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Organizational frontlines in the digital age: The Consumer–Autonomous Technology–Worker (CAW) framework

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ABSTRACT

While organizational frontlines in the digital age involve complex interactions between consumers, autonomous technology (AT), and frontline workers, research so far largely focuses on the effect of AT on either the consumer or the worker. Bridging the fields of marketing and organizational behavior, we develop the Consumer–Autonomous Technology–Worker (CAW) framework, which reflects the implications of consumer–worker–AT interactions. We consider that AT can be consumer-facing, such as service robots, or worker-facing, such as AT-enabled knowledge-based systems supporting a worker's decision-making. Drawing on illustrative interviews in hospitality contexts with workers who co-work with robots and the consumers served, we develop research propositions that highlight avenues for future research. We expect consumer–worker relations to strengthen when AT augments instead of replaces the worker. Human leadership is critical for consumers' and workers' acceptance of AT, while AT anthropomorphism is less critical in the presence of a human worker.

1. Introduction

Across business disciplines, understanding the impact of autonomous technology (AT) such as artificial intelligence (AI) and robotics has rapidly been rising to the top of many researchers' agendas (Brynjolfsson & McAfee, 2017). At a macro level, organization and management scholars have investigated the broader strategic implications of AT for competitive advantage and organizational design (Krakowski et al., 2022), such as how AT-enabled digital knowledge engineering can improve decision-making (Csaszar & Steinberger, 2022).

At a micro level, researchers in areas like marketing and organizational behavior have investigated human–machine interactions and focused on both external and internal stakeholders (Odekerken-Schröder et al., 2022). An area of particularly intense interest is how individuals—consumers or workers—feel about, and react to, the deployment of AT. Consumer behavior researchers have investigated consumer reactions to medical AI (Longoni et al., 2019), service robots (Mende et al., 2019), and automation of various tasks (Leung et al., 2018). Organizational behavior researchers have investigated human–machine teams' performance of tasks, such as army vehicle control and disaster response (Gombolay et al., 2015; Hinds et al., 2004).

One limitation of the current body of work is its assumption that consumers and workers interact with AT in isolation (De Keyser et al., 2018; Fügener et al., 2021; Hogreve et al., 2022; Odekerken-Schröder et al., 2022). However, especially at the organizational frontline, which is "the point of contact between an organization and its customers that promote, facilitate, or enable value creation and exchange" (Singh et al., 2017, p. 4), interaction in isolation is unlikely the case. Instead, consumers interact with frontline workers while algorithms support or automate part of the service provision, where AT can be more consumer-facing, such as self-service technology, or worker-facing, such as AT-enabled knowledge-based systems supporting human decision-making.

Only recently has the perspective begun to change from AT interacting with one human in isolation to viewing it as co-existing with human workers, leveraging their complementarities in the workplace and putting human–AT collaboration at the center (De Keyser et al., 2018; Fügener et al., 2021; Hogreve et al., 2022; Odekerken-Schröder

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et al., 2022; Tsai et al., 2022). Workers can for instance complement AT by adding social warmth to the interaction, while AT can support the worker with factual information, quick complex calculations and free up worker's time by taking over repetitive tasks. Given that one-third of current full-time occupations are expected to be transformed into augmented services delivered by teams of humans and AT within the next decade (Gray & Suri, 2017; Lu et al., 2020), investigating how consumers react to AT–worker teams has been identified as a top research priority in both marketing and management (Lu et al., 2020; Ostrom et al., 2021). Therefore, for a fuller understanding of how AT affects consumers and workers, human–machine interactions need to be understood in the richer social context of the organizational frontline.

Previous studies have largely assumed that AT will replace human workers in the organization, and have focused on the interaction between a dyad consisting of a consumer and AT (e.g., Brynjolfsson & McAfee, 2014). Research on AT–human teamwork has primarily focused on how the human side of the team perceives the cooperation in which AT supplements workers (Gombolay et al., 2015; Hinds et al., 2004). In this investigation, we broaden the focus of research beyond consumer–AT interactions and worker–AT interactions in isolation and consider the more complex nature of consumer–worker–AT interactions in combination. Our examination makes three primary contributions. First, by considering the social context in which consumers and workers interact with technology at the organizational frontline, we develop an integrative Consumer–AT–Worker (CAW) framework and offer eight core propositions that note gaps in the literature and highlight avenues for future research. Effective interaction and collaboration between humans and AT are key to the success of AT-enabled knowledge-based systems, making these insights especially relevant.

Second, we illustrate the relevance of our framework and the research propositions we develop with a series of interviews conducted in hospitality contexts. We interviewed not only workers who were co-working with robots while serving consumers but also consumers who were interacting with a human–robot team.

Third, our results build a bridge between two fields that are conceptually and substantively connected but that have been advancing in isolation, namely, behavioral research in marketing and organizational behavior, which have shared conceptual foundations by being concerned with individuals' cognitive, affective, and behavioral responses. By bringing together insights from these two fields, we demonstrate that their joint consideration is generative to move beyond simple conceptualizations of AT as replacing workers. Our broader perspective adds more theoretical insights to consider how AT shapes crucial interactions between actors in the organizational frontline. In the coming years, more research will be required to delineate the patterns of interaction and influence that drive the effectiveness of knowledge-based systems. Non-permeable disciplinary boundaries are unlikely to serve this endeavor well.

2. Background and definitions

Autonomous technology (AT), defined as machines capable of performing actions without (or with minimal) human intervention that can change their behavior in response to unanticipated events (Watson & Scheidt, 2005), has developed remarkably over recent decades and has become a top priority of both researchers and managers. Given AT's capacity to automatically perform tasks that were traditionally the domain of humans, digital knowledge engineering is concerned with how AT-enabled knowledge-based systems can mimic, support, or improve human decision-making (Csaszar & Steinberger, 2022). AT-enabled systems come in many forms and flavors and researchers use different categorizations to indicate their differences. For example, according to the target of interaction, it can be divided into more consumer- or worker-facing (De Keyser et al., 2018); according to the degree of tangibility, it can be divided into robotic AT with physical presence, virtual AT with virtual representation, or embedded AT that is invisible to the user (Glikson & Woolley, 2020). Consumer-facing AT-enabled applications can be chat bots or voice assistant devices like Amazon Alexa that help consumers to choose products and services, but also embodied robots that guide consumers through a store (Guha et al., 2021). An example for a worker-facing AT-enabled application is medical AI that provides the doctor with a diagnosis (Longoni et al., 2019), or large language models such as ChatGPT that help a customer service rep to respond to an unhappy customer.

