74) | 5.69 (1.84) | 5.96 (1.90) |
| Visualization               | 20                  | 5.31 (1.62) | 5.88 (1.22) | 6.41 (0.94) |
| Written Expression          | 15                  | 5.31 (1.44) | 6.31 (0.95) | 6.69 (0.48) |
| Depth Perception            | 17                  | 5.29 (1.44) | 6.09 (1.16) | 6.67 (0.72) |
| Oral Expression             | 18                  | 5.29 (1.36) | 5.94 (1.09) | 6.47 (0.72) |
| Manual Dexterity            | 17                  | 5.19 (1.66) | 6.00 (1.27) | 6.47 (0.99) |
| Gross Body Coordination     | 16                  | 5.19 (1.11) | 6.20 (0.77) | 6.80 (0.41) |
| Speech Recognition          | 17                  | 5.18 (1.44) | 5.86 (1.10) | 6.50 (0.76) |
| Gross Body Equilibrium      | 16                  | 5.13 (1.42) | 6.17 (1.03) | 6.67 (0.65) |
| Written Comprehension       | 19                  | 5.12 (1.38) | 5.87 (1.09) | 6.43 (0.68) |
| Fluency of Ideas            | 16                  | 5.07 (2.09) | 5.73 (1.71) | 6.27 (1.49) |
| Deductive Reasoning         | 17                  | 5.04 (1.41) | 5.67 (1.40) | 6.33 (1.29) |
| Inductive Reasoning         | 16                  | 4.96 (1.45) | 5.73 (1.05) | 6.35 (0.99) |
| Speech Clarity              | 17                  | 4.94 (1.60) | 5.82 (1.42) | 6.53 (0.94) |
| Dynamic Flexibility         | 15                  | 4.79 (1.37) | 5.93 (1.07) | 6.38 (0.77) |
| Explosive Strength          | 17                  | 4.66 (1.68) | 5.28 (1.55) | 6.00 (1.15) |
| Wrist-Finger Speed          | 15                  | 4.64 (2.21) | 5.43 (1.87) | 5.93 (1.64) |
| Multilimb Coordination      | 15                  | 4.63 (1.31) | 5.50 (1.29) | 6.35 (0.94) |
| Extent Flexibility          | 17                  | 4.60 (1.59) | 5.53 (1.41) | 6.14 (1.35) |
| Oral Comprehension          | 19                  | 4.56 (1.34) | 5.47 (1.12) | 6.35 (0.86) |
| Finger Dexterity            | 20                  | 4.46 (1.89) | 5.21 (1.57) | 5.86 (1.35) |
| Speed of Closure            | 16                  | 4.43 (1.50) | 5.57 (1.28) | 6.21 (1.31) |
| Flexibility of Closure      | 14                  | 4.38 (1.58) | 5.25 (1.29) | 6.21 (1.12) |
| Speed of Limb Movement      | 16                  | 4.31 (1.73) | 5.17 (1.66) | 5.96 (1.42) |
| Originality                 | 19                  | 4.21 (1.84) | 4.94 (1.80) | 5.61 (1.88) |
| Problem Sensitivity         | 15                  | 4.00 (1.24) | 4.91 (1.45) | 5.68 (1.27) |
| Rate Control                | 16                  | 3.96 (1.87) | 4.69 (1.81) | 5.63 (1.46) |

The mean scores are presented, alongside the standard deviation in parentheses.

The table is sorted based on the mean score for the current time period.

Source: Own elaboration

#### 4. Discussion

A careful approach is required when attempting to predict the future of technological automation in the service industry. The automation probability values found in this study are similar to those reported by Frey and Osborne (2017), who used a broad assessment of occupation

**Table 4**  
Automation probability for each occupation across each time period.

| Occupations     | Present | Medium-term | Long-term |
|-----------------|---------|-------------|-----------|
| Chef/cook       | .722    | .834        | .912      |
| Waiter/waitress | .725    | .836        | .916      |
| Chambermaid     | .724    | .835        | .914      |
| Receptionist    | .721    | .833        | .913      |

Source: Own elaboration

content. However, the high automation probabilities for these occupations do not mean hotels will start to use an army of machines. Although such businesses have increased the number of technologies used in their operations, they continue to hire workers (see [INE, 2024](#) for the case of Spain).

On occasion, the automation issues that have affected agricultural and industry workers have been extrapolated to the case of service workers. But, in the past, an industry worker may have simply tightened screws for the whole day. Automating this task, once a machine was able to perform it, was a straightforward procedure.

Automation in the service sector may not be as simple. Service workers usually perform a wide variety of tasks during their day. In other analyses carried out by this research team, we found that a hotel chambermaid may complete up to 41 different tasks in one day, and each of these tasks may require a combination of skills, knowledge, and abilities that are applied in a continuous and simultaneous manner. Relatedly, [Frey and Osborne \(2017\)](#) warned that the integration of various specific technological capabilities into well-functioning holistic solutions is an important challenge that will take time to complete.

