Memory-based contextual awareness supporting intelligent action planning for a mobile unmanned system in industrial setting (PROMEN-AID) (D3.18 - SGA3)

Figure 1: Demonstrator in realistic environment

Naïve worker presence in the environment (left), KAIROS robot with cognitive implementation of working memory model (bottom right).

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Description in GA:	This demonstrator entails a simulation model, publically accessible on EBRAINS, which illustrates efficacy of the developed functional cognitive architecture in supporting the desired behaviour for the system, relying on a physics simulation. It also includes implementation of relevant technological bricks on a real-world system, demonstrated in an industrially relevant environment.
Abstract:	Deliverable D3.18 entails a solution to enable a smooth co-existence between robots and human workers in an industrial setting mediated by the implementation of cognitive model of working memory. We implemented two robot working memory configurations onto a mobile manipulator RB-KAIROS+ robot (Robotnik): A GRU-based one and a bioinspired alternative called WorkMATe, which enabled the robot to adapt its navigation strategy depending on the presence of human workers. To evaluate the two working memory configurations against a non-adaptive behaviour, we tested a possible coworking scenario between two ostensible workers and the RBKAIROS+ robot navigating in two mocked industrial set-ups. The application of behavioural adaptation through a working memory component was highly beneficial as it led to reduced energy consumption and, more importantly, to fewer acceleration anomalies in robot navigation than the non-adaptive one. This suggests that a robot's adaptive navigation through working memory can increase workers' safety and improve the efficiency of the human-robot system as a whole in industrial applications.

Keywords:	Functional neural models, functional architectures, embodiment, simulation, robotics, real-world systems, real-time systems, automation and control, neuromorphic computing.
Target Users/Readers:	Robotics community, automation, control and AI community, computational neuroscientists, cognitive neuroscientists.

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History of Changes made to this Deliverable (post Submission)

Date	Change Requested / Change Made / Other Action
9 OCT 2023	Deliverable submitted to EC
	Resubmission with specified changes requested in Review Report Main changes requested: 1. This work is interesting from the practical (even industrial) viewpoint, but the neuroscience inspiration and synergy with the unique strengths and objectives of HBP are doubtful. This point must be clarified in the revised version of the deliverable. 2. Additionally, the aim from the GA was to provide a publicly accessible simulation model on EBRAINS and from the document it is not clear whether this has been achieved or not. This must be done in the revised text, by providing a clear link to EBRAINS.
	Revised draft sent by WP to PCO. Main changes made, with indication where each change was made: The deliverable was extended to include 1. A Section detailing the links of results obtained to specific objectives of the HBP, in particular making explicit the direct connection from work in cognitive neuroscience, emerging from T3.7, to the developed technology, 2. An additional paragraph in the section discussing the relationship of the work to EBRAINS.
	Revised version resubmitted to EC by PCO via SyGMa

1. Context

The work conducted within Work Package 3 (WP3) is structured around PROMEN-AID integrative demonstrator, which motivates contributions from and active collaboration of most tasks (and corresponding areas of expertise) in the WP. These demonstrators address a range of functions involving the working memory, progressing towards cognitive skills, including planning and decision-making that leverage on the use of working memory. They operate at different levels of description and biological plausibility, from standard and popular neural networks (e.g. GRU) to more complex and innovative neural networks (e.g. Workmate). These demonstrators implement a functional modular approach, helping prototype a supporting modular cognitive framework, in close collaboration with EBRAINS Service Categories (SCs).

1.1 Outline of the Showcase Demonstrator: Sensorimotor adaptation based on cognitive-inspired model of working memory

Amongst various contexts, robots became an integral part of industrial working processes. Unlike ordinary industrial tools, however, robots are supposed to perform their given tasks autonomously in a shared environment with human workers. Therefore, developments in human-robot interaction (HRI) are increasingly driven by the idea of human-robot co-existence and collaboration. To enable smooth human-robot co-working, two perspectives need to be regarded. On the one hand, some technological requirements need to be met: Robots should be capable of localising themselves with respect to their surroundings. To ensure a comfortable and safe HRI, robots need to adapt to the dynamics of a shared environment, which are determined by humans' activities, intentions, and needs. On the other hand, the humans' perspective needs to be taken into consideration: Robots should meet potential users' expectations and needs to evoke positive perceptions.