The scholarly perspective's recent change to that of collaboration between humans and AT has occurred for two reasons. First, research has predicted that AT will not "take over our jobs" but rather will work side-by-side with humans in teams (Brynjolfsson & Mitchell, 2017; Waytz & Norton, 2014). Second, when working together, human and AT teams can achieve results that outperform results obtained when working on their own (Fügener et al., 2021). We start with highlighting key insights on the AT–consumer and AT–worker dyads in a selective literature review and then turn to an integrative discussion of what we know, and what we still need to know, about interactions and relationships among the three actors jointly.

2.1. Insights on the AT–consumer dyad

In recent years, the impact of AT on consumers has received much attention in the field of consumer behavior. Researchers initially began by demonstrating that, all else being equal, consumers often react negatively to firms' introduction of AT such as smart algorithms or service robots. This "algorithm aversion" (Dietvorst et al., 2015) has been documented in a wide range of contexts (for reviews, see Burton et al., 2020; Castelo et al., 2019; Mahmud et al., 2022) and has highlighted many processes and boundary conditions to this effect. For example, algorithm aversion is stronger for subjective tasks (Castelo et al., 2019), when moral trade-offs are more salient (Dietvorst & Bartels, 2021), and when the decision is emotionally complex (Yalcin et al., 2022b). This literature reveals the beliefs consumers hold about the relative abilities of humans and machines. For example, AT is perceived as unable to account for consumers' unique circumstances (Longoni et al., 2019) and as lacking emotional capability (Kim et al., 2022).

Aversion is less when consumers can exercise some control over the algorithmic output (Dietvorst et al., 2018), when consumers understand how AT makes decisions (Cadario et al., 2021), when consumers are empowered to better understand and adapt device settings (Uysal et al., 2022), and for utilitarian products (Longoni & Cian, 2022). Other studies show indifference between human or algorithmic decision makers that are viewed as more objective than humans (Yalcin et al., 2022a), or even algorithm appreciation (e.g., Logg et al., 2019).

Most of this research has examined situations where a consumer has to decide whether to rely on algorithmic or human advice. However, as companies must often decide whether to use human or machine labor for a given task, consumers' reactions to replacing human with AT workers are also important. For instance, consumers can experience discomfort when interacting with a service robot that automates tasks formerly performed by workers (Mende et al., 2019). In situations where technology replaces consumers' own labor, consumers react negatively to automation of a task that is central to consumers' identity (Leung et al., 2018). Machine labor is also linked to uniqueness perceptions and motivation: Consumers have lower appreciation of robotic (vs. human) labor when the product connotes abstract constructs like group membership or values, owing to a reduced ability to satisfy uniqueness motives (Granulo et al., 2021).

How consumers react to AT over time critically depends on its representation. While robotic AT is initially trusted less, trust may build during subsequent episodes, while for virtual and embedded AT, literature shows that initial high trust decreases over time (Glikson & Woolley, 2020). Taken together, prior studies show that consumers' reactions to AT as workers serving them greatly depend on the use, type of and experience with AT.

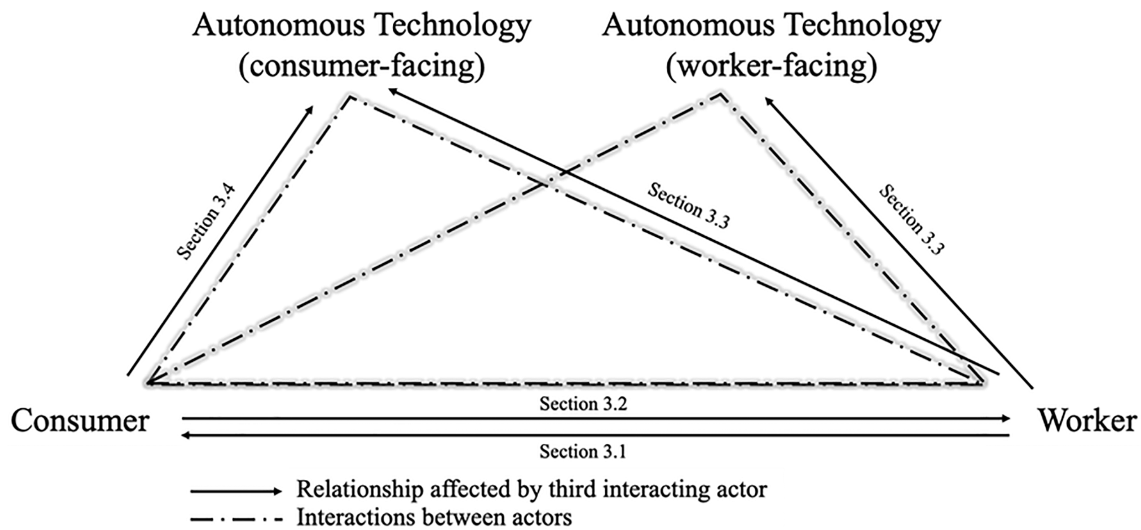

Fig. 1. The Consumer–AT–Worker (CAW) Framework.

2.2. *Insights on the AT–worker dyad*

AT offers new possibilities for ways in which workers and machines can work together, leading to the debate on whether AT can replace workers by "automating" their tasks or help workers by "augmenting" their work (Lebovitz et al., 2022). For example, some tasks that require speed and accuracy align well with capabilities of AT, whereas other tasks that require skills such as creativity and judgment align better with competencies of workers (Rai et al., 2019). These differences create an opportunity for workers to work together with AT so they can complement each other in terms of competencies and skills. Leveraging the complementarities of humans and machines can lead to an increase in organizational performance, in particular regarding flexibility, speed, decision-making, and personalized processes (Tsai et al., 2022; Wilson & Daugherty, 2018). For example, humans and AT working together can outperform AT or humans working alone (Fügener et al., 2021). At the German automobile producer BMW, human–robot teams proved to be 85% more productive than either a human or a robot (Hollinger, 2016).

However, one issue for the worker is that AT often appears to be a "black box" because how the AT algorithm arrives at a certain output is unclear (Mirbabaie et al., 2022). Workers can experience uncertainty when AT diverges from their initial judgment without providing a clear and underlying reason, yet they need to integrate the AT knowledge in the decision that they have to stand behind as human experts (Pachidi et al., 2021). In this respect, a distinction may be made between engaged and unengaged augmentation (Lebovitz et al., 2022). In engaged augmentation, professionals integrate AT knowledge by building an understanding of the AT claim *and* their willingness to adjust their own knowledge on the basis of AT. In unengaged augmentation, professionals do not relate AT knowledge to their own understanding, but rather blindly accept or ignore AT knowledge.

Besides being potentially complementary in terms of competencies and skill sets, AT and human workers may play different roles and form different types of hierarchy in joint teamwork. That is, as AT is evolving, it can take on the roles of follower, partner, or leader in the workplace. So far, research on human–machine teaming has largely focused on AT as a follower, which fits with the classic view on machines serving humans as a tool. The question, then, is often technical and centers on how human instructions can best be conveyed to AT, for instance, through signal detection and machine learning (Tsai et al., 2022).

