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Intelligent Automation in Hospitality: Exploring the Relative Automatability of Frontline Food Service Tasks

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Purpose

Automation poses to change how service work is organized. However, there is a lack of understanding of how automation influences specific sectors, including specific hospitality jobs. Addressing this gap, this paper looks at the relative automatability of jobs and tasks which fall within one specific hospitality context: frontline food service.

Design/methodology/approach

Study 1 analyzes the UK Office for National Statistics' Standard Occupational Classification (2020) data to determine the degree to which frontline food service jobs consist of tasks requiring mechanical, analytical, intuitive or empathetic intelligence. Study 2 contrasts these findings to current state of intelligent automation technology development through interviews and a focus group with food service technology experts (n=13).

Findings

Of all the tasks listed under food service in the ONS SOC 2020, 58.8% are found to require mechanical, 26.8% analytical, 11.3% intuitive and 3.1% empathetic intelligence. Further, the automatability of these tasks is found to be driven by three streams of technology development in particular: 1) autonomous navigation, 2) object manipulation, 3) natural language processing.

Originality

Hospitality management literature has started to conceptualize a move from mechanical and analytical service tasks to tasks centred around intuition and empathy. While previous studies have adopted a general view to what this might mean for hospitality jobs, this paper develops a novel, task-centric framework for Actioning Intelligent Automation in Frontline Food Service.

Keywords: conversational agent, chatbot, service robot, artificial intelligence, intelligent automation, food service, first principle

Article classification: Research paper

1. Introduction

The last few years have seen hospitality operators start delegating an increasing number of frontline tasks to machines, from artificially intelligent (AI) customer service assistants (e.g. chatbots) to service robots (Huang et al., 2021; Ivanov and Webster, 2019; McLeay et al., 2021). While the overall use of technology in hospitality, e.g. tablets or self-service kiosks, has been well-researched, the increasingly smart nature of emerging technology, facilitated by cheaper, more pervasive sensing technology and illustrated through more complex service interaction (Mercan et al., 2021; Tuomi, Tussyadiah and Hanna, 2021), gives rise to new operational and strategic challenges and opportunities. In particular, recent hospitality management literature has been vocal about how such "intelligent automation" of frontline service work calls for hospitality jobs to be redesigned in order to capitalize on the unique capabilities of both humans and machines (Tussyadiah, 2020). The COVID-19 pandemic has exacerbated these calls (Gaur et al., 2021). However, understanding the (potential and desired) applications and implications of intelligent automation on actual hospitality jobs may be difficult, as hospitality management literature tends to often adopt a somewhat general rather than a task or even a job-specific view on automation (Cain, Thomas and Alonso, 2019). In the rare instances where the impacts of intelligent automation on specific hospitality jobs are addressed (c.f. Tuomi, Tussyadiah and Stienmetz, 2020), the discourse tends to assume a managerial rather than a technical point of view.

Drawing on first principles thinking, a paradigm of problem-solving which dates back to such seminal thinkers as Aristotle and Euclides (Verkerk and Krass, 2019), this paper seeks to assess the relative automatability of frontline service work in hospitality by contrasting state-of-the-art developments in automation technology to specific jobs and tasks in one common hospitality context: frontline food service. In doing so, the paper conceptualizes and puts forward a novel framework for Actioning Intelligent Automation in Frontline Food Service, as well as discusses the subsequent frontline service job design implications of doing so. In particular, the paper builds on Huang and Rust's (2018; 2021) Service Task Intelligence Framework, and aims to address the following research questions:

1) What are the foundational mechanisms (i.e. first principles) that underlie frontline service work in food service, and to what degree do those mechanisms consist of tasks which require mechanical, analytical, intuitive, or empathetic intelligence?

2) In what specific ways does the emergence of intelligent automation technology, particularly intelligent conversational agents and service robotics, impact these principles?

The paper consists of six sections. First, the notion of first principles thinking - the systematic act of breaking analyzed phenomena down into their constitutive parts - is highlighted as the conceptual approach adopted in this paper. This is illustrated in practice through Huang and Rust's (2018; 2021) Service Task Intelligence Framework, which breaks service tasks into actions that require different types of intelligence to complete, increasing in complexity from mechanical (easiest to automate) to empathetic (hardest to automate) intelligence. Second, an overview of intelligent automation technology is provided using Tussyadiah's (2020) recent Framework of Intelligent Automation in Tourism, whereby key technologies facilitating automation in hospitality contexts are reviewed. After reviewing literature, the two following sections present the methods and key findings of this exploratory study. Finally, the remaining two sections of the paper discuss the theoretical and practical implications of intelligent automation for food service, as well as highlight the limitations of this study and point towards avenues for future research into automated food service.

2. First Principles of Service Work: Jobs, Tasks, and Actions

The Greek philosopher Aristotle is often cited to have defined first principles as "the first basis from which a thing is known" (Cohen and Reeve, 2020). First principles thinking is, therefore, a technique of systematic questioning, whereby assumptions of a phenomenon are broken down into their most basic components and then re-assembled from the ground up (Verkerk and Grass, 2019). Several seminal thinkers from Descartes to Kant and Marx have wrestled with Aristotelian first principles, and the influence of first principles thinking can be observed in modern management theory, e.g., the Process Theory (Van de Ven and Poole, 1995). More recently, spurred by interest from several high-profile proponents, for example Ray Dalio and Elon Musk (Dyer, Furr and Hendron, 2019), first principles thinking has re-emerged as a powerful way for addressing complex societal challenges or wicked problems (Verkerk and Grass, 2019). For example, Musk, faced with the challenge of how expensive sending people to space, let alone Mars might be, is quoted to have broken the problem of space travel into first principles as follows: 1) One needs a rocket to travel to space. 2) Rockets tend to be expensive and single-use. 3) What are the fundamental reasons for why rockets are expensive and single-use? 4) How do we make each part of the process of making a rocket less expensive and re-usable?