Robot working memory architectures were found to be useful to achieve the technological requirements for an efficient and safe human-robot co-existence because they enable autonomous and environmental aware robot actions (see, e.g., Reich et al. (2020); Joo et al. (2019); Jung et al. (2019)). Similar to human working memory (see Baddeley (2000, 2010)), robot working memory architectures enable a robot to store, organise, and process data. Using robot working memory architectures, a robot is supposed to 'learn' based on prior experiences, that is, to 'decide' what information to use in order to improve future behaviour according to the dynamics of shared environments. One state-of-the-art working memory architecture that is commonly used in machine learning is GRU (Gated Recurrent Unit, Cho et al. (2014)). GRU is a sort of recurrent neural network architecture (RNN) that is often used to process data sequences, such as language input (see Cho et al. (2014)). Learning is enabled by iterative adjustments of internal parameters (see Cho et al. (2014)). However, current state-of-the-art architectures were limited in controlling and prioritising stored information as required to solve more complex tasks. Kruijne and colleagues thus proposed WorkMATe (Working Memory Architecture for Task Execution), a biologically inspired working memory architecture whose key components include a gated memory circuit driven by internal actions.

More precisely, training occurs in a biologically inspired manner based on attentional feedback and reward prediction errors. That is, the system optimises its behaviour based on reward feedback similar to biological dopamine-based processes that enable animals and humans to learn and adapt their behaviour (see Glimcher (2011); Wang et al. (2018)). WorkMATe enables to store and process multiple inputs separately and to update and transfer trained adaptations to new contexts and stimuli. All this makes Workmate well suitable for complex memory tasks and allows for flexible and task-oriented memory control. Allowing for flexible and task-oriented robot behaviour, working memory architectures were found to make robot navigation smooth and efficient (see Li et al. (2022); Reich et al. (2020)). Investigating robot memory, however, mainly the technological perspective was taken into consideration. Implementation processes and technological benefits such as behavioural adaptations when sensing humans and objects (e.g., leaving space, slowing down, and stopping) were assumed to make robot navigation safer and more predictable for humans (see Li et al. (2022)).

However, so far, it was not questioned how humans in fact perceive a robot equipped with memory functions. In the first place, robots are meant to facilitate humans' lives in various contexts. As such, the human perspective should be taken into the focus of present HRI research. Humans' prior experience, attitudes, and perceptions have been shown to strongly affect people's willingness to use robots and their evaluations of HRI (Bernotat and Eyssel (2017b); Bernotat et al. (2017); Bernotat and Eyssel (2018); Bernotat et al. (2021); Meyer zu Borgsen et al. (2017); Schiffhauer et al. (2016)). A vast body of research thus calls to involve potential users' perceptions and preferences already in the research and development processes of new technologies to create positive user experiences (e.g., Ben Allouch et al. (2009); Bernotat and Eyssel (2017a); Diehl et al. (2017); Lacroix et al. (2023); Mahmood et al. (2000); Robinson et al. (2020); Schiffhauer et al. (2016)).

Despite these calls for more user-centred approaches, the human perspective has not yet gained much attention in prior research and implementation processes of robot working memory. To close this research gap, we put the human perspective into focus during the implementation and training of two working memory configurations on an industrial RB-KAIROS+ robot (Robotnik (Valencia, Spain)): One working memory architecture was based on GRU (Cho et al. (2014)) and the other was based on WorkMATe, the biologically-inspired alternative. Following a human-centred approach, we considered potential users' ideas and perceptions of a comfortable and efficient human-robot co-existence right from the beginning of the implementation and training processes. More precisely, we conducted two online user studies.