Research has less frequently addressed the perspective of AT-as-partner. Here, the social interaction between a human and a machine and the cueing of social signals is an important topic of investigation (Loth et al., 2015). A study on algorithm-based customer relationship management technologies indicates that such technologies enhance performance only if the sales force does not fear being replaced (Vomberg et al., 2022). Furthermore, the emotions workers experience in the use of AT also affect the use of such technologies (Gkinko & Elbanna, 2022).

The perspective of AT-as-leader is rather new, particularly to the management and economics field (Chugunova & Sele, 2022; Tsai et al., 2022). However, in platform-based services such as meal delivery and taxi driving, machine leadership is present in that AT determines the worker's task and compensation (Ostrom et al., 2021; Möhlmann et al., 2021). Research on leadership in human–machine teams has revealed that co-workers blame robot supervisors for mistakes more often than they blame human supervisors, yet they may appreciate the removal of "the ego of the team leader" from the decision-making process (Gombolay et al., 2015; Hinds et al., 2004). Research shows that in emergency situations robot leaders can also outperform humans (Hou & Jung, 2018).

Organizational behavior researchers so far have focused mostly on how human workers and AT react to each other's input and instructions. Literature examining how human workers and AT engage in a dyadic or even a team relationship to interact with a consumer is much scarcer, and exploring AT–worker interaction in more complex configurations has been identified as an important avenue for future research (Tsai et al., 2022).

3. Consumer–AT–Worker (CAW) framework

The joint presence of consumers, workers, and AT shapes the psychology of both consumers and workers. In our examination, we take a cross-disciplinary perspective and integrate marketing and organizational behavior literature. Human–technology interactions do not occur in a vacuum, but in a rich social context where the presence and behavior of others can have important repercussions for how an individual perceives interaction with a given technology (Barrett et al., 2012; Chugunova & Sele, 2022; Sergeeva et al., 2017). The following examples illustrate this effect.

- A consumer using Ikea Kreativ to redesign her living room may have a radically different experience when the interaction with the app takes place in the presence of an employee who can advise and offer support, versus when it does not.
- A worker carrying out office tasks with the help of AT, such as a bank clerk consulting a worker-facing AT system to determine what loan terms to offer a certain consumer, may find that his/her perception of

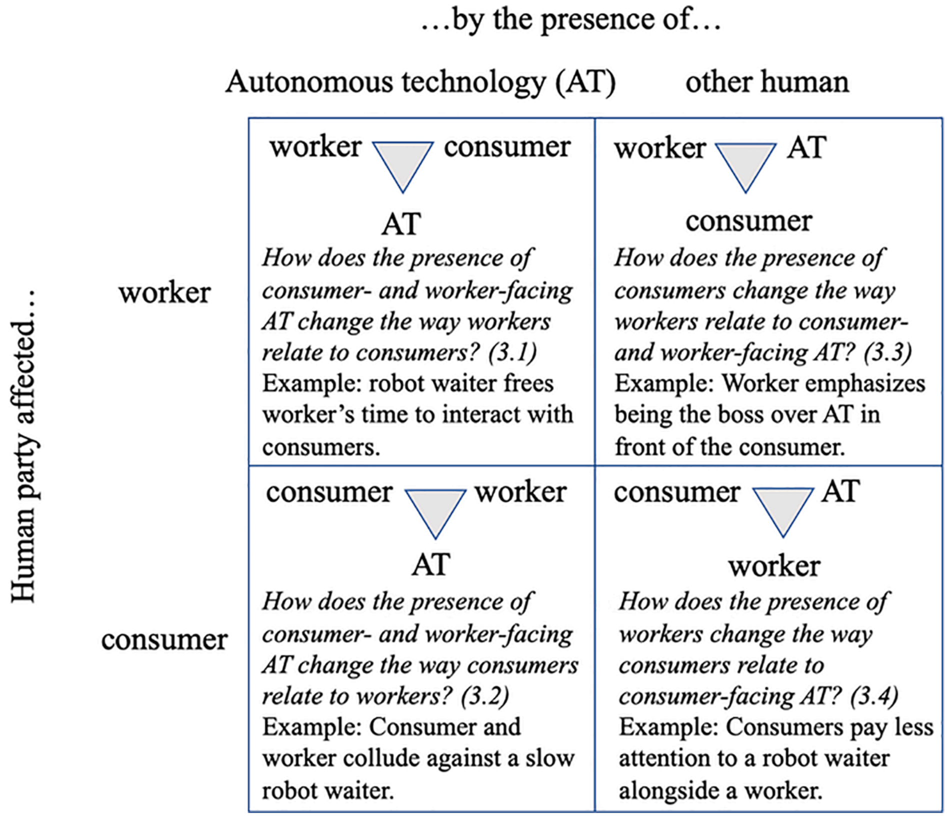

Fig. 2. Relationships within the Consumer–AT–Worker (CAW) Framework.

the interaction depends on whether those tasks take place in the presence of the consumer.

- An employee serving a consumer alongside a robot may find that both worker satisfaction and consumer experience are affected by which tasks are allocated to the worker and to the robot. For instance, consider a situation where the worker takes the consumer's orders and the robot executes them (e.g., a T-shirt's customized stitching) versus a situation where the roles are reversed.

To fully understand situations such as these, we expand the focus of analysis to the complex configuration of consumer, worker, and consumer- or worker-facing AT, as visually depicted in Fig. 1. Our CAW framework illustrates how the three actors jointly engage in interactions, as illustrated by the dashed lines in Fig. 1. We also consider that the various AT systems can differ in the extent to which they are consumer-facing (i.e., mainly interacting with the consumer while the worker supports this interaction) or worker-facing (i.e., mainly interacting with the worker while supporting the worker in interaction with the consumer) (De Keyser et al., 2018). The solid lines represent how one actor relates differently to another one due to the presence of the third actor, as we discuss in the following sections and sum up in Fig. 2.

Our basic premise is that the relations between the parties change when AT is integrated into the organizational frontline, which we discuss in four parts (Fig. 2) and illustrate with the example of robot waiters in hospitality settings. We first distinguish between the human party—consumer or worker—who relates differently to another party owing to changes in the configuration of the organizational frontline (represented by the solid lines in Fig. 1). We then distinguish between whether the change is brought about by the presence of the other human or by AT. We also consider that the extent to which AT is consumer- or worker-facing can make a difference (De Keyser et al., 2018). While we acknowledge that reality is much more complex with relationships between the parties changing simultaneously, for dispositional clarity we focus on the way one human party relates to one other party in isolation. For each quadrant we develop research propositions, which we discuss in the following section.