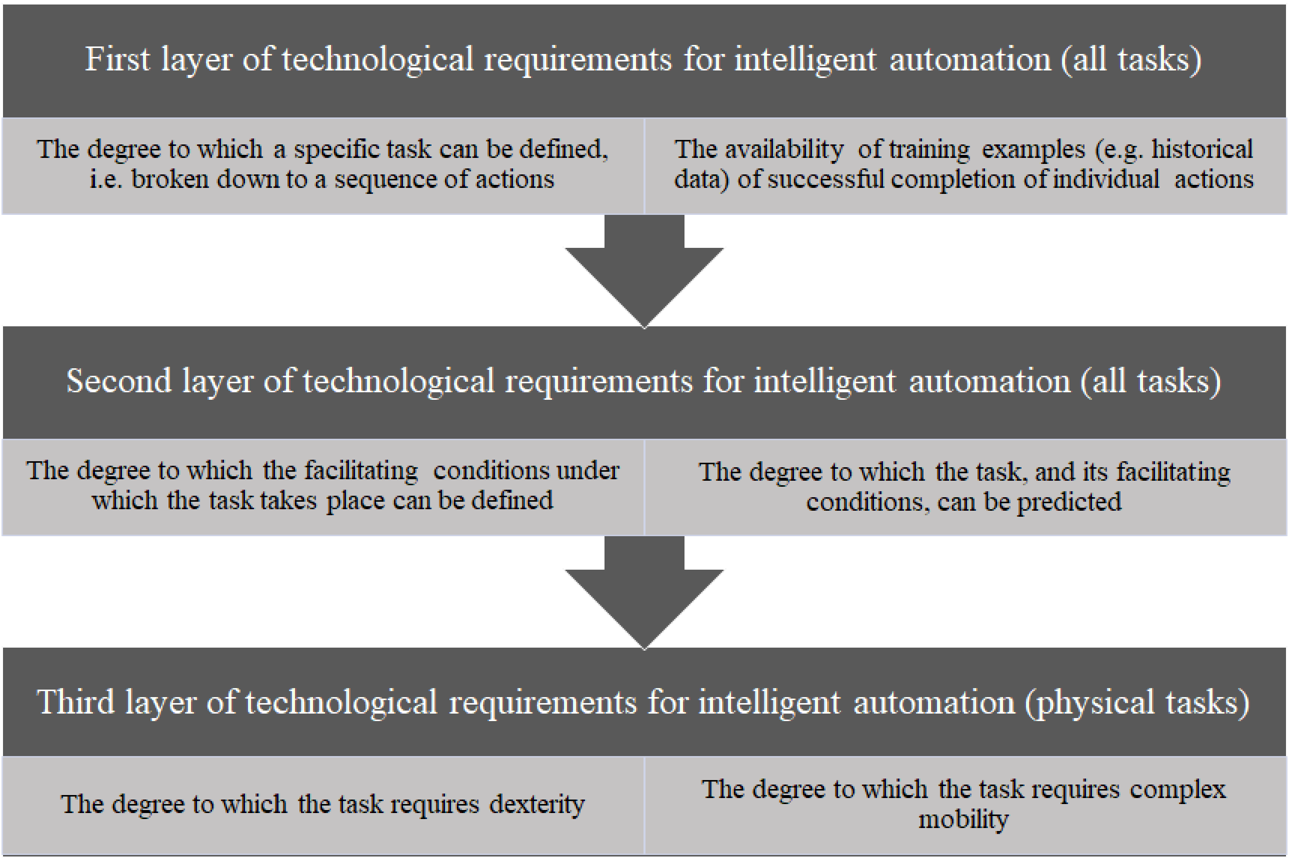
To illustrate how a first principles thinking approach might be applied to actioning intelligent automation in hospitality service work, it is useful to start by making some foundational observations. First, in this study a pragmatic view to labor economics is assumed by asserting that the concept of "work" is underlined by the notion of a "job". Jobs, on the other hand, consist of a varying number of definable "tasks". Borrowing a definition from the UK Office for National Statistics (ONS SOC, 2020), tasks refer to all the different things an employee needs to complete in accordance to their employing organization's wishes – or get fired. The multitude of these tasks, in turn, consist of "actions", that is, all the different elements that constitute the completion of a desired goal. For example in the context of hospitality, a travel agent, among other things, helps customers to plan, choose, and arrange holidays. For that they need to - inter alia - collect, collate, and present information, negotiate prices, and of course make bookings. All of these can be considered as separate tasks which can be broken further down into a set of actions.

Recent service management literature has started to categorize service tasks and their constitutive actions depending on the type of intelligence their completion requires. Providing a comprehensive synthesis of different types of intelligences needed in service, Huang and Rust (2018) conclude that service tasks may require either mechanical, analytical, intuitive, or empathetic intelligence. Put together, the combination of these four intelligence types may result in either mechanical-oriented, thinking-oriented, or feeling-oriented service jobs (Huang, Rust and Maksimovic, 2020). According to Huang and Rust (2018), mechanical-oriented jobs consist mainly of simple, standardizable, repetitive and transactional tasks; thinking-oriented jobs consist of rule-based tasks or tasks requiring logical thinking and decision-making, often informed by the analysis of large quantities of data; and feeling-oriented jobs consist of experiential, highly contextual, social, or emotional tasks which in some way require empathy or emotional intelligence.

Building on the type of intelligence a given job and its constitutive tasks and actions require, Brynjolfsson and Mitchell (2017) discuss the automation potential of different types of tasks. Central to this discussion is the notion of machine learning, defined broadly as the capability of a computer system to learn desired properties from data without explicit instruction (Russell and Norvig, 2020). Brynjolfsson and Mitchell (2017) put forward several principles for capitalizing on machine learning, whereby the systems' ability to automate specific tasks is dependent on the degree to which the automated task and the conditions within which it occurs can be defined and predicted, the degree to which historical data on examples of successful completion of the task is readily available, whether the task stays the same over time or not, the complexity of the task, and, in the case of physical tasks, the degree to which the task requires dexterity and complex mobility (see Figure 1).

Illustrating these principles in practice, Kucera et al. (2017) suggest distinguishing between "readily automatable" and "not-readily automatable" tasks. Huang and Rust (2021) provide a few, generic examples of what this might mean in the context of hospitality. They list ordering and service delivery in fast-food restaurant contexts as an example of a readily automatable, mechanical task, while dealing with customer complaints in luxury service contexts (e.g. fine-dining) represents a not-readily automatable, feeling-oriented task. However, these examples leave much granularity to be desired, as a large proportion of hospitality service tasks fall somewhere between these polar opposites. Further research to better understand the relative automatability of a much broader set of hospitality tasks is thus required to better understand the theoretical and managerial implications of intelligent automation in hospitality service contexts.

Figure 1: Relative automatability of hospitality tasks through intelligent automation, adapted from Brynjolfsson and Mitchell (2017) and Russell and Norvig (2020).



3. Intelligent Automation Technology in Hospitality

As the field is still emerging, intelligent automation as a term remains somewhat abstract, capturing a myriad of different technologies and approaches. In her review of intelligent automation technologies in tourism, Tussyadiah (2020, 4) defines intelligent automation as the “implementation of an integrated system of next-generation technologies, including artificial intelligence, robotics, and the internet-of-things, to autonomously operate service tasks within tourism environments without human intervention”. Breaking the constitutive elements of intelligent automation into distinct streams of technology development, Russell and Norvig (2020) list six disciplines: natural language processing (so that the system can communicate), knowledge representation (so that the system can store information), automated reasoning (so that the system can use the stored information to make inferences), machine learning (a specific technique for extrapolating patterns of behavior in data), computer vision (needed for the system to perceive its environments), and robotics (so that the system can take action, based on its inferences, in the real world, e.g. navigate or manipulate objects). Contrasting intelligent automation with self-service technology, Tuomi, Tussyadiah and Hanna (2021) stress the dimensionality of the interaction. While interaction with self-service technology (e.g. a check-in kiosk) tends to be pre-determined and static, drawing resemblance to service scripting, features of intelligent automation (e.g. collecting sensor data and drawing dynamic conclusions) make the interaction more complex through e.g. communication via natural language or gestures.

Recent years have seen various examples of intelligent automation emerge in the context of hospitality. For example in terms of natural language processing, Taco Bell has adopted a chatbot that lets customers ask questions and place orders on the move (Addady, 2016). Starbucks has gone a step further with its own chatbot that can answer questions and take orders but also recognize voice commands (Perez, 2017). Combining knowledge representation, automated reasoning, and machine learning, McDonald’s has applied intelligent automation to offer digital menus which dynamically change according to e.g. stock levels and the weather

(Tiffany, 2019). More recently, the Golden Arches has also expanded its intelligent automation technology use to personalized offers and recommendations through its new MyMcDonald's Rewards initiative (Wolfe, 2021).

In terms of computer vision, burger restaurant rival White Castle has started to dabble in computer vision to speed-up its drive-thru experience through license plate recognition technology facilitating more personalized ordering experiences (Metz, 2021). Finally, in terms of service robots, several have started to appear and scale up in various hospitality settings around the world (Tuomi, Tussyadiah and Stienmetz, 2020). For example, Japan-based Henn-na Hotel, recognized by the Guinness World Records as the world's first robot hotel, has expanded its operations from the initial launch of their robot hotel concept in 2015 to 16 properties in 2020, with seven additional sites scheduled to open by 2021 and a vision for further expansion to over a hundred sites by the end of the decade (HIS Group, 2020; Nagao, 2018). Similarly, the Beijing-based hotpot restaurant chain Haidilao has ramped-up its use of service robotics. After testing a robot waiter for the first time in late 2018, the company has as of 2020 expanded operations to 179 venues around the world with a vision of eventually integrating service robots to over 5000 locations (Du and Maki, 2018; Haidilao, 2019). Table I collates examples of intelligent automation technology in hospitality.

Table I: Examples of intelligent automation technologies in hospitality.