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2. Working Memory Demonstration in realistic scenario

In the following sections, we summarise the developments conducted in PROMEN-AID. The project focuses on sensorimotor adaptation based on working memory and describes the different demonstrations of a cognitive framework with incremental TRL starting from a discussion of the different scientific and technical issues encountered. Further, in the following sections we describe how these issues were addressed, and we articulate the relation between the work presented and ongoing development of EBRAINS, in particular as pertains to the use of working memory in artificial robotic agents.

2.1 Scientific and Technological Background

Automatic machines and robots traditionally supported human activities, especially in the industry field. The recently increased diffusion of robots in our everyday life is bolstering the effort to create robots able to cooperate with humans rather than being mere tools. Indeed, the upcoming Industry 5.0 revolution [1] describes robots as co-workers, not only in stationary work cells (e.g., a robotic arm handing over objects to a human worker), but also freely navigating around the workspace (e.g., a rover robot delivering objects from storage to an assembling area). The latter scenario poses great concerns on how to guarantee workers' safety, requiring robots to be constantly human-aware. Robot human awareness for safety has been defined based on three pillars [2]:

- Comfort: the robot's behaviour should be safe (i.e., avoid harming others) and perceived as safe;
- Naturalness (or Legibility): the robot's behaviour and decisions should be easy to predict;
- Socialness: the robot should respect the social rules of the context in which it is employed (e.g., the social norm of staying to the right when passing by others).

Several solutions have been developed to equip navigating robots with human awareness. The traditional approach relies on the Proxemics theory from Hall [3], i.e., the definition of personal space that others (both agents and objects) should not invade to preserve one's comfort. In those solutions, humans are usually treated as moving obstacles, and represented as a 2D-Gaussian high-cost region in the cost map (i.e., the mapping between physical locations and the difficulty for the robot of traversing them) of the robot's local planner. Several contributions applied the proxemics principle both in simulations [4]–[6], and in on-the-field studies [4], [5], [7]–[12]; however, this approach could not always be feasible. If the workspace is dynamic and/or crowded with workers continuously wandering around (e.g., in an intra-factory logistics scenario), it could be difficult to maintain an updated, reliable cost map. The result would be the well known "freezing robot problem" [13], or an erratic plan, competing with the naturalness principle of human awareness. We speculate that, rather than keeping track of every dynamic obstacle affecting the robot's plan, it would be better to adapt its behaviour with simple rules that would allow a smooth, comfortable and natural interaction, along with a lower computational load. Moreover, human detection is usually performed with absolute systems, either based on vision [4], [7], [12], [14] or other sensors workers are asked to wear [8]. Such methods could either not be feasible because they imply the modification of the workspace or could be in contrast to other workers' safety equipment. When achieving human awareness through robots' egocentric perception (usually a combination of vision and other sensors, like LIDARs) [5], [9]–[11], [15], novel challenges arise like how long to retain the detected humans' presence; or how to deal with noisy, scarce, or missing perception. Not considering such issues could result in a mostly reactive adaptation, with the robot taking care of humans only when they are detectable, without considering their point of view. In similar scenarios, humans usually rely on working memory, i.e., the amount of information that can be held - usually for approximately 15 seconds [16], [17] - in mind and used in the execution of cognitive tasks [18]. Humans take advantage of working memory when interacting with each other [19], especially in dynamic [20] and cognitive-demanding [21] collaborative tasks. In the autonomous navigation field, working memory has been used to keep track of static objects in sonar-based perception [22] or to retain the personal space of static humans [23]. In addition, Samsani et al. [24] studied a working-memory-based architecture for robot navigation in crowded, dynamic spaces; however, in simulations only.