To illustrate each of the quadrants of Fig. 2, we draw on vivid excerpts from anecdotal evidence and a series of interviews we conducted in hospitality contexts. We conducted 15 interviews with workers co-working with robots and nine interviews with the consumers interacting with these workers and robots. Appendices A-C give more detail about the interview procedure and the questions asked to workers and customers. Both the worker and the consumer interviews emphasized the collaboration between the worker and the robot, in line with our view that the system of worker–AT–consumer needs to be considered as a whole. Furthermore, both sets of interviews included questions addressing the two fundamental dimensions in the workplace: task accomplishment—the arrangement, structure, and organization of the work—and relationship support—the interpersonal, "people" dimension of work (Tsai et al., 2022).

3.1. How the presence of AT changes the way workers relate to consumers

Organizational behavior research has not yet deeply explored the question of how human workers would relate to consumers in the presence of AT. However, prior research and evidence point to a central issue of how the competencies and skill sets of both AT and human workers are combined in serving consumers. If the joint work of human workers and AT can be designed to be complementary (i.e., complementary configuration), this joint work will likely enhance the quality of interactions between human workers and consumers (Rai et al., 2019; Tsai et al., 2022; Wilson & Daugherty, 2018). In contrast, if the joint work is designed or arranged in a way that AT simply replaces human workers (i.e., supplementary configuration) and human workers are not trained in new and unique skills, the joint work between AT and human workers will likely jeopardize the quality of interactions between human workers and consumers (Vomberg et al., 2022).

In one complementary configuration, AT takes on more routine,

Table 1
Research propositions within the Consumer–AT–Worker (CAW) framework.

	Main idea(s)	Illustrative evidence	Research proposition
3.1 How the presence of AT changes the way workers relate to consumers			
Consumer-facing AT	AT is taking over routine tasks and allows workers to focus on relational tasks.	*"Since Bellabot, there is more time to have a conversation with the guests. We save time, which is time we can spend with guests"* *"The worst thing would be definitely be if the robot would replace the human. The best thing would be if the robot made the life of the human easier like in this case with walking less and serving plates."*	**RP1:** Workers are more likely to forge stronger relationships with consumers when (a) in an AT–worker team, AT's tasks are more routine or analytical and workers' tasks are more relational or creative and (b) workers are provided with training to develop unique skill sets and do not develop fear of AT as their replacements.
Worker-facing AT	See above, and AT takes over analytical tasks and allows workers to focus on creative tasks.	AT customer service system that provides frontline workers with draft reply that can be customized with personal notes. *"Ella did not change our job – she took over some of the heavy parts of our job."*	
3.2 How the presence of AT changes the way consumers relate to workers			
Consumer-facing AT	More human solidarity, fostering consumer–worker relationships— or, dehumanization of the worker leads to a weaker relationship between consumer and worker.	*"Like, in the old situation, I came to the desk and said "well, I have a meeting with this and that" and the receptionist will look that up on the computer. So, there is not really quality time with the receptionist as well. Now I feel like there is some more time to have a chit-chat with the receptionist"*	**RP2a/b:** The presence of consumer-facing AT leads to (a) consumers having a stronger relationship with workers because of their shared humanness, or (b) a weaker relationship because the worker is objectified.
Worker-facing AT	AT perceived as the ally of the human worker because both belong to the same organization.	*"She [Ella] more and more becomes a member of the team. If she is not operating for a day, people start to miss her."*	**RP2c:** The consumer may perceive in particular worker-facing AT as the worker's ally, therewith (c) weakening the consumer-worker relationship.
	AT could be used as a scapegoat in case of service failures; service recovery by worker can strengthen human–worker relationship.		**RP3:** Ways to overcome consumer inferences of lower worker competence include (a) using worker-facing AT as a scapegoat when service failures occur, and (b) letting the human worker do the service recovery.
Both types of AT	Consumers seem reluctant to accept consumer-facing or worker-facing AT in a leadership role.	*"The food is being brought to the tables by robots and humans in collaboration. The robot can do some funny things like sing a birthday song and you can pet it since it looks like a cat, but all the verbal communication is still with the waiter."*	**RP4**: Putting AT in the lead weakens consumers' relationship with workers.
3.3 How the presence of consumers changes the way workers relate to AT			
Consumer-facing AT	The worker needs to be in a leadership role, particularly when the consumer is present and the AT is consumer-facing.	*"I still decide what happens; she is more or less my sidekick, but I know where her on/off button is placed. So, will she ever replace me fully? No, of course not."* *"Bellabot does not substitute me, but makes it easier for me to do my job."*	**RP5**: Human workers relate more positively to AT when human superiority to AT is reinforced, and conversely more negatively to AT when human superiority to AT is violated.
Worker-facing AT		Worker-facing AT is in the lead in platform-based services where the consumer is not present. *"You want to frame it like the robot needs the employee and not the other way around"*	**RP6:** Positive and negative effects are enhanced (a) in the presence of the consumer and (b) by the extent to which AT is consumer-facing. (c) Positive effects are enhanced and negative effects weakened for robotic AT compared with virtual or embedded AT.
3.4 How the presence of workers changes the way consumers relate to AT			
Consumer-facing AT	Presence of workers should facilitate consumers adopting and relating to AT by compensating for AT's shortcomings.	*"I think my experience would not be just okay if I did only interact with the robot. Now, I would say, because of the combination of human and robot, that the interaction was valuable for me."* *"The interaction with the robot is practical and fun, and I would describe the interaction with the human as more valuable"* *"More and more is being automated, just like these QR codes. So, I will not be surprised if in 20 years the waiters are mostly replaced by robots. If that happens, I am not going out for dinner anymore."*	**RP7:** The presence of the worker makes consumers (a) relate more easily to consumer-facing AT in the short term, yet (b) rely less on consumer-facing AT in the long term. The type of AT (robotic, virtual, embedded) is an important contingency factor for the adoption path.
	Worker presence will decrease the impact of AT anthropomorphism.	*"Well, it is not just the robot since there is also a receptionist present most of the time."* *It was fun and a bit strange at the same time. The host was also there, of course, and with every interaction I had with the robot I felt myself looking at the host for reinsurance"*	**RP8:** The presence of the worker reduces the impact of anthropomorphism on how consumers relate to consumer-facing AT.
Worker-facing AT	n.a.	n.a.	n.a.

menial tasks so that human workers can better focus on customized, emotion-related tasks that can add unique value to consumer experiences (Huang & Rust, 2021; Larivière et al., 2017; Wirtz et al., 2018). An example involving *consumer-facing AT* is restaurant service robots that bring meals from the kitchen to the table or robot receptionists that take over administrative tasks. Frontline workers are then free to focus on developing their relationship with the consumer. Several of our interviewees in hospitality services confirmed that a complementary task arrangement in which AT takes over the routine work and human workers attend to the emotional needs of consumers not only improves workers' relationship with consumers, but also makes the work of serving consumers more joyful and meaningful for human workers. Interviewee #8 from an organization that relies on humanoid robot Pepper as a receptionist commented:

Fig. B.1. Robot "Whizz".