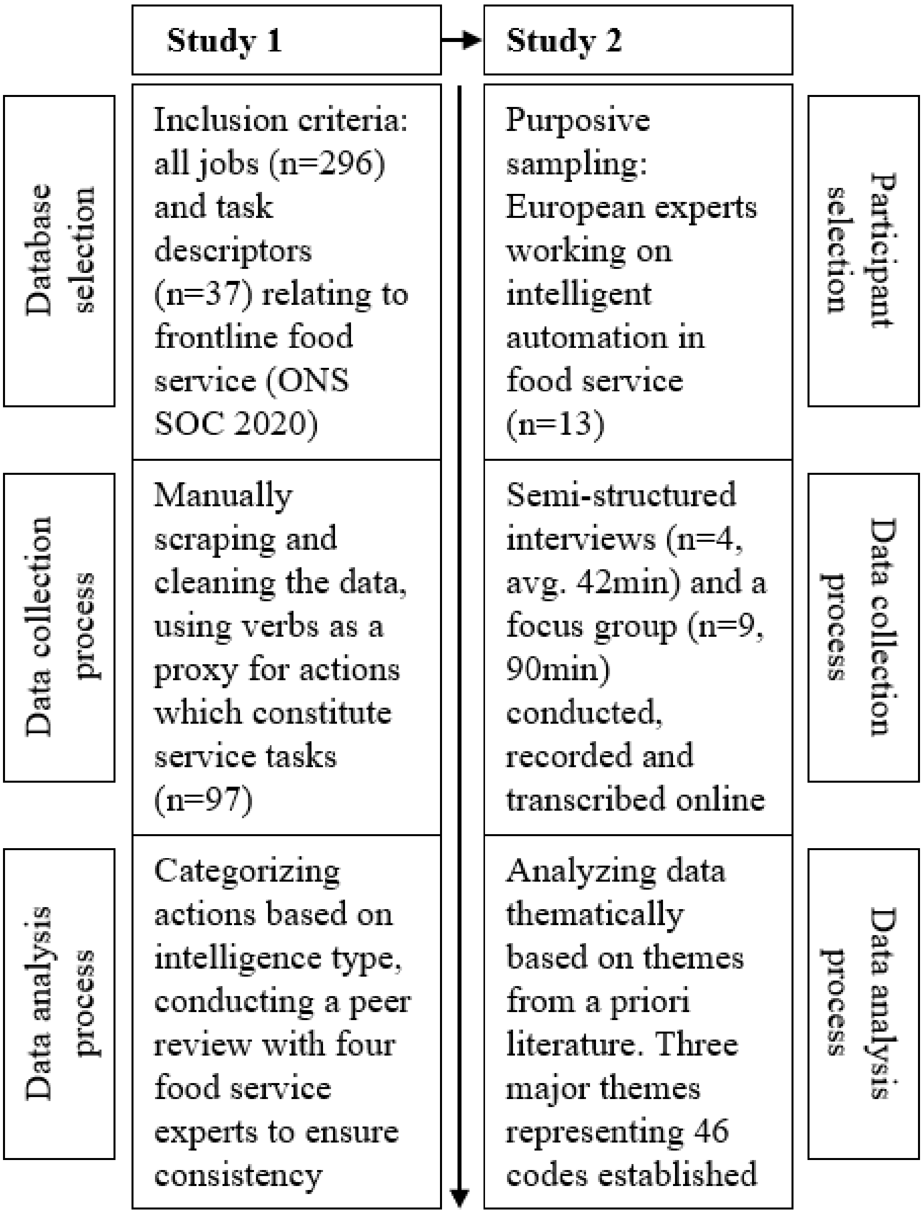
Discipline of Intelligent Automation / Intelligence Categorization from Theory	**Practical Use-Example**	**Mechanical Intelligence**	**Analytical Intelligence**	**Intuitive Intelligence**	**Empathetic Intelligence**
Natural Language Processing	Taco Bell's TacoBot Starbuck's MyBarista	x	x		
Knowledge Representation	McDonald's Dynamic Menus	x			
Automated Reasoning	McDonald's Dynamic Menus	x	x		
Machine Learning	McDonald's MyMcDonalds Rewards	x	x	x	
Computer Vision	White Castle's Craver Nation	x	x		
Robotics	Henn-na Hotel Haidilao	x	x		

According to Ivanov and Webster (2017; 2019), automating different processes in hospitality services has various benefits and costs that businesses should consider carefully. Benefits, they argue, include for example savings in labor costs. As discussed by Ivanov and Webster (2017), service robots for example do not need salaries (they are usually leased for a fixed cost), they do not take breaks or holidays, and they never go on strike or call in sick. Overall, Noone and Coulter (2012) argue that the application of intelligent automation technologies may offer hospitality businesses improvements in demand prediction, quality control, and process management. However, increased automation may not always be beneficial either. As discussed by Sprenger and Mettler (2015), automated systems need regular maintenance and software updates. Hospitality employees may also feel threatened by new technology (Kong et al. 2021), or need to be re-trained to work alongside artificially intelligent agents. The operational infrastructure may also need to be re-designed to better suit automation (Tuomi, Tussyadiah and Hanna, 2021). For example, special beacons might need to be installed to the servicescape to guide robot navigation (Burgard et al., 2012). There might also be issues with customer and employee acceptance of robots, whereby some may reject the idea of increased automation (Montealegre and Cascio, 2017), while others may even show aggressive behavior towards robots (Darling, 2015). Overall, Tuomi, Tussyadiah and Hanna (2021) argue that more consideration should be given to designing solutions that integrate intelligent automation technologies seamlessly to the service system.

4. Method

To understand the foundational mechanisms underlying frontline service work in food service, as well as the specific ways in which the emergence of intelligent automation technology might impact these, two exploratory studies were conducted in February-March 2021 using both secondary (Study 1) and primary (Study 2) data. Study 1 sought to compile a comprehensive list of all of the specific tasks common frontline food service jobs consist of and contrast it against Huang and Rust's (2018; 2021) Service Task Intelligence Framework, while Study 2 sought to assess the relative automatability of said frontline food service tasks and actions given the current state of intelligent automation technology development as illustrated by Tussyadiah (2020). Figure 2 presents an overview of the research design adopted in this study.

Figure 2: Overview of the research design adopted in this study.



4.1 Study 1

First, the UK Office for National Statistics (ONS SOC, 2020) Standard Occupational Classification (SOC) database was accessed to determine the specific tasks and actions frontline food service jobs consist of. The SOC is a UK government-compiled open-access database which seeks to systematically list and define all occupations that exist within the UK job market. Compiled every ten years, the latest edition (2020) consists of nine major occupation groups, 26 sub-major occupation groups, 91 minor occupation groups, and 421 unit-groups. Put together, the different levels of occupation groups capture thousands of unique job titles and task descriptors (ONS SOC, 2020). Previous research has adopted a similar approach, drawing on Standard Occupational Classification indices to examine e.g. the likelihood of different jobs to get offshored (Blinder, 2009), shift to a stronger remote-work focus (Lund et al., 2020), or get replaced by different types of machine learning systems (Brynjolffson and Mitchell, 2017; Frey and Osborne, 2017). However, previous studies have mostly used SOC indices to understand macroeconomic changes to the labor market. In contrast, this study is one of few to focus on a specific area of economic activity, food service.

To that end, the ONS SOC was chosen for this study over other, similar occupational classification indices such as the US Bureau of Labor Statistics' (2018) or the International Labour Organization's (ILO, 2004) databases, as the ONS SOC was deemed to present the most up-to-date, comprehensive, and detailed classification system for studying occupations that fall within frontline food service. Put together, the ONS SOC includes eight unit-groups that fall within food service. These are: '5434 – Chefs', '5435 – Cooks', '5436 – Catering and Bar Managers', '9261 – Bar and Catering Supervisors', '9263 – Kitchen and Catering Assistants', '9264 – Waiters and Waitresses', '9265 – Bar Staff', and '9266 – Coffee Shop Workers'. These eight unit-groups capture a total of 296 different food service job titles, e.g., 'mixologist', 'tea maid', 'table-clearer', and 'chef de rang', as well as provide a textual description of a total of 37 different tasks that fall within frontline food service.