2.2 Specifications of the Demonstration

As the industry is moving towards automation but mastering precious adaptation capabilities typical of human workers is still very difficult for artificial agents. On the other hand, home automation is also increasingly using robotic platforms to fulfill automation tasks. These activities need to enable safe human-machine interaction in robotics settings. Human-robot collaborative (HRC) spaces and in general collaborative robots (cobots) require specific expertise, knowledge and management skills from the workers in both manufacturing environments and casual scenarios [42]. The incorporation of technology (e.g. robots, machines, and digitalisation) may enhance task performance, productivity and consistency of results, but may also induce stress, mental fatigue or lack of engagement in the activities. Further, the workers are hardly accustomed to collaborations with a robotic partner and this makes the situation even more problematic. The successful interaction between humans and machines—particularly robots—will depend and builds on whether and how human acceptance and trust in robots is engaged with the users [43].

The Proactive Memory iN AI for Development (PROMEN-AID) is part of the Human Brain Project (HBP) Specific Grant Agreement 3. The HBP SGA3 (PROMEN-AID) project tries to address this context by introducing cognitive-inspired functional architecture of short-term and long-term memory. The architecture enables safe human-machine interaction in robotics settings (cobots) thanks to innovative implementation of cognitive model of working memory. Furthermore, PROMENAID provides the opportunity to test and showcase robotic platform implementations with specific capabilities to perceive the environment and relating it with previous experiences. The understanding of the environment in relation to the memory of previous experience endows the robotic platform with the capability of contextualising the situation. This improves the interaction and coordination of robots with human partners in the environment and fosters a more versatile performance of artificial robotic agents by enhancing the adaptation of the agent in the context of other human partners (e.g., movement restrictions in the shop floor delimited routes or areas). The main advantage is that the robotic platform not only adapts to the interactive context where it operates but it improves the awareness of the operating context where naïve human individual move. The awareness or contextualisation interestingly leverages on persistent sensorial persistence and on previous robot first-hand experiences giving the robot the opportunity to continuously grow its knowledge about the social environment. The model used in PROMEND-AID includes such functions in the cognitive architecture that allows the robotic platform to adapt to the human partner, in regards to their common experience. The advantage is that the artificial intelligence provided with this cognitive inspired solution continuously improves its knowledge along with successive experiences and it is not limited to a static AI implementation, which is typical of numerous applications in industrial markets.

Considering that, Industry 4.0 contributes to environmental and social sustainability in terms of the lower environmental impact of production, as well as reduction of physical demand on the workers not mentioning an increase in the flexibility of work organisation. The digitisation of the manufacturing process also with cognitive computational models of intelligence can have deep social implications as it alters inter- and intra-organisational relationships. Manufacturers should take responsibility for their digitisation process and steer it in a direction that simultaneously safeguards economic, social, and environmental sustainability [42].

Specifically, PROMENAID delivers a cognitive-based dedicated tool useful for companies to maintain high manufacturing performance and improve the technology acceptance of robotic solutions in manufacturing shop floors.

2.3 Relation to EBRAINS

The work involved relies on the HBP's Research Infrastructure and actively contributes to its co-design. In particular, it directly builds upon the implementation of working memory Workmate developed within the HBP project to support multisensory integration in robotics platform that efficiently sense and act in the environment. The specific framework developed to support three demonstrators with increasing level of technology readiness to facilitate integration for stakeholders and interested companies. It was designed in collaboration between the technical engineering and scientific coordination task (Task 3.4), with expertise on development of functional cognitive architectures. Further, the work conducted contributes to defining requirements in terms of required tools and services to exploitation of HBP technologies to other stakeholders and companies.

This is in particular the case for aspects related to how working memory can improve the effectiveness of robotic agents that interact in realistic environment. The three demonstrators provide a meaningful number of distinct evidences of the benefit of such approach, helping establish interest in stakeholder on what is useful for the robotic platform to support autonomous intelligent behaviours. This work is enabling for the robotic platforms innovative and ready-to-use implementations of working memory. This allows for use of sensorial stabilisation that provides smoother motor behaviours for real-time interaction (also with human partners) in real-world visual processing. Relevance of this work extends beyond the traditional robotic automatic ground vehicle (AGV) solutions since the sensorimotor loop is generalised and also other action-perception loops in robots can be improved. It is of our interest in PROMEN-AID to provide attractive alternatives for stakeholders and companies to currently use our cognitive-based solution in any robotic platform.