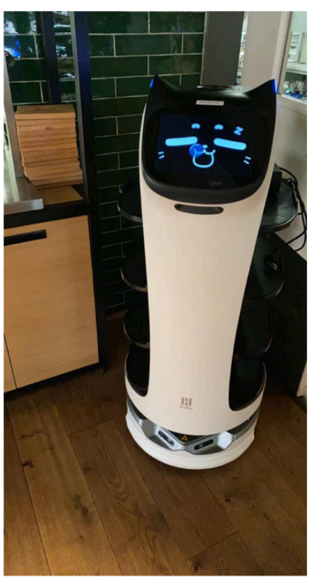

Fig. B.2. Robot "Bellabot".

> The contact has changed, because the robot takes over the practical things. But the amount of contact has remained the same. I would say that basically the contact hasn't really changed. Perhaps it has become a bit more substantive? Yes, that's it I think. More substantive.

Interview #8 from this organization further added:

> [T]he receptionist is more like a welcoming host and moves throughout the space and actively approaches guests. After welcoming the guests, the host refers the guests to Pepper. Based on the response of guests towards Pepper, the host does or does not help the guests with checking in. Normally, I was sitting behind a reception desk and guests would come to me. Now, the reception desk is gone and, therefore, I must approach guests actively…. In my opinion, the guests like the new way of working. I think it makes them feel more welcome and the setting becomes more informal: There is nothing standing between me and the guest.

In a comparable complementary configuration for *worker-facing AT* in the realm of customer service, AT takes care of finding and providing factual information, thus freeing up workers for the more relational aspects of their job. For instance, a large European airline introduced an AT system that would take incoming consumer requests from social media channels, analyze their content, and offer the frontline worker a draft reply. Often this would feature boilerplate information and links to pages where consumers could perform various tasks (e.g., submit claims for lost baggage). Frontline workers customize these messages by adding a personal note or choosing an appropriate emoji, aspects of the job that the workers found more joyful and meaningful (Elbers, 2016). Thereby, the AT system had the potential to increase both productivity and the quality of worker–consumer relations.

In a second complementary configuration or type of task division between AT and human workers, AT performs complex analytical tasks so that human workers can better focus on uncertain and creative tasks, both of which are often required for problem-solving or (strategic) decision-making. For example, AT can provide the doctor with a medical diagnosis, allowing the doctor to focus on considering the patient's unique situation, which AT is not able to process (Longoni et al., 2019). The AT–doctor team may then provide better diagnostic experiences to patients and the presence of AT can enhance the doctor–patient interaction.

In a nutshell, if the AT–worker teamwork operates in a way that can tap into the unique and complementary competences and skill sets of both AT and human workers, the quality of worker–consumer interaction is likely enhanced by the presence of AT. However, AT–worker teamwork may not always enhance the quality of worker–consumer interaction. When human workers perceive AT as their replacement, they are likely to react negatively to AT, become insecure about their own abilities and roles and may fear losing their specific skills (Moulaï et al., 2022; Raisch & Krakowski, 2021; Vomberg et al., 2022). This likely negatively spills over to relationships with consumers. Thus, when introducing AT to work together with workers, organizations should not only provide a collaborative complementary narrative but also offer training so workers can acquire new skills and perform tasks that cannot be carried out by AT in the joint work. Such skills or tasks are typically related to attending to and satisfying the unique socio-emotional needs of consumers.

Importantly, future research should empirically test the key mechanisms outlined above. Translating these mechanisms into propositions (see Table 1), we propose that human workers are more likely to forge stronger relationships with consumers when (a) they are in an AT–worker team where AT's tasks are more routine or analytical and workers' tasks are more relational or creative and (b) they are provided with training to acquire unique skill sets and do not develop fear of AT as their replacements (RP1) (Huang & Rust, 2022). Future research will benefit from delving into specific managerial practices related to these two major contingencies, such as the degree to which work designs consider AT's and workers' unique competencies and skills and the degree to which the organization adapts and provides training to workers to work in AT–worker teams. Such research also needs to account for differences between consumers, where some consumers may have a stronger inherent desire for social interactions, whereas others prefer speed and efficiency.

> **RP1:** Workers are more likely to forge stronger relationships with consumers when (a) in an AT–worker team, AT's tasks are more routine or analytical and workers' tasks are more relational or creative and (b) workers are provided with training to develop unique skill sets and do not develop fear of AT as their replacements.

Table C.1
Overview of interviews.

Interview code	Interviewee role	Type of Robot	Experience with robots (in years)
INT01	Manager	Ella	Less than six months
INT02	Robot operator	Ella	Less than six months
INT03	Cleaner	Intellibot	More than a year
INT04	Manager	Whiz	Less than six months
INT05	Robot operator	Intellibot	More than a year
INT06	Manager	Intellibot	More than a year
INT07	Receptionist	Pepper	More than a year
INT08	Receptionist	Pepper	More than a year
INT09	Robot operator	Whiz	Less than a year
INT10	Robot operator	Whiz	Less than a year
INT11	Manager/waiter	Bellabot	Less than six months
INT12	Waiter	Bellabot	Less than six months
INT13	Waiter	Bellabot	Less than six months
INT14	Waiter	Bellabot	Less than six months
INT15	Host/receptionist	Pepper	More than three years
C01	Customer	Bellabot	N/A
C02	Customer	Pepper	N/A
C03	Customer	Bellabot	N/A
C04	Customer	Pepper	N/A
C05	Customer	Pepper	N/A
C06	Customer	Pepper	N/A
C07	Customer	Pepper	N/A
C08	Customer	Bellabot	N/A
C09	Customer	Pepper	N/A

3.2. *How the presence of AT changes the way consumers relate to workers*

As previous literature shows that a robotic labor force leads to more solidarity among human workers (Jackson et al., 2020), *consumer-facing AT* could lead to more solidarity between human parties, resulting in stronger consumer–worker relationships. Importantly, human intergroup differences, including racial and religious differences, may be less consequential for the way consumers relate to workers because the focus is on what they have in common compared to AT. Furthermore, AT taking over more routine tasks frees up the worker to forge a stronger bond with the consumer, as also noted by an interviewed customer:

> Like, in the old situation, I came to the desk and said “well, I have a meeting with this and that” and the receptionist will look that up on the computer. So, there is not really quality time with the receptionist as well. Now I feel like there is some more time to have a chit-chat with the receptionist.