Following Huang and Rust's (2018; 2021) Service Task Intelligence Framework, frontline food service tasks were coded based on one of the four intelligences required for their completion, i.e., mechanical, analytical, intuitive, or empathetic intelligence. The coding was carried out manually by two independent researchers. As a single task descriptor might have consisted of many different actions, the verbs used in the task descriptors were used as a proxy for determining the intelligence required for completing each part of the overall task. Using verbs as a proxy for the relative nature of a task is in line with major paradigms in educational theory, whereby for example Bloom's seminal taxonomy (Bloom, 1956) uses verbs as a proxy for determining different layers of knowledge acquisition. For example, one of the five task-descriptors the ONS SOC lists under "5434 – Chef" is: "plans menus, prepares, seasons and cooks foodstuffs or oversees their preparation and monitors the quality of finished dishes". Here, six verbs relating to different types of intelligence were identified and coded following Huang and Rust (2018): to 'plan' entails boundedly rational decision-making and thus denotes intuitive intelligence; to 'prepare, 'season' and 'cook' require precision and rely on repetition and thus denote mechanical intelligence; and to 'oversee' and 'monitor' imply analytical, rule-based decision-making which is characteristic of analytical intelligence (Huang and Rust, 2018).

All 37 different tasks listed under different frontline food service jobs were coded following the same principles, resulting in 97 verbs denoting different types of actions being coded into one of the four intelligences. Table II provides an example of the coding process. As mentioned, overall the ONS SOC (2020) consists of 9 "major groups" (of which "5 - Skilled trade occupations" is one), 25 "sub-major groups" (of which "54 - Textiles, printing and other skilled trades" is one), 90 "minor groups" (of which "543 - Food preparation and hospitality trades" is one), and 412 "unit groups" (of which "5434 - Chef" is one). During the coding process the entire database (i.e. all of these "groups") were manually analyzed to identify all of the occupations that fall within the context of the research, frontline food service. Overall, 296 different job titles were identified to fall in this category, and within those 296 different job titles, 37 unique task-descriptors were found.

Table II: Example of the systematic coding process adopted in this study.

Major Group - Occupation	Task-Descriptor Example	Actions	Intelligence Required
Major Group 5 – Skilled trade occupations Sub-Major Group 54 – Textiles, printing and other skilled trades Minor Group 543 – Food preparation and hospitality trades Unit Group 5434 – Chef	"Plans menus, prepares, seasons and cooks foodstuffs or oversees their preparation and monitors the quality of finished dishes."	Plan Prepare Season Cook Oversee Monitor	Intuitive Intelligence Mechanical Intelligence Mechanical Intelligence Mechanical Intelligence Analytical Intelligence Analytical Intelligence

To check for analytical consistency of the coding process, a combined peer-review and member's check consisting of a two-step intercoder reliability test was conducted. All of the task descriptors and the definitions of the coded themes (mechanical, analytical, intuitive, or empathetic intelligence) were sent by email to four independent coders for re-coding. To capture as wide a range of expert opinion and critical judgement as possible, the independent coders were selected using purposive sampling based on their first-hand expertise in different frontline food service management contexts. Coder 1 was a food service academic with a long background in hospitality management, including operational experience, Coder 2 was a senior hospitality management executive with expertise in food and beverage management, particularly in silver service, Coder 3 worked as a junior manager / team lead in a quick service restaurant setting, and Coder 4 held an entry-level operational food service position at a coffee shop. Following Tuomi and Tussyadiah (2020), intercoder reliability was assessed against two measures: Percent Agreement (PA) and Cohen's Kappa (CK). A moderate (>.41) or substantial (>.61) agreement was established across all four coders against both measures (Landis and Koch, 1977), indicating a sufficient level of analytical consistency. The results of the intercoder reliability check are presented in Table III.

Table III: Results of the intercoder reliability check.

Measure & Coder / Major Theme	PA C1	CK C1	PA C2	CK C2	PA C3	CK C3	PA C4	CK C4
Mechanical	0.88	0.75	0.91	0.82	0.9	0.8	0.81	0.61
Analytical	0.78	0.51	0.8	0.60	0.85	0.53	0.89	0.75
Intuitive	0.85	0.51	0.85	0.65	0.91	0.79	0.86	0.58
Empathetic	0.96	0.48	0.93	0.54	0.92	0.46	0.96	0.65

Coder 1 (C1) Hospitality academic
Coder 2 (C2) Senior management
Coder 3 (C3) Junior management
Coder 4 (C4) Operations staff
PA=Percent Agreement
CK=Cohen's Kappa

4.2 Study 2

Having broken frontline food service jobs down into tasks and tasks further down into their constitutive actions (i.e. verbs acting as proxies for different types of actions), as well as contrasted these to Huang and Rust's (2018) Service Task Intelligence Framework, Study 2 sought to assess the relative automatability of said tasks and actions given the current state-of-the-art of intelligent automation technology development. Again, a purposive sampling strategy was adopted, whereby semi-structured interviews (n=4, ID: 1-4) as well as one intensive focus group (n=9, ID: 5-13) were organized with European experts from the technology industry, working on different types of technological solutions for the use frontline food service automation. Experts working in developing automation technology for the use of the food service sector were deemed as the most appropriate stakeholder group to provide realistic insight on the relative automatability of different frontline food service tasks because of their first-hand knowledge of the practical constraints and capabilities of the underlying technology. Participants were recruited through the researchers' professional network, and included computer scientists, data scientists, roboticists, mechanical engineers, and machine learning engineers. The interviews lasted for 42 minutes on average, while the focus group lasted for 1 h 30 min. Because of the COVID-19 pandemic, all sessions were conducted online, through a teleconferencing platform. Further, in the case of the focus group two breakout rooms were used to facilitate better participant interaction and mitigate for groupthink, whereby the session had three parts: introduction and initial round of ideas with everyone in the same virtual room (20min), small group session with 4 and 5 participants randomly assigned into two breakout rooms (both of which had a member of the research team also present to facilitate the discussion, 50min), and finally a round-up of key discussion points and final thoughts on the topic with everyone gathered again in the same virtual room (20min).

All sessions were audio recorded and manually transcribed and anonymized. Interview questions centred on the relative automatability of different mechanical, analytical, intuitive, and empathetic tasks found in frontline food service and as illustrated by Study 1. The aim was to establish the degree to which current automation technology allows for different types of food service tasks, occurring under different boundary conditions (e.g. in quick service, fine dining, open layout premises, different types of kitchens, etc.), to be automated. Data was analyzed thematically by two independent coders (the research team) drawing on a priori themes established by Huang and Rust (2018; 2021). Table IV presents an overview of Study 2 participants.

Table IV: Basic characteristics of interview participants.

ID	Position	Country
1	CEO of an NLP Company	Finland
2	CEO of a Robotics Company	Finland
3	CTO of a Robotics Company	Finland
4	Founder of a Food Technology Company	Finland
5	Founder of a Customer Service Automation Company	Finland
6	Machine Learning Engineer	Finland
7	Machine Learning Engineer	Finland
8	Roboticist	Finland
9	Data Scientist	Sweden
10	Mechanical Engineer	Germany
11	Roboticist	Germany
12	Roboticist	United Kingdom
13	AI Researcher	United Kingdom

5.0 Findings

The analysis of ONS Standard Occupational Classification data found frontline food service work to consist of eight occupation unit-groups which capture 296 unique job titles. These eight occupation unit-groups consisted of 37 unique tasks, which in turn consisted of 97 unique actions as illustrated (Table V). Overall, in the content analysis of the task-descriptors, a strong skew towards tasks requiring mechanical and analytical intelligence over intuitive and empathetic intelligence was found. Of the 97 frontline food service actions coded in this study, 57 (58.8%) were found to fall within Huang and Rust's (2018) characterization of 'mechanical intelligence', 26 (26.8%) within 'analytical intelligence', 11 (11.3%) within 'intuitive intelligence', and only 3 (3.1%) within 'empathetic intelligence'. Examples of different types of intelligences required by different types of frontline food service tasks (and their constitutive actions) included: "sets tables with clean linen", "presents bill and accepts payment" (mechanical intelligence); "monitors work schedules to meet the organisation's requirements" (analytical intelligence); "advices on selecting food and drinks" (intuitive intelligence); and "resolves operational problems" (empathetic intelligence). A full breakdown of all the task-descriptors and their related actions and intelligences per occupation unit-group is presented in Appendix 1.