Our results show that the probability of automation for the four occupations analyzed is very similar. The main reason is the high level of correlation in the importance of abilities across these occupations, as shown in [Table 2](#). However, the tasks performed by workers in these roles differ significantly. This suggests that abilities may not be the most appropriate way to characterize an occupation when assessing the potential impact of technology. Abilities alone do not seem to capture all the nuances involved in performing a job. It is therefore questionable whether the set of abilities required in an occupation provides a reliable perspective on what technology must achieve to replace workers. In this case, at least, the type of abilities required does not appear to offer sufficient differentiation. In recent years, several technological innovations have been introduced in the hospitality industry, yet most have not succeeded in fully automating jobs. Many have remained at the prototype stage or proved unsuccessful (e.g., Henna Hotel), while others have been limited to performing specific tasks (e.g., Flippy, a robot capable of preparing burgers and fries). While most of these technologies are likely capable of performing many of the abilities required in the occupations they target, there are many additional elements to consider beyond abilities alone. Tacit knowledge, which is not included in most job descriptions, can also pose an important constraint to automation technologies.

Experts in digital technologies tend to trust the capacity of technology to be able to do almost anything given enough time. In fact, literature has already warned that technology experts tend to overestimate the capabilities of technology ([Savage et al., 2021](#)). Therefore, future research could benefit from including the perspectives of workers. This might reveal the importance of tacit knowledge as a barrier to work automation ([Autor, 2022](#)). [Table 3](#) shows that experts believe that digital technologies are currently able to perform certain abilities (e.g., number facility, memorization) but may be limited for others (e.g., problem sensitivity, originality). However, in general, experts perceive that, in the long-term, technology will be able to develop almost any ability. The lowest probability value for the long-term time period was 5.61 (on a scale of 1–7) for the skill of originality. Furthermore, only 6 of the 48 skills analyzed had mean probability values below 6 for the long-term case. We would also like to acknowledge that all the experts

were from Europe. Therefore, the answers may be biased, as participants from other regions (e.g., the USA or Asia) may have different perspectives.

It can be problematic to evaluate the probability of automation of an occupation through discrete elements of that job. In a job, humans perform multiple tasks simultaneously, apply different skills, and use different abilities in a continuous way. In service jobs, employers need the flexibility that workers can easily provide, and such flexibility is often not mentioned in job descriptions because it is common sense that workers provide it. Therefore, in line with Lee (2020), the assumption that all human activities can be modelled in a discrete manner may not be valid in the occupational domain. Melián-González and Bulchand-Gidumal (2025) state that job automation should be analyzed at the task level rather than the job level. A task-based analysis will likely show that technology will automate certain tasks but not others. This frees up workers' time, which can translate into a reduction in the labor force or allow workers to focus on other high-value tasks. However, no level of analysis (e.g., abilities or tasks) can fully capture the complexity of a job or the context in which it is performed. For example, extreme heat conditions in the case of a chef/cook or the need to change between rooms in the case of a chambermaid.

According to our results using the ability approach, the four analyzed occupations have a high probability of being automated by robotics and AI (.72, .83, and .91 in the short-, medium-, and long-term respectively). However, it should be noted that even if a technology is able to perform a certain task, this does not mean that the technology will be implemented immediately. There are many other issues involved (Tussyadiah, 2020), such as the costs of the technology, the process of replacing or rearranging personnel, and required changes to organizational procedures. Even when a technology capable of performing a certain task is implemented, this still does not mean that the implementation will be successful. The case of self-checkouts at supermarkets is probably the best example of this issue, as this technology has been used for more than 30 years and is currently being removed by certain supermarket chains. Lastly, as previously mentioned, the abilities are not independent of each other. A job, or even just one task, requires several of them to be performed adequately. Combining them into one device can be far more complicated than apparent.

Appendix. . Examples of abilities in the four occupations

| Role          | Ability                                                                                                                                         |                                                                                                                           |
|---------------|-------------------------------------------------------------------------------------------------------------------------------------------------|---------------------------------------------------------------------------------------------------------------------------|
|               | Time sharing                                                                                                                                    | Information ordering                                                                                                      |
| Chambermaids  | While cleaning a guest room, communicating with supervisors, checking for forgotten guest items and noting room elements that need to be fixed. | Following a strict sequence for preparing the room (make the bed – dust surfaces – prepare the bathroom – vacuum – etc.). |
| Chefs/cooks   | Performing multiple cooking tasks simultaneously, such as grilling meat, boiling pasta, and cutting vegetables.                                 | Ensure freshness of food and ingredients by checking for quality, keeping track of old and new items, and rotating stock. |
| Receptionists | Answering the phone while checking in a guest which in turn involves completing the formalities in the software and speaking with the guest.    | Entering all guest data in the hotel booking system in the defined sequence.                                              |
| Waiters       | Taking plates to a table while noticing that other tables require attention or customers asking for the check with a visual cue.                | Prepare tables for meals, including setting up items such as linens, silverware, and glassware.                           |

Data availability

Data will be made available on request.