Yet, building on research showing that pairing a person and an object in an advertisement leads to dehumanization of the person (Herak et al., 2020), the involvement of consumer-facing AT could also lead to dehumanization and objectification of workers. Moreover, anecdotal reports indicate that people’s interaction with AT differs from their interaction with humans—for instance, by being less polite (Baig, 2018; Burton & Gaskin, 2019) or cheating more (Cohn et al. 2022)—leading to worries that this interaction style can spill over to the consumer–worker interaction, particularly for female workers (Puntoni et al., 2021; Robinson et al., 2020). Future research therefore needs to clarify whether *consumer-facing* AT leads to an objectification of the worker and weaker consumer–worker relationships, or in contrast forges stronger bonds between them where human prejudice and discrimination play a smaller role (RP2).

Yet, the opposite is also conceivable. Given that AT and the worker are affiliated with the same organization, the consumer could also get the impression that both parties “conspire” against her, in particular if persuasion attempts are involved. This potential negative effect on the consumer-worker relation could be particularly strong if AT is *worker-facing,* and could be mitigated by making AT more *consumer-facing* and (credibly) introduce it as a neutral entity.

> **RP2:** The presence of *consumer-facing* AT leads to (a) consumers having a stronger relationship with workers because of their shared humanness, or (b) a weaker relationship because the worker is objectified. The consumer may perceive in particular *worker-facing* AT as the worker’s ally, therewith (c) weakening the consumer-worker relationship.

If AT is *worker-facing*, consumers may moreover infer that workers are less competent because they need AT support and have less leeway for decision-making because AT sets the boundaries (Chugunova & Sele, 2022). Consumers might also observe workers failing to master cooperation with AT and note the resulting frustration, which again undermines consumers’ perceptions of worker competence, resulting in weaker consumer-worker bonds.

However, a worker may also exploit in particular worker-facing AT advantageously by using it as a scapegoat when service failures occur. According to balance theory (Heider, 1958), the consumer-worker relationship could be more balanced and therefore stronger with AT as joint enemy, in line with literature that shows that a service failure caused by a robot negatively affects consumers to a lesser extent (Merkle, 2019). Since consumers appreciate human service recovery (Choi et al., 2021), recovery can be a strategy to strengthen consumer–worker relationships.

Table C.2
Coding example.

1st order code	Quote	2nd order code	Aggregate dimension
Customer responses	*“They are testing what the robot does in different situation.”*	Customer experience (How do customers experience quality of services with the robots)	Changes in occupation of hospitality staff in the work with customers
Customer opinions	*“Everyone is curious about how it works, how long they have been here for, what we think about the robots.”*		

Therefore, the potential (dis)advantages of using AT as a scapegoat in the case of a service failure together with human service recovery should be empirically verified (RP3), also considering the limits of such scapegoating. First, consumers may expect workers to intervene instead of blaming dysfunctional AT for failures. Second, AT's ability to perform consistently and reliably (Huang & Rust, 2021) may lead consumers to generalize service failures as "failure of the system." Third, blaming consumer-facing AT when consumers in fact do not have the impression that it created the problem will likely backfire.

RP3: Ways to overcome consumer inferences of lower worker competence when collaborating with AT include (a) using worker-facing AT as a scapegoat when service failures occur, and (b) letting the human worker do the service recovery.

One important contingency factor affecting how consumers relate to workers once AT is involved is the framing of the AT–worker collaboration. Prior research shows that consumers are less loyal to a robot physician leading a human nurse compared to a human physician leading a robot nurse (Shanks et al., 2021), and more accepting of AT when it supports rather than replaces a human worker (Chugunova & Sele, 2022; Longoni et al., 2019; Peng et al., 2022). This finding also resonates with our illustrative evidence that the interviewed customers emphasized that the human is still in the lead:

> The food is being brought to the tables by robots and humans in collaboration. The robot can do some funny things like sing a birthday song and you can pet it since it looks like a cat, but all the verbal communication is still with the waiter.

In sum, consumers seem reluctant to accept either consumer-facing or worker-facing AT in a leadership role, and in particular consumer-facing AT visibly leading a human likely jeopardizes the relationship between the consumer and the worker (RP4).

Moreover, previous research suggests that human leadership is particularly important for hedonic relational services (Huang & Rust, 2021; Wirtz et al., 2018) and tasks that require warmth (Peng et al., 2022). Future research should therefore investigate the trade-offs of putting AT in the lead, where utilitarian transactional service is one area where AT leadership could be beneficial (Huang & Rust, 2021). However, a question persists as to whether the weakening of human relationships is compensated for by the efficiency gains of AT deployment.

RP4: Putting AT in the lead weakens consumers' relationship with workers.

3.3. How the presence of consumers changes the way workers relate to AT

Although research and evidence remain scarce, two theoretical perspectives may shed light on how the physical presence of consumers affects how workers interact with consumer- and worker-facing AT: the (stereotype) expectancy violation theory (Bettencourt et al., 1997; Jussim et al., 1987) and the social presence theory (e.g., He et al., 2012). The default expectation—widely embraced by consumers, workers, organizations, and society—is that humans are always "the boss" or the leader of AT (Tsai et al., 2022). Even in less common scenarios in which AT may be more competent than human workers and give instructions to human workers (e.g., meal delivery workers receiving tasks produced from algorithms, doctors getting diagnoses supplied from algorithms), human workers still have autonomy and can ignore instructions or suggestions provided by AT.

Following the expectancy violation theory, any incidents or scenarios that reinforce the expectation of the default hierarchy will likely cause positive perceptions, experiences, or interactions of human workers with AT. In contrast, any incidents or scenarios that violate the expectation of the default hierarchy will likely lead human workers to negatively relate to AT in the joint work (Bettencourt et al., 1997; Jussim et al., 1987). Prior research implies certain support for this mechanism. For example, co-workers tend to blame robot supervisors for mistakes more often than they blame human supervisors (Gombolay et al., 2015; Hinds et al., 2004). This tendency may be explained by the fact that when mistakes occur, the default inferior in the hierarchy (i.e., robot supervisors) is more likely to be blamed or scapegoated than the default superior (i.e., human supervisors).

Building on previous literature showing that the social presence of others can both enhance positive and degrade negative experiences (Dahl et al., 2001; He et al., 2012), we expect the expectancy-reinforcing and expectancy-violating effects to be further strengthened in the presence of the consumer. For consumer-facing AT, our illustrative evidence from the interviews shows how workers emphasize that they command their robotic "assistants" in front of consumers. For example, in one organization that "employs" Pepper, Interviewee #15 noted:

> Earlier, I just pressed her on/off button, and she started doing her thing by asking people if they wanted to know more about the department. Over time, [Pepper] is capable of much more, like navigating guests and interacting with them. Now, I call Pepper my lovely assistant, and I tell guests that "we" are their hosts and they can reach out to "us" if they have questions… I still decide what happens; she is more or less my sidekick, but I know where her on/off button is placed. So, will she ever replace me fully? No, of course not.