Table V: Breakdown of frontline food service actions and required intelligences by occupation, adapted from ONS (2020).

Occupation	Actions	Intelligence	%
5434 – Chef	Requisition, purchase, prepare, season, cook, instruct, fetch, clean, clear, examine, ensure, co-ordinate, oversee, monitor, supervise, organise, manage, maintain, plan	Mechanical	42.9 %
		Analytical	47.6 %
		Intuitive	9.5 %
		Empathetic	0 %
5435 – Cook	Requisition, purchase, check, prepare, season, cook, sell, fetch, clear, clean, co-ordinate, plan	Mechanical	78.6 %
		Analytical	7.1 %
		Intuitive	14.3 %
		Empathetic	0 %
5436 – Catering and Bar Manager	Purchase, check, use, supervise, verify, keep, account for, plan, decide, direct, arrange, prevent, discuss	Mechanical	21.4 %
		Analytical	35.7 %
		Intuitive	35.7 %
		Empathetic	7.2 %
9261 – Bar and Catering Supervisor	Report, supervise, co-ordinate, establish, monitor, meet, determine, recommend, liaise, resolve	Mechanical	9.1 %
		Analytical	63.6 %
		Intuitive	9.1 %
		Empathetic	18.2 %
9263 – Kitchen and Catering Assistant	Clean, prepare, carry, tidy, dispose of, prepare, serve, accept, give, keep	Mechanical	90.9 %
		Analytical	9.1 %
		Intuitive	0 %
		Empathetic	0 %
9264 – Waiter and Waitress	Set, present, describe, take, pass, serve, accept, advise	Mechanical	88.9 %
		Analytical	11.1 %
		Intuitive	0 %
		Empathetic	0 %
9265 – Bar Staff	Assist, wash, clean, take, mix, serve, receive, keep	Mechanical	87.5 %
		Analytical	12.5 %
		Intuitive	0 %
		Empathetic	0 %
9266 – Coffee Shop Worker	Take, make, serve, receive, give, clean, tidy, dispose, keep	Mechanical	88.9 %
		Analytical	11.1 %
		Intuitive	0 %
		Empathetic	0 %

As discussed in the literature review, service management and information systems scholars have postulated that an increasing number of mechanical and analytical service tasks will increasingly get delegated to different types of intelligent systems (Brynjolfsson and Mitchell, 2017; Huang and Rust, 2018). This will inevitably bring about new service jobs, transform existing service jobs, and in both cases change the skillsets required for undertaking tasks and actions in service production and delivery (Ling et al., 2021; Tuomi, Tussyadiah and Stienmetz, 2020b). Previous literature has been vocal about how intelligent automation facilitates a shift towards frontline service tasks which require intuitive and empathetic intelligence (Huang and Rust, 2021), signalling a move away from 'dirty, dull, and dangerous' vocational jobs to more 'professional' jobs in hospitality (Ivanov and Webster, 2019). In the context of frontline food service, this would mean automating standardized or transactionalized service tasks which support the production and delivery of the main service offering, e.g. data-driven flavor-paring to support menu development, robotized mise en place to support final dish assembly, or automated repeat ordering or guest check-out to support service staff to focus more on delivering high-touch service, e.g. giving recommendations (Fusté-Forné, 2021; Tuomi, Tussyadiah and Hanna, 2021).

Given the disruptiveness of the ongoing transformation, this move should no doubt also be reflected in the ways in which jobs and tasks are described (and worded) in Standard Occupational Classification databases such as the one analyzed in this study. However, this seems not to be the case yet, as the vast majority of tasks listed on the 2020 ONS SOC under frontline food service related occupations clearly imply mechanical and, to a lesser extent, analytical intelligence tasks over intuitive and empathetic intelligence tasks. Given how linguists have for decades noted the influence of language on shaping how individuals perceive the world, a much more distinct shift from relying on verbs that simply imply "doing" over "thinking" and "feeling" when describing frontline food service tasks in Standard Occupational Classification databases is strongly suggested and should be expected.

In terms of the relative automatability of the different mechanical, analytical, intuitive and empathetic frontline food service tasks and actions identified herewith, three interconnected themes in intelligent automation technology development were identified in the interviews and focus group with technology developers. These findings extend Tussyadiah's (2020) Framework for Intelligent Automation in Tourism by bringing granularity and context-specificity to previous conceptualization of intelligent automation. The three themes identified in this study were: 1) the impacts of autonomous navigation on food service, 2) the impacts of object manipulation on food service, and 3) the impacts of natural language processing on food service.

The next three sub-sections discuss these three streams of intelligent automation technology development in detail, drawing a clear link between Huang and Rust's (2018; 2021) Service Task Intelligence Framework and the actual state and current challenges of intelligent automation technology development and deployment as it relates to frontline food service management.

5.1 Autonomous Navigation in Food Service

A mechanical system that is able to autonomously navigate between points of interest without colliding with objects is perhaps one of the most tangible, and publicly visible, form of mechanical intelligence in frontline hospitality (Huang and Rust, 2018). Autonomous navigation is realized in practice by mapping out the environment (for example through different simultaneous localization and mapping techniques), choosing the most appropriate route (i.e., path-planning), and taking action, i.e. actuating the decision. Due to surging research and investment interest in self-driving cars, development in this area of intelligent automation technology is rapid and new research papers as well as systems which navigate autonomously in human environments such as restaurants, hotels, or airports come out frequently (Tuomi, Tussyadiah and Stienmetz, 2020a). Service companies have started to enter this space by deploying ever-nimbler mobile hospitality robots such as Bear Robotics' Servi (Albrecht 2020a), which is able to deliver food and drink orders from the kitchen to the service area, deliver empty dishes back to be washed, as well as facilitate order- and payment-taking through the service robots' interactive touchscreen. Commenting on the relative automatability of navigation tasks in frontline food service contexts, participants noted:

> *"For handling meal deliveries, robots are good at delivering stuff from one place to another, but they are not so good for unpacking, or manipulating objects that need more dexterity. For those you need to make use of human's dexterity and flexibility."* (ID2)

> *"If you can map the space, our technology can do the heavy lifting."* (ID8)

Besides the complexity of the actual navigation task, crucial to the relative automatability of navigation are the conditions within which the navigating take place. In general, the more predictable and stable the conditions are, the easier it is to carry out navigation tasks without collision. To facilitate collision-free navigation under unpredictable conditions, changes to the servicescape may need to be made (Fu, Hou and Yang, 2009). Reflecting on first-hand experience of recent mobile food service robot implementation projects, participants noted:

> *"We added these side-lasers to the robot actually, I think they are pretty mandatory. They scan the environment vertically, which improves safety and the robots' agility a lot."* (ID2)

> *"We used magnetic tape* […] *to have that extra reassurance the robot would do what we wanted it to do and go where we wanted it to go as it was a relatively busy environment. We could've used another extra navigation guidance technique which includes LIDAR but we decided to just use the tape.* (ID11)

5.2 Object Manipulation in Food Service

Similar to autonomous navigation, the manipulation of different types of objects is another very active area in service robotics research. According to Billard and Kragic (2019), the general rule of thumb is: the more dexterity manipulating a given object requires, the more difficult it is to automate. Particularly elusive is the manipulation of deformable objects, i.e. things that are very fragile, flexible, or malleable. In food service, object manipulation is most often applied back-of-house to automate various kitchen processes (Mims, 2021). Offering one the highest-profile example of this type of automation in the context of food service, Miso Robotics' Flippy has as of November 2020 graduated from flipping burgers to cooking 19 different food types (Ramirez 2020), while its "cousin", Moley's robotic kitchen-on-rails promises to pick-up, measure, and cook semi-complex meals from scratch (Albrecht 2020b). Commenting on the relative automatability of object manipulation in frontline food service, participants noted:

> *"Wherever you have a routine-like work situation, apply robots there, and wherever the situation is constantly changing, it's unpredictable, use humans there. Humans can adapt to change better."* (ID13)

> *"There are different types of ingredients we can't currently handle. Spaghetti is a particular problem. Or wakame. Anything where it's very stringy and long, it's very difficult to be accurate in the way you portion control it. We haven't found a good solution for that yet."* (ID12)

> *"When we work with a restaurant group, we look at their menu and go, of the thirty things you want to serve, these 22 we can do easily and well with a robot, and these are the eight that require some human manipulation because we don't yet have a robot technology that can do that. A good example is wraps. We can take wraps, lay them flat on a surface, and load the flat wrap with all of the things you might want to have in a wrap. But the actual process of folding a wrap is quite a dexterous, complex process, so in most cases it's not economically viable to do that with a machine at the moment; it's better to do that with a human. But what we find is you can get a better-quality wrap that way, as you can be very accurate about what's gone into it, so you don't make mistakes in the filling. Fast casual restaurant groups are very specific*

about the quantities of protein and fats that go in there, so they can really watch their margins on those things." (ID12)

Similar to autonomous navigation, object manipulation may require service providers make changes to the servicescape by e.g. installing rails to facilitate robot movement or protective screens to improve employee safety (Mims, 2021). Further, while the manipulation of objects may seem like a straightforward, mechanical service task (Huang and Rust, 2018), the wide variety of ingredients in need of manipulation in food production settings seem to bring interesting complexity to the discussion. As illustrated, in the case of deformable ingredients (Billard and Kragic, 2019), object manipulation becomes a task requiring analytical capability as well as intuition (or "thinking" and "feeling" as put by Huang and Rust, 2021), whereby applying e.g. too much pressure or moving at high velocity may break the manipulated ingredient. In the context of food service this is particularly true given the heterogeneity, that is, the natural variability in object shape and size, inherent to fresh produce. Deciding where to best apply object manipulation in frontline food service settings is therefore highly dependent on what is being manipulated. To add further complexity, in their study Zhu and Chang (2020) found support for the use of anthropomorphic robot hands to positively impact food quality perceptions. Food service managers should therefore pay attention to the type of actuator (e.g. anthropomorphic or not) used in carrying out manipulation tasks to improve customer satisfaction outcomes.

5.3 Natural Language Processing in Food Service

Besides physical movement, that is, navigation or manipulating objects, frontline food service and indeed most frontline service work is heavy on communication between people: taking orders, giving recommendations, serving food, taking payments, dealing with complaints, etc. (Huang and Rust, 2018). This is particularly true for hospitality contexts (Pillai and Sivathanu, 2020). Indeed, in terms of tasks requiring human-to-human communication, natural language processing, which consists of natural language understanding and natural language generation, is one the most widely applied intelligent automation techniques in commercial service settings right now (Adam, Wessel and Benlian, 2020). The rise in so-called conversational interfaces (Ling et al., 2021) is often attributed to advances in a specific type of machine learning architecture, the transformer. Transformers allow for the parallel processing of sequential data, that is, individual words or tokens that follow one another to make up full sentences. This facilitates more efficient training of ever-larger language models and more nuanced inference of natural language enquiries, resulting in more human-like computer generated language (Tuomi, 2021).

However, despite advances in transformer models, making sense of routine enquiries, for example taking repeat orders, understanding the number of people in a party, or identifying the specific seat preferred by customers, is still far easier than understanding and generating language in highly contextual settings, for example giving a recommendation based on customers' individual wishes or resolving complaints (Tuomi, Tussyadiah and Stienmetz 2020a). This is simply because the communication task in the former is more mechanical-oriented and often transactional in nature, while in the latter the communication task is more thinking and feeling-oriented and might rely on intuition (Huang, Rust and Maksimovic, 2020). Commenting on the relative automatability of different types of communication tasks in food service settings, one participant working in food service focused e-commerce automation noted:

"I see there to be two types of customer service problems. First is transactional problems. Nobody likes to contact customer services, they contact because they have a problem of some sort. So they have an expectation of the company, and the company doesn't deliver as expected, and they can't find the information on their own or can't do something on their own, so they contact them to resolve the issue. In these situations you don't really need the customer service employee: in these situations, the human is really just an API between different systems. They take the customer's request, look up something from another system, and then return to the customer with an answer. But then there are a lot of customer service enquiries where the customer doesn't really know what the problem is. They misunderstood something, or whatever. In these situations the customer service employees' role isn't really to solve the problem, but to

understand how the problem arose and help the customer to understand that maybe they were actually at fault. Essentially to be there for the customer, to hear them, to say that unfortunately we have this policy, and I can't solve your problem, but I'm here for you, I understand your anger, I take you seriously. And I think this is a bit fuzzy, it's hard to define where or when we get to this or what exactly falls to this second category of tasks. But it's super important. And I don't think we can or should automate that humanness, that empathy. I think that should stay human." (ID1)

Summing-up different streams of intelligent automation technology development and reflecting on the process of automating frontline food service tasks, one participant observed:

> *"I think in a lot of use-cases it's not really the technology that's limiting adoption any more. However, I think using a robot like ours successfully would require a concept designed for the robot from the beginning, where things like this have been thought out from the get go. Like, what the role of the robot should be. What, or which tasks, is the robot replacing. And then make it cost-efficient enough so that you can justify the relatively large up-front investment the robot requires. And then I think you would just need somebody who's innovative enough to try a new concept like this in real life. I think in solutions like this there will always be risks, as it is a new thing.* […] *Taking an existing service process, chopping it into small pieces and then automating a specific piece is quite difficult. I think better would be designing the whole thing with the robot in mind."* (ID2)

6.0 Discussion and Conclusions

6.1 Conclusions

Automation poses to change how hospitality work is organized (Tuomi, Tussyadiah and Hanna, 2021). However, there is a lack of understanding of how automation influences specific sectors, including specific hospitality jobs. Addressing this gap, this paper looks at the relative automatability of jobs and tasks which fall within one specific hospitality context: frontline food service, by analysing the UK Office for National Statistics' Standard Occupational Classification (2020) data to determine the degree to which frontline food service jobs consist of tasks requiring mechanical, analytical, intuitive or empathetic intelligence (Study 1), as well as contrasting these findings to current state of intelligent automation technology development by conducting interviews and a focus group with food service technology experts (Study 2). Of all the tasks listed under food service in the ONS SOC 2020, 58.8% are found to require mechanical, 26.8% analytical, 11.3% intuitive and 3.1% empathetic intelligence. Further, the automatability of these tasks is found to be driven by three streams of technology development in particular: 1) autonomous navigation, 2) object manipulation, 3) natural language processing. The next two sections discuss the theoretical and practical findings of our research in greater detail.