References

Autor, D.H., 2015. Why are there still so many jobs? The history and future of workplace automation. *J. Econ. Perspect.* 29 (3), 3–30.  
Autor, D., 2022. The labor market impacts of technological change: from unbridled enthusiasm to qualified optimism to vast uncertainty (No. w30074). National Bureau of Economic Research.

This work opens the door to several research opportunities. One important future line of research would be to analyze and explicitly document all the behaviors that take place in a job but are not currently included in job descriptions or databases. This would reveal barriers to automation not considered in the literature. Another possible line of research would be related to the integration of tasks into one device. This would affect the design of more powerful technology for automating jobs.

Our results suggest that, from a technical standpoint, the probability of automating the occupations examined is very high. Nevertheless, as discussed, numerous human and organizational factors hinder the development and implementation of technologies capable of fully automating and replacing workers. Advancing in this field requires identifying and addressing the key constraints to job automation. These barriers involve not only specific worker behaviors but also organizational challenges such as process redesign, interdepartmental coordination, resistance to change, client preferences, and legal or regulatory constraints.

CRediT authorship contribution statement

Jacques Bulchand-Gidumal: Writing – review & editing, Writing – original draft, Project administration, Methodology, Investigation, Formal analysis, Conceptualization. Gabriela Cabello-Pestano: Methodology, Data curation. Santiago Melián-González: Writing – review & editing, Supervision, Methodology, Formal analysis, Conceptualization.

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Declaration of Competing Interest

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Bessen, J.E. (2016). How computer automation affects occupations: Technology, jobs, and skills. Boston University School of Law. Law and Economics Research Paper. No. 15-49. Available at SSRN: (<https://ssrn.com/abstract=2690435>).  
Felten, E., Raj, M., Seamans, R., 2021. Occupational, industry, and geographic exposure to artificial intelligence: a novel dataset and its potential uses. *Strateg. Manag. J.* 42 (12), 2195–2217.  
Frey, C.B., Osborne, M.A., 2017. The future of employment: how susceptible are jobs to computerisation? *Technol. Forecast. Soc. Change* 114, 254–280.  
INE. (2024). Establecimientos Estimados, Plazas Estimadas Y Personal Empleado Por Tipo De Alojamiento Y Por Comunidades Y Ciudades Autónomas. Available at (<https://www.ine.es/jaxiT3/Tabla.htm?t=2942>).  
Ivanov, S., Webster, C., 2020. Robots in tourism: a research agenda for tourism economics. *Tour. Econ.* 26 (7), 1065–1085.

- Lee, E.A., 2020. *The coevolution: the entwined futures of humans and machines*. MIT Press, Cambridge: MA.
- MacCrory, F., Westerman, G., Alhammadi, Y., & Brynjolfsson, E. (2014). Racing with and against the machine: Changes in occupational skill composition in an era of rapid technological advance. In *Proceedings of the International Conference of Information Systems (ICIS)*. Auckland, NZ.
- Melián-González, S., Bulchand-Gidumal, J., 2025. A framework for research on the automation of work. *Technol. Forecast. Soc. Change* 215, 124093.
- \*O\*Net. (n.d.). Browse by Abilities. Available at (<https://www.onetonline.org/find/descriptor/browse/1.A>), accessed 18 July 2024.
- Savage, T., Davis, A., Fischhoff, B., Morgan, M.G., 2021. A strategy to improve expert technology forecasts. *Proc. Natl. Acad. Sci.* 118 (21), e2021558118.
- Shin, H., Ryu, J., Jo, Y., 2025. Navigating artificial intelligence adoption in hospitality and tourism: managerial insights, workforce transformation, and a future research agenda. *Int. J. Hosp. Manag.* 128, 104187.
- Tuomi, A., Tussyadiah, I.P., Hanna, P., 2021. Spicing up hospitality service encounters: the case of Pepper™. *Int. J. Contemp. Hosp. Manag.* 33 (11), 3906–3925.
- Tuomi, A., Tussyadiah, I.P., Stienmetz, J., 2021. Applications and implications of service robots in hospitality. *Cornell Hosp. Q.* 62 (2), 232–247.
- Tussyadiah, I., 2020. A review of research into automation in tourism: launching the annals of tourism research curated collection on artificial intelligence and robotics in tourism. *Ann. Tour. Res.* 81, 102883.
- Yuan, B., Liu, X., 2025. Machines replace human: the impact of intelligent automation job substitution risk on job tenure and career change among hospitality practitioners. *Int. J. Hosp. Manag.* 126, 104099.