This excerpt shows that even though the interviewee treated Pepper as a teammate and greatly enjoyed working with her to serve consumers, the interviewee was still the one in charge. Interviewee #2 from an organization that "employs" Ella, a social cleaning robot, added:

> You need to figure out how to work with her. Especially in the beginning, you have to be alert to what she is doing and what is most practical. I think it helps if you are eager to learn and interested in technology. Right at the start, I did my research at home and looked her up, and watched instruction movies and such. I feel responsible, so I want to know everything there is to know. Also, when people approach her or interact with her, I always go and watch [to be sure] everything is okay.

This excerpt shows that while treating Ella as a teammate, frontline workers felt responsible for Ella in their joint services to consumers. This reaction shows that if the expectation of the default hierarchy in which humans are superior to AT is met and reinforced, the presence of consumers will likely strengthen the positive perceptions, experiences, or interactions of human workers with AT.

In contrast, when the expected human-superior-to-AT hierarchy is violated, not only will human workers be likely to relate negatively to AT, but such negativity will also likely be worse in the presence rather than the absence of consumers. In other words, we expect that the expectancy-violating effect will be stronger in consumer-facing AT (e.g., waiting tables in restaurants) than in worker-facing AT (e.g., platform-based meal delivery services; Ostrom et al., 2021; Möhlmann et al., 2021). Prior research implicitly hints at this mechanism. For example, employees are hesitant to work with AT because all conversations and situations may be recorded and used against them later (e.g., when giving wrong advice to a customer; Paluch et al., 2021). This response may be explained by the fact that the default human-superior-to-AT hierarchy is violated and AT is allowed to play a leader's role in monitoring employees' work behaviors and therefore is able to exert coercive power over human workers.

In addition, we also expect the expectancy-reinforcing and expectancy-violating effects to be stronger for robotic AT than for virtual or embedded AT. This is because as far as (cognitive) trust is concerned, physical appearance increases human trust in AT (Glikson & Woolley, 2020). This is also aligned with social identity theory that humans are more identified with similar others (i.e., robotic AT) than dissimilar ones (i.e., virtual or embedded AT). This means that human workers may feel more ready to accept robotic AT as superior than virtual or embedded

AT, given that the former's greater physical resemblance to humans; this also means that on the flip side, they are less upset when feeling inferior to robotic AT than to virtual or embedded AT, given that "losing" to more human-like AT is more emotionally acceptable that to (total) machines.

Future research could empirically test the expectancy-reinforcing and expectancy-violating mechanisms we suggest above. Summarizing and framing these mechanisms into propositions, we propose that human workers are more likely to have positive interactions or relations with AT when the human superiority to AT or AT inferiority to human workers is reinforced (RP5) and vice versa. We also expect such effects to be enhanced in the presence of consumers, and by the extent to which AT is consumer-facing (RP6).

RP5: Human workers relate more positively to AT when human superiority to AT is reinforced, and conversely more negatively to AT when human superiority to AT is violated.

RP6: Positive and negative effects are enhanced (a) in the presence of the consumer and (b) by the extent to which AT is consumer-facing. (c) Positive effects are enhanced and negative effects weakened for robotic AT compared with virtual or embedded AT.

3.4. How the presence of workers changes the way consumers relate to AT

In situations where consumers react negatively to AT, for instance because of "algorithm aversion" (e.g., Longoni et al., 2019), teaming up AT with a human worker could increase consumers' acceptance of AT by compensating for its shortcomings. A quote from our interviews suggests that interaction with AT in the presence of a human is more desirable than interaction with AT only:

> I think my experience would not be just okay if I did only interact with the robot. Now, I would say, because of the combination of human and robot, that the interaction was valuable for me.

However, a greater understanding is needed for the underlying mechanisms for this effect. A well-documented key barrier to adopting AT is consumers' perception of loss of control over the AT service outcome (De Bellis & Johar, 2020). The presence of human workers could, for instance, simply distract consumers from the loss of control, create an illusion of control over the outcome owing to their mere presence, or actually provide higher control by reacting to consumer requests and influencing the AT.

Another important issue relates to the consumer input data that AT-based systems require (Puntoni et al., 2021), which consumers who are increasingly concerned about their privacy may be less willing to disclose (e.g., Davenport et al., 2020; Guha et al., 2021; Park et al., 2021). However, as of now, research has not investigated how the presence of human workers influences consumers' privacy concerns. Human workers could, again, simply distract consumers from their privacy concerns, or human contact partners could increase consumers' data security perceptions since consumers then have someone whom they believe to be accountable.

While the presence of the human worker may for these reasons improve the relationship between consumers and AT, a long-term dark side is possible in that the consumer may be inclined to rely less on AT and turn to the human worker instead. This is in particular likely if the worker was first removed from the interaction when AT was introduced, and subsequently is reintroduced to smooth the adoption of AT. The type of AT may be an important contingency here (RP7). Trust in robotic AT has been found to increase over time (Glikson & Woolley, 2020), yet the presence of the worker could actually interrupt this buildup of trust. For virtual and embedded AT where trust tends to decline over time though, the presence of the worker could help mitigate this decline. Future research should investigate the optimal adoption path, and its contingencies, in AT–worker collaborations.

RP7: The presence of the worker makes consumers (a) relate more easily to consumer-facing AT in the short term, yet (b) rely less on consumer-facing AT in the long term. The type of AT (robotic, virtual, embedded) is an important contingency factor for the adoption path.

The presence of the worker may also affect the relevance of AT's level of anthropomorphism for its relationship with the consumer. Despite the fact that some research has shown anthropomorphism to elicit negative reactions owing to the uncanny valley effect (Mori et al., 2012), other research shows that anthropomorphism leads to higher levels of trust among consumers, which also increases their intention to use (van Pinxteren et al., 2019). A recent *meta*-analysis (Blut et al., 2021) shows that consumers' anthropomorphism of robots overall exerts strong positive effects on consumers' intentions to use robots. However, interactions that are worse than expected may be viewed more negatively as well, given that anthropomorphism also increases expectations regarding an AT agent's performance (Crolic et al., 2022; Garvey et al., 2023). Importantly, all of these prior studies focus on AT in isolation.

When paired with a human worker, AT could appear more "machinized" owing to contrast effects, weakening the assumed positive effect of its level of anthropomorphism. Alternatively, the social presence of a human worker could simply distract consumers from the AT or make consumers turn to the human worker for an emotional connection (van Doorn et al., 2017), which could also weaken effects of the anthropomorphism of AT on the consumer–AT relation. Therefore. anthropomorphism conceivably may not play a major role at all if AT teams up with a human worker (RP8).

RP8: The presence of the worker reduces the impact of anthropomorphism on how consumers relate to consumer-facing AT.