6.2 Theoretical Implications

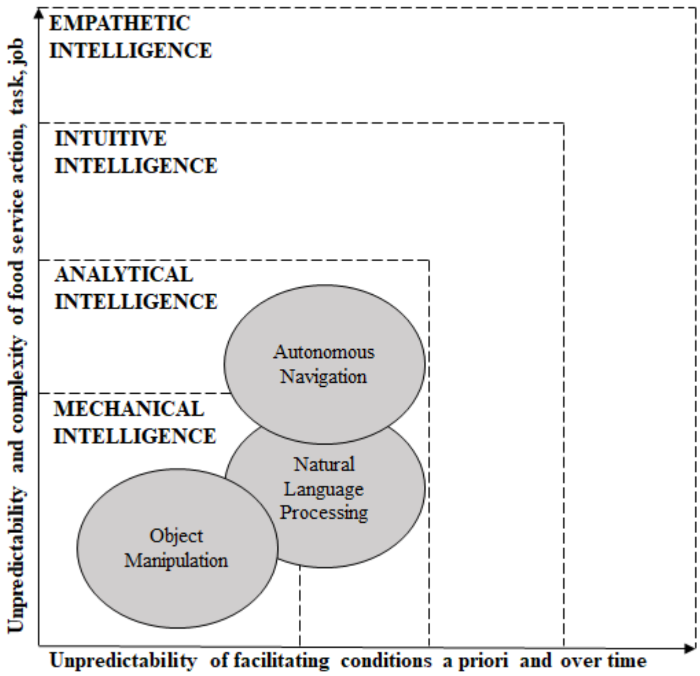
Drawing our first principles informed exploratory studies (Study 1 and Study 2) together, we suggest as a theoretical contribution of our research a conceptual framework for Actioning Intelligent Automation in Frontline Food Service (Figure 3). Our framework seeks to relate the first principles of frontline food service to intelligent automation by distinguishing between the structure of intelligent automation in food service, that is, what are the most feasible elements that may be automated, as well as the mechanism underlying the automation, that is, how actioning intelligent automation in food service would look like as a process. Our framework refines and extends previous conceptualizations by Brynjolfsson and Mitchell (2017) and Huang and Rust (2018; 2021) for the context of knowledge creation in hospitality management, and in doing so moves the academic discourse around intelligent automation in service from service tasks to service actions. As mentioned, we identify three specific streams of technology development (namely, autonomous navigation, object manipulation, and natural language processing) as the key facilitating technologies of intelligent automation in frontline food service.

First, we establish that the relative automatability of frontline food service actions, tasks, and ultimately jobs is dependent on: 1) The unpredictability and complexity of the automated frontline food service action, task, or job, and; 2) The unpredictability, both a priori and over time, of the conditions which facilitate the automated frontline food service action, task, or job. Further, in line with Brynjolfsson and Mitchell (2017), we argue that the more complex and/or the more predictable a given frontline food service action, task, or job is, as well as the more predictable (both a priori and over time) the conditions within which the automated frontline food service action, task, or job occur are, the higher its relative automatability will be. By demonstrating the usefulness of breaking service tasks into their constitutive parts (that is, service actions) in the context of frontline food service, we suggest that further studies should apply our model to study other service sector contexts, i.e. analyze the tasks and actions (and the relative automatability thereof) in e.g. health care or financial services contexts (cf. Flavián et al., 2021).

Second, we argue that the relative automatability of frontline food service actions, tasks, and jobs increase in four distinct phases or levels of abstraction, all of which have distinct characteristics in terms of factors that may either enable or limit the action/task/job's relative automatability. These levels of abstraction correspond with the four categories of service task intelligence put forward by Huang and Rust (2018; 2021), whereby the relative automatability of a service task moves from mechanical and analytical intelligence (highest potential for automation given current technology) to intuitive and empathetic intelligence (lowest potential for automation given current technology). In particular, in terms of mechanical and analytical intelligence, we find that the relative automatability of a particular frontline food service action is determined by 1) the availability of training examples (e.g., historical data which illustrates how the automated task should be carried out) and 2) the degree to which a specific task can be defined, i.e. broken down to a sequence of steps that can be coded into a system (Brynjolfsson and Mitchell, 2017).

Based on our empirical findings, we observe that the vast majority of current applications of intelligent automation technology in frontline food service falls within these two categories intelligent automation. Finally, in terms of intuitive and empathetic intelligence, we see that the relative automatability of these types of frontline food service tasks is determined by 1) the overall make-up of tasks, that is, the degree to which a task consist of readily automatable actions (e.g. mechanical, analytical, intuitive, or empathetic actions) (Huang and Rust, 2018; 2021) and 2) by the availability of organizational resources, e.g. specific know-how and goodwill of actioning intelligent automation in the first place (Tuomi et al., 2020).

Figure 3: Framework for Actioning Intelligent Automation in Frontline Food Service.



6.3 Practical Implications

Across the four phases of our framework for Actioning Intelligent Automation in Frontline Food Service, a different set of hospitality management questions with regards to automated frontline food service actions, tasks, and jobs arise. We argue that first, hospitality businesses looking to proactively action intelligent automation in their service operations should determine which actions do specific food service tasks consist of and what is the relative automatability of said actions. After this the focus should move to tasks, i.e. determining which tasks do specific food service jobs consist of, and what is the relative automatability of said tasks. Finally, the overarching management question to pose when considering intelligent automation is: what is both the realistic and desired level of automation the service organization should go after? In essence, given what can be automated, what should be automated (Tuomi, Tussyadiah and Hanna, 2021)? Following Grover, Kar and Dwivedi (2020), we see the setting of such a strategy to be influenced by two primary factors in particular: what do the organization's employees want, and what do the organization's customers ask for.

6.3.1 Recommendations for Intelligent Automation Systems Designers

In terms of employees, recent hospitality management literature has suggested that automation efforts in hospitality and tourism should be driven by a desire to increase the decency of service employment, including reducing friction at work through effective human-machine cooperation, improving working conditions through for example safer and more convenient working conditions, and increasing employees' level of empowerment through better opportunities for career progression (Tuomi et al., 2020). Others have called for a move towards job crafting, highlighting the need to give service employees more authority over actively shaping and re-shaping the actual contents of their jobs (Oldham and Fried, 2016). Imperative to this is separating the notions of person-job fit and intelligent automation technology-job fit from each other and assessing both against their own set of criteria (Tuomi, Tussyadiah and Hanna, 2021), as what can and what should be automated are two different, albeit interconnected, questions and strategic management decisions.

Understanding the fundamental make-up of service tasks, as well as assessing their relative automatability against the current degree of intelligent automation technology development, is imperative for re-thinking frontline food service production and provision processes. Breaking frontline food service jobs down to tasks and tasks further down to their constitutive actions helps hospitality practitioners better understand which specific service jobs are most at risk of automation, and where new skills and human capability are still required. Using our framework for Actioning Intelligent Automation in Frontline Food Service as a tool for assessing the relative automatability of tasks and actions allows hospitality companies to start re-structuring job profiles and their accompanied task-descriptors accordingly (i.e. allocating the not-readily automatable parts to human staff), as well as put in place training and development programmes for those most likely to be impacted by intelligent automation (i.e. those whose job consists primarily of readily-automatable tasks).

6.3.2 Recommendations for Intelligent Automation Service Managers

In terms of customers, research has suggested a move towards seamless customer journeys and personalized service offerings in food service (Tuomi and Tussyadiah, 2020). Applying intelligent automation technology in frontline food service to ease points of friction and wait should therefore directly bring benefit to customers. For example, Japan-based sushi restaurant chain Hamasushi uses a service robot to manage its walk-in and take away queues, effectively reducing customer wait times. Similarly, McDonald's recently reported how its AI-based dynamic menu system had sped-up ordering by circa 20 seconds (Kelso, 2020), while the company's other AI initiative, a natural language processing system, had streamlined its drive-thru ordering experience (Metz, 2021). To ensure a smooth transition to increasingly automated service encounters, Belanche, Casaló and Flavián (2020) emphasize the importance of communicating the systems' level of intelligence (i.e., mechanical, analytical, intuitive, or empathetic, Huang and Rust, 2018) clearly to the customer, so that they may best align their expectations of the service to match the actual, automated service offering. Pillai and Sivathanu (2020) arrive at similar conclusions, whereby perceived intelligence of e.g. chatbots has been found to play a role in chatbot adoption intention, highlighting the importance of implementing intelligent automation systems which are easy to access, have user-friendly interfaces, are human-like, and can communicate natively across different languages. Our findings are in line with these notions, whereby the design of service offerings which incorporate elements of intelligent automation might be most effective when designed from the ground-up, rather than trying to re-purpose an existing service process into an automated format.