Other prospective applications include unmanned vehicles (drones), industrial robotic actuators but also driving automation. This development provides EBRAINS a unique capability contributing to its unique value proposition. Finally, the work conducted contributes to the development of closed-loop demonstrators showcasing the type of research made possible by combining cognitive models of working memory with embodiment agents and robotic platforms, which corresponds to the specific value proposition of the EBRAINS framework. As such, the work performed will expand the portfolio of content available for the EBRAINS framework. We will investigate, in the near term, the opportunity of hosting and making discoverable such models to other stakeholders and companies.

Specific links to EBRAINS: The central ambition of the work presented, as described in the GA, entails the "development of demonstrator(s) for brain-based technology targeting industrial needs. This(-ese) demonstrator(s) will contribute to developing technological maturity of algorithmic solutions investigated in the WP, applying them to help solve practical problems, the specifications of which are defined in collaboration with industrial partners or stakeholders." This ambition was fulfilled, beyond the initial expectations set by the core HBP partners (see discussion in 2.4 on the relation of this work to HBP objectives). The additional ambition of making models available on EBRAINS was targeted in partnership with collaborators from the Infrastructure Work Packages. The simulation demonstrator developed has been made directly available (see Section 2.6). More specifically, the work performed is conducted in collaboration with embodiment (T3.4) and technical integration activities (T3.10) in the work Package (WP3), affording direct support to achievement of objectives of Service Category 4 (**SC4**) Closed loop AI and robotics workflows: design, test and implement robotic and AI solutions (form WP5). Specifically, all models developed (including functional cognitive models, integrated functional architectures, digital simulation models), used tools and workflows (e.g. digital simulation technology), where transparently shared with SC4 under coordination from T3.10. In particular, access afforded to tools and workflows were of direct relevance to developments in T5.8 (and, to a lesser extent, T5.9), whereas models made available were of support to T5.10. Note in addition that, inclusion of the presented activities in the work plan directly emerged from measures taken in pursuit of project Impact 4 (Expected Impact on Industry), in particular from one of several "dedicated Open Calls" intended to "support and boost user-driven RTD activities" (see discussion in the SGA). These measures were explicitly designed to reinforce relevance of the Research Infrastructure (RI) to industry, results of these measures, as described in the present document are of direct support to the design and development of EBRAINS.

2.4 Links of results obtained to specific objectives of the HBP

The work presented productively connects academic research in cognitive neuroscience (on working memory, results from T3.7) with specific industrial applications in robotics, supporting development of EBRAINS by providing concrete examples of brain-based innovation in ICT, demonstrating the types of tools, models, and services useful in connecting academic investigations in neuroscience with industry-driven RTD, and providing examples of models and demonstrators of value in populating provided services (in particular, SC4). This work directly addresses Project Objective 1 (**PO1**): "Establish a sustainable European scientific research infrastructure, EBRAINS, leading to an increased use and adoption of… model building, simulation, … and virtual experiments for… brain-inspired sciences" in that it demonstrates the manner in which SC4 may support model building, simulation, and virtual experiments for brain-inspired ICT research. This work is also in direct support of **PO5** "Enhance real-world task performance through… cognitive architectures running on… the Neurorobotics Platform," providing simulation models demonstrating the use of HBP-developed, brain-based, context awareness technology for smart unmanned systems. It similarly addresses Work Package Objective 3.1 (**WPO3.1**).

Furthermore, the collaborations that have supported the presented work were of direct support to the emergence of project Outcome 1 (**OC1**), with in particular efforts expanded on the development of artificial cognition technology, in the form of context awareness for the artificial agent, which contributed to informing developments in EBRAINS of "research tools, allowing constantly updated knowledge on… brain-inspired AI to be quickly shared across Europe, leading to a considerable increase in… research on advanced AI produced by the communities." More centrally, activities were included in the work plan to support emergence of **OC5** and **OC9**. Specifically, developments helped inform developments in SC4 intended to support "roboticists… for the development of controllers," so that "as a result, they will be able to deliver new… special purpose robots" (OC5). The context-aware architecture developed was made possible by a number of "closed-loop functions based on insights into human cognition," and tools developed in the process are effectively allowing industry (i.e. the industrial partner in PROMED-AID, Robotnik, P146-ROB), by project's end, to "develop advanced prototypes for industrial robots," including in particular models of "advanced autonomous systems."