4. Conclusions

Success or failure of AT implementation in organizations depends critically on the human factor. In the digital age, organizational frontlines involve complex interactions between consumers, AT, and frontline workers that are not covered in previous literature, which largely examines dyadic consumer–AT *or* worker–AT interactions in isolation. The complex interactions between consumers, workers, and AT need to be studied simultaneously to do justice to the complex and rich social context of the organizational frontline (Lu et al., 2020; Ostrom et al., 2021). Bridging the fields of marketing and organizational behavior, we develop the Consumer–Autonomous Technology–Worker (CAW) framework to study the implications of such complex interactions. We consider that AT can be consumer-facing, such as service robots employed in the organizational frontline, or worker-facing, such as AT-enabled knowledge-based systems supporting a worker's decision-making.

Building on previous literature, we develop research propositions that highlight avenues in the CAW framework for future research. We supplement our theorizing with illustrative interviews in hospitality contexts with workers co-working with robots and with the consumers that are served. We show that integrating AT into organizational frontlines will profoundly change the relationships between the actors, and that these changes are contingent on a series of factors. A first critical factor is the division of labor between AT and worker, where we expect consumer–worker relationships to strengthen when AT augments instead of replaces the worker (Tsai et al., 2022; Vomberg et al., 2022).

Second, the holding of the leadership role by the worker is critical for several reasons. Workers are more accepting of AT when they "call the shots," reinforcing the expectation of AT in a serving role (Bettencourt et al., 1997; Tsai et al., 2022). In line with social presence theory (He et al., 2012), such human leadership is particularly important when consumer-facing AT makes the hierarchy visible in front of a consumer. Likewise, consumers likely relate less strongly to a worker commanded by AT.

Third, whether the AT forges stronger or weaker consumer–worker relationships remains unclear. On the one hand, AT involvement could lead to stronger relationships where human intergroup differences based on, for example race and religion, matter less (Jackson et al., 2020). On the other hand, interhuman relationships can be weakened because the worker is dehumanized (Herak et al., 2020). This is therefore an important area for future inquiry, where research should also identify contingencies that potentially influence this effect.

Fourth, while researchers have begun to study how the integration of AT affects service failure and recovery (Choi et al., 2021), insights into how AT can be effectively leveraged to strengthen consumer–worker relations when mistakes occur in the organizational frontline are very much needed. Is AT a suitable scapegoat, or does scapegoating AT backfire on the worker?

Fifth, although AT anthropomorphism has been studied extensively in previous literature as a predictor of AT acceptance (Blut et al., 2021), we predict that the presence of a human worker greatly reduces its significance.

5. Limitations

We acknowledge numerous limitations. First, we consider a situation involving one consumer, one worker, and one AT, so we do not consider group decisions. Second, our interviews document predominantly positive responses to robots as embodied AT, which can be due to the relatively short time frame of implementation - usually less than one or two years – and that the robots take over menial tasks like carrying plates or administration. In other applications, responses are potentially more mixed or negative.

Third, we assume that although AT is deployed mainly by companies, it can also be deployed by consumers, leading to two ATs involved in the organizational frontline interaction (Hogreve et al., 2022). Fourth, we did not include organizations as a fourth important player, although AT–human collaboration can have a profound impact on organizations. Examples include the impact of AT involvement on corporate culture and human capital, given that workers unlearn skills, as well as issues around the sharing of (tacit) knowledge both between workers and over time (Raisch & Krakowski, 2021). Fifth, we do not consider stakeholders outside the company—for example suppliers, NGOs, government, competitors, and policy makers. Nonetheless, our CAW framework is an important first step in exploring the complex configuration between workers, AT, and consumers in the organizational frontlines in the digital age.

CRediT authorship contribution statement

Jenny van Doorn: Writing – review & editing, Writing – original draft, Conceptualization. **Edin Smailhodzic:** Writing – review & editing, Writing – original draft, Methodology, Data curation, Conceptualization. **Stefano Puntoni:** Writing – review & editing, Writing – original draft, Conceptualization. **Jia Li:** Writing – review & editing, Writing – original draft, Conceptualization. **Jan Hendrik Schumann:** Writing – review & editing, Writing – original draft, Conceptualization. **Jana Holthöwer:** Writing – review & editing, Writing – original draft, Conceptualization.

Declaration of Competing Interest

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

Data availability

No data was used for the research described in the article.

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Appendix A. Interview protocol

Employees:

1. How long do you work in this function at the firm, since when are you cooperating with a robot in the provision of services, what kind of robot is it, since when does the organization use robots, and what for?
2. Can you describe the robot you are currently working with?
3. How would you describe the collaboration between you and the robot?
4. What tasks are executed by the robot that you previously conducted?
5. What additional/new tasks are you executing since the implementation of the robot? What is your opinion regarding these other/new tasks?
6. How does the robot impact your typical workday compared to the previous situation without a robot?
7. How does working with the robot affect your tasks?
8. What additional skills did you need to learn to collaborate with the robot?
9. How has the robot changed the way you interact with your customers?
10. How has the robot changed how the customers interact with you?
11. How does working with the robot change how customers perceive you?

Customers:

1. Gender/age
2. How often and for how long do you use the services of this firm?
3. How many times have you experienced being served by robots and employees together?
4. How do you experience the interaction with the team of human and robot employees?
5. How do you experience satisfaction with the service involving robots in comparison with the service delivered only by a human employee?
6. How does the interaction with the team of human and robot employees affect the service in terms of efficiency/convenience?
7. How different is the service now compared to when you used it without a robot?
8. How does the robot change the way you interact and perceive this organization and its employees?
9. What is the best/worst thing about having a robot involved in the provisions of services?
10. Is there anything I missed that you would like to mention about how joint service by robot and employee together changed your perception of the employees/organization/interactions?

Appendix B. Robots "Whizz" and "Bellabot"

See Fig B.1 and Fig B.2.

Appendix C. Interview procedure

To provide illustrative quotes, we conducted 15 interviews with the frontline service employees who had direct interaction with the customers (see Table C.1). In addition, we interviewed 9 customers who interacted with employees and robots. The selection of interviewees was based on several criteria, namely they had to work in the hospitality service, collaborate with robots in their daily work, and also interact with customers while working with the robots. In particular, their experience is from working at the reception, serving food and drinks, and cleaning services. We selected the customers who had an experience of being served without and with robots. Duration of the interviews ranged from 5 to 30 min.

To analyze data from interviews, we relied on thematic analysis. In particular, we got familiar with the data, coded the data, discovered themes and relationships. In particular, we relied on Gioia approach in our data analysis (Gioia et al., 2012). In doing so, we went through the first order codes, second order codes and aggregate dimensions. In the Table C.2, we provide an example of our coding.

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