6.4 Limitations and Future Research

Despite conducting two studies, the research presented here has limitations that should be considered. First, it is important to note that the ONS Standard Occupational Classification (ONS SOC, 2020) database used in this research is only a proxy of all of the possible tasks and actions a given frontline food service job consists of. In particular, in its current state the ONS SOC (2020) inadequately captures all of the emotional labor, creativity, and innovation that goes into producing and providing frontline food service experiences. Some common frontline food service tasks that have not been adequately described in the ONS SOC include dealing with complaints and other types of feedback, building rapport and long-term relationships with customers, upselling or designing, running or managing other forms of promotional initiatives, or innovating the service offering (what is served) and process (how service is carried out). While the ONS SOC offers a standardized way for assessing job-task make-ups, the lack of textual description of these more creative types of frontline food service tasks undoubtedly influences the findings presented in this study. Future research should therefore seek to establish a more comprehensive picture of different types of tasks and actions found in actual frontline food service contexts rather than rely on Standard Occupational Classification indices, and use frameworks such as the Service Task Intelligence Framework by Huang and Rust (2018), as well as other frameworks, e.g. Murphy, Gretzel and Pesonen's (2019) Robotic Service (rService) or Gursoy et al. (2019) and Lin et al.'s (2020) Artificial Intelligence Device Use Acceptance (AIDUA) Model, to re-assess the relative automatability of frontline food service work through quantitative and qualitative methodologies.

Second, the ONS SOC (2020) does not adequately account for the diversity of all possible food service contexts and the resulting heterogeneity of frontline food service work. For example, the generic task of "serving food and drinks" may in practice be completely different in quick service, fast casual, casual, smart casual, or fine dining food service settings. In a similar vein, the notions of "serving" and "being served" are boundedly socio-cultural and context-dependent phenomena, whereby service conventions, established norms and the etiquette of producing and providing service in e.g. a French full-service restaurant will undoubtedly differ from doing the same in a Japanese or an American full-service restaurant. If broader generalizability of the results presented in this study is desired, future research should aim to extend the discussions presented herewith into specific frontline food service contexts, including different types of frontline food service operations and different types of established service cultures.

Finally third, it should be noted that the labels allocated to each of the codified frontline food service tasks (mechanical, analytical, intuitive, and empathetic) are only an approximation, inherently rooted in each of the coders' own, subjective biases. Even though agreement between multiple coders was established by conducting a two-step intercoder reliability check with four independent coders, with coders' expertise varying from senior and junior management to food service operations and hospitality management research, the final evaluation of each task and their allocated intelligence type is still inherently subjective and should therefore be taken as an indication only. Instead of relying solely on "eyeballing" the coded labels (Blinder, 2009; Frey and Osborne, 2017), future studies should aim to establish more standardizable coding schema, include task intelligence indicators that go beyond the scope of the ONS SOC, as well as bring together service operators, service employees, and service technology developers under one single study.

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Appendix 1: Food Service Occupation Breakdown in terms of tasks, actions, and intelligence required for completing the task, adapted from Huang and Rust (2018) and the ONS SOC (2020).

Occupation	**Task-Descriptor**	**Action**	**Intelligence**
5434 – Chef	• Requisitions or purchases and examines foodstuffs from suppliers to ensure quality. • Plans menus, prepares, seasons and cooks foodstuffs or oversees their preparation and monitors the quality of finished dishes. • Supervises, organises and instructs kitchen staff and manages the whole kitchen or an area of the kitchen. • Ensures relevant hygiene and health and safety standards are maintained within the kitchen. • Plans and co-ordinates kitchen work such as fetching, clearing and cleaning of equipment and utensils.	Requisition	Mechanical
		Purchase	Mechanical
		Prepare	Mechanical
		Season	Mechanical
		Cook	Mechanical
		Instruct	Mechanical
		Fetch	Mechanical
		Clean	Mechanical
		Clear	Mechanical
		Examine	Analytical
		Ensure **x2**	Analytical **x2**
		Co-ordinate	Analytical
		Oversee	Analytical
		Monitor	Analytical
		Supervise	Analytical
		Organise	Analytical
		Manage	Analytical
		Maintain	Analytical
		Plan **x2**	Intuitive **x2**
5435 – Cook	• Requisitions or purchases foodstuffs and checks quality. • Plans meals, prepares, seasons and cooks foodstuffs. • Cooks and sells a range of meals, such as fish and chips, over the counter. • Plans and co-ordinates kitchen work such as fetching, clearing and cleaning of equipment and utensils.	Requisition	Mechanical
		Purchase	Mechanical
		Check	Mechanical
		Prepare	Mechanical
		Season	Mechanical
		Cook **x2**	Mechanical **x2**
		Sell	Mechanical
		Fetch	Mechanical
		Clear	Mechanical
		Clean	Mechanical
		Co-ordinate	Analytical
		Plan **x2**	Intuitive **x2**
5436 – Catering and Bar Manager	• Plans catering or bar services and supervises staff. • Decides on range and quality of meals and beverages to be provided or discusses customer's requirements for special occasions. • Purchases or directs the purchasing of supplies and arranges for preparation of accounts.	Purchase	Mechanical
		Check	Mechanical
		Use	Mechanical
		Supervise	Analytical
		Verify	Analytical
		Keep **x2**	Analytical **x2**
		Account for	Analytical
		Plan	Intuitive
		Decide	Intuitive
		Direct	Intuitive

	• Verifies that quality of food, beverages and waiting service are as required and that kitchen and dining areas are kept clean in compliance with statutory requirements. • Checks that supplies are properly used and accounted for to prevent wastage and loss and to keep within budget limit.	Arrange Prevent Discuss	Intuitive Intuitive Empathetic
9261 – Bar and Catering Supervisor	• Directly supervises and co-ordinates the activities of bar, waiting and catering staff. • Establishes and monitors work schedules to meet the organisation's requirements. • Liaises with managers and other senior staff to resolve operational problems. • Determines or recommends staffing and other needs to meet the organisation's requirements. • Reports as required to managerial staff on work-related matters.	Report Supervise Co-ordinate Establish Monitor Meet **x2** Determine Recommend Liaise Resolve	Mechanical Analytical Analytical Analytical Analytical Analytical **x2** Analytical Intuitive Empathetic Empathetic
9263 – Kitchen and Catering Assistant	• Cleans or prepares food for cooks by hand or machine. • Carries meat, vegetables and other foodstuffs from delivery van to storeroom and from storeroom to kitchen. • Cleans and tidies service area, kitchen surfaces, crockery, cutlery, glassware, kitchen utensils and disposes of rubbish. • Prepares and serves beverages and light refreshments, accepts payment and gives change. • Keeps service area well stocked.	Clean **x2** Prepare Carry Tidy Dispose of Prepare Serve Accept Give Keep	Mechanical **x2** Mechanical Mechanical Mechanical Mechanical Mechanical Mechanical Mechanical Mechanical Analytical
9264 – Waiter and Waitress	• Sets tables with clean linen, cutlery, crockery and glassware. • Presents menus and wine lists to patrons and may describe dishes and advise on selection of food or wines. • Takes down orders for food and/or drinks and passes order to kitchen and/or bar. • Serves food and drinks. • Presents bill and accepts payment at end of the meal.	Set Present **x2** Describe Take Pass Serve Accept Advise	Mechanical Mechanical **x2** Mechanical Mechanical Mechanical Mechanical Mechanical Intuitive

9265 – Bar Staff	• Assists in keeping bar properly stocked. • Washes used glassware and cleans and tidies bar area. • Takes customer orders and mixes and serves drinks. • Receives payment for drinks.	Assist	Mechanical
		Wash	Mechanical
		Clean	Mechanical
		Take	Mechanical
		Mix	Mechanical
		Serve	Mechanical
		Receive	Mechanical
		Keep	Analytical
9266 – Coffee Shop Worker	• Takes customer orders, makes and serves coffee and other refreshments. • Receives payment for drinks and gives change. • Cleans and tidies service area, kitchen surfaces, crockery, cutlery, glassware, kitchen utensils and disposes of rubbish. • Keeps service area well stocked.	Take	Mechanical
		Make	Mechanical
		Serve	Mechanical
		Receive	Mechanical
		Give	Mechanical
		Clean	Mechanical
		Tidy	Mechanical
		Dispose	Mechanical
		Keep	Analytical