The collaborations established are of significant relevance to expected project Impact 3 (**IMP3**: Impact on Technological Development), as they provide a working blueprint for the "emergence of a rich ecosystem of academic and industrial research, which will explore and, ultimately, commercialise completely novel applications." The process followed in achieving the presented results also supports realization of Impact 4 (IMP4: Impact on Technology), providing a working example for EBRAINS to follow on tools and services to "support technical developments in areas of clear industrial relevance," and in particular research and development work targeting technology supporting productive coexistence of human workers and mobile robotic systems, thus directly addressing "the development of collaborative robots on the factory floor." As a result of the efforts in PROMEN-AID, "Small- and medium-sized innovative companies" (such as Robotnik) "that strive to develop new products based on the understanding of information processing in the human brain" (such as pertaining to context awareness) may in the future "find the EBRAINS service offering uniquely adapted to their R&D needs" as a result of the pioneering work conducted in this direction, during SGA3, in active collaboration across the PROMEN-AID partners, contributors in T3.4 and T3.10, and SC4 developers in WP5.

2.5 Links to peer reviewed publications

The work described in the present document has led to the following peer reviewed publications,

Estefanía Estevez-Priego, Nikolaos Liappas, María Eugenia Beltrán Jausauras, Giuseppe Fico, Maria F. Cabrera-Umpiérrez and María T. Arredondo Waldmeyer. "Exploiting a human-robot interaction framework using adaptive and proactive memory systems." in Proc. 2023 IEEE 19th International Conference on Body Sensor Networks (BSN), 2023.

L. Landolfi, D. Pasquali, A. Nardelli, J. Bernotat and F. Rea, "Working Memory-Based Architecture for Human-Aware Navigation in Industrial Settings," 2023 32nd IEEE International Conference on Robot and Human Interactive Communication (RO-MAN), Busan, Korea, Republic of, 2023, pp. 1878-1885, DOI: 10.1109/RO-MAN57019.2023.10309344

J. Bernotat, L. Landolfi, D. Pasquali, F. Rea, "Remember Me -User-Centered Implementation of Working Memory Architectures on an Industrial Robot" Frontiers in Robotics and AI, 10 (2023), DOI: 10.3389/frobt.2023.1257690

Nardelli, D. Pasquali, L. Landolfi, J. Bernotat, F. Rea, "Application of Working Memory Adapted Navigation for Human Robot Interaction in an Industrial Context." In Proc. of the 7th HBP Conference on Interdisciplinary Brain Research, Rey Juan Carlos University, Madrid, Spain, 2022.

2.6 How to access the demonstrator

The simulation demonstrator (including all relevant models) can be downloaded from GIT from the following location, https://gitlab.iit.it/cognitiveInteraction/PROMENAID.git

A short video descriptive of the status of the different demonstrators can be found in the video section of the aforementioned GIT repository. In particular, for the experiment in IIT the reference video demonstrate the behaviour of the robot in three conditions with GRU network, with no-memory, and with Workmate, respectively in the following files: IIT_EXP_GRU_LEGO_cut.mp4, IIT_EXP_No_memory_LEGO.mp4, and IIT_EXP_WorkMate_LEGO_cut.mp4. For the experiment in ROB, the video files show the main results in ROB_EXP_Promen_AID_pilot.mp4. The other videos support the main video showing some details of the same experimental trial such as ROS signals (ROB_EXP_ROS_signals,mp4) the robot`s view (ROB_EXP_camera_frontal.mp4), the behaviour of the robot from external camera (ROB_EXP_externalCameraVideo.mp4) and from mobile camera (ROB_EXP_KairosInRob.mp4)

3. Demonstrator Description

In the following, we discuss the different demonstrators that we provided within the PROMEN-AID project. We distinguish between the preliminary demonstrators in laboratory (IIT), the demonstrator in relevant environment (UPM) and the demonstrator in realistic environment (ROB) specific contributions to the showcase demonstrator, which define specifications for the M42 showcase, and activities that extend beyond the scope of the demonstrator, including collaborations emerging from the work conducted.

3.1 Showcase in Lab IIT

The major aim of User Study 1 was to investigate participants' judgements of the RB-KAIROS+ robot's appearance, movements, and perceived memory functions when presented in its initial state, i.e., with no working memory configuration implemented. Following prior research (Bernotat and Eyssel (2017b); Bernotat et al. (2017); Bernotat and Eyssel (2018); Bernotat et al. (2021); Meyer zu Borgsen et al. (2017); Schiffhauer et al. (2016)), we controlled for the effects of participants' attitudes toward robots, social desirability, situational motivation to participate in the study, experience with technology and robots, and demographics on participants' evaluations of the robot. To potentially inspire further developments toward efficient and positively perceived robot navigation, the secondary aim of User Study 1 was to explore participants' ideas of robot memory in general and what aspects of the robot's movements participants found positive and what aspects they would change. User Study 2 served to evaluate the RB-KAIROS+ robot's appearance, movements, and perceived memory functions after the implementation and training of GRU and WorkMATe compared to no working memory in a between-subjects study. Analogous to User Study 1, the effects of participants' attitudes, experience levels, social desirability, motivation to take part in the study, and demographics were controlled for. Both, User Study 1 and User Study 2 were conducted online to reach large and heterogeneous samples in Germany and Italy (in User Study 1, furthermore an English-speaking sample was recruited by sharing the link in Great Britain and Australia.

3.1.1 Research Aims

Compare the behaviour of the KAIROS robot using two different implementations of working memory configuration versus the absence of working memory models: WorkMate (developed within the HBP), vs. GRU (more traditional implementation) vs. no memory. The comparison is studied online in User Study 1 and User Study 2 and in a laboratory environment.

Besides a technological evaluation of the GRU and WorkMATe (vs. no working memory) implementations (see section on lab study at IIT), two online user studies were performed which investigated on participants' evaluation of the robot in terms of

- robot appearance
- robot movements
- perceived robot memory functions

At the same time, the effects of participants' positive and negative attitudes toward robots, social desirability, situational motivation to participate in the study, experience with technology and robots in general, with the RB-KAIROS robot, and demographics were controlled for. This allowed us to investigate psychological factors that affected participants' perceptions of the robot.

In addition, in the online User Study 1, we furthermore enquired participants' ideas of robot memory and aspects they liked about the robot's behavior and aspects they would change. This ought to facilitate future developments of a comfortable memory-based robot navigation.

3.1.2 Procedure Online Study 1 and Online Study 2

Online User Study 1 and User Study 2 were conducted via SurveyMonkey and SoSciSurvey platforms for online studies. The link to the studies was shared via social media platforms and Universities in Italy and Germany (User Study 1 was furthermore shared in Great Britain, and Australia). This served to get large and heterogeneous samples, which is advantageous to generalise the findings.

In both online studies, participants were asked to watch a short video sequence of about 2 minutes. In the video, the RB-KAIROS robot was displayed with either WorkMATe vs. GRU vs. no memory implemented. To test the robot's adaptation to the presence of humans, we simulated an industrial workspace which was ~~-~~divided in two areas: An area in which two ostensible workers were around transporting objects from one table to an opposite one while one worker crossed the room from East to West and the other from North to South to force as many crossings with the robot as possible.

After having watched the video sequence, participants were asked to complete a short questionnaire which assessed the measures: robot appearance, robot movements, perceived robot memory functions (dependent measures), participants' positive and negative attitudes toward robots, social desirability, situational motivation to participate in the study, experience with technology and robots in general, experience with the RB-KAIROS robot, and demographics (covariates). Participation took about 15 minutes in total.

User Study 1 provided insights about participants' (professionals and laypeople) ideas of memory, which were closely associated with data processing and (autonomous) learning and adaptation. Participants had quite clear ideas of robot memory and formulated very precise suggestions on how a safe, efficient, and comfortable robot navigation could be realised. Their suggestions might thus be useful for further research and development of memory-based robot navigation. In User Study 2, the implementation of robot working memory GRU and WorkMATe resulted in more positive evaluations of robot's perceived memory functions. That implies that memory-based adaptations of robot navigation were visible and were deemed positive. Both studies unveiled that participants' attitudes toward robots and experience level with robots, rather than their demographic background, is decisive for positive perceptions of HRI. In both, User Study 1 and User Study 2, our measures on robot appearance, robot movements, and perceived memory functions were found to be very reliable which means that they are well suitable for further research on memory-based robot navigation in industrial settings. The outcome of User Study 1 and User Study 2 was submitted as a journal paper to Frontiers.

To develop and evaluate our architecture, we used the same setup that was used in User Study 1 and User Study 2 and which allowed us to imitate a possible industrial. The setup comprised two rooms: in the populated area (e.g. an assembly space) workers performed a simple pick-and-place task that required them to cross the room from one workstation to another; in the unpopulated area (e.g. a storage space) instead, no human workers were allowed. The two areas were divided by a corridor, so seeing one area from the other was impossible. We realised two workspace mock-ups: the Big Room with 14.4m2 of unpopulated and 19.8m2 of populated areas; and the Small Room with 7.02m2 of unpopulated and 15.21m2 of populated areas. For this study, we implemented, trained, and compared two memories for the working-memory node mentioned above, namely GRU [35] and WorkMATe. The GRU (Gated Recurrent Unit) [35] is arguably the simplest state-of-the-art computational circuit commonly used in machine learning devised to learn rules from sequences. We realised the network in Python with the Tensorflow 2 Keras library; it comprises an Embedding Layer (6 units, vocabulary size of 7), a GRU Layer (6 units, stateful, with 0.004 l2 regularisations), a Dropout Layer (0.1 dropout rate) and a Dense Layer (3 units, one for each modality with softmax activation function). Reported hyper-parameters were obtained after 4-fold grid-search cross-validation on the collected data (see section II-E1). The WorkMATe is a novel, more biologically plausible implementation of working memory developed by Kruijne et al. Like the GRU, WorkMATe relies on gating to select whether to store information. However, WorkMATe relies on biologically inspired attentional feedback; also, it is meant to be trained via reinforcement learning, including a biological reward prediction error. To develop robust models able to be applied in diverse working environments (i.e., different rooms, displacement of ARUCOs markers, workers' behaviour, robot's path), we applied the following procedure: (i) firstly, we performed a Data Collection in the Big Room; (ii) then, we used the collected data to train and validate the GRU and WorkMATe models; (iii) finally, we evaluated the trained models in a modified Big Room (by changing the robot's path, ARUCOs displacement, and workers' trajectories), and in a novel Small Room. 1) Data collection: Following six predefined waypoints, the robot navigated in a loop between the populated and unpopulated areas. We recorded six sessions of approximately 10 minutes - we opted for separate sessions to avoid tiring the human actors. The RB-KAIROS+ robot always moved with a fixed velocity of 0.35 m/s in all directions. However, for three sessions, it moved holonomically, while it moved differentially for the remaining three. Finally, the robot performed ten loops for each session, alternating clockwise and anticlockwise directions as data augmentation. Hence, our data set includes 60 loops: 15 clockwise differential, 15 clockwise holonomic, 15 anticlockwise differential, 15 anticlockwise holonomic. Two actors performed a simple pick-and-place task in the populated area, crossing the room. Actors were instructed to move from one workstation to another following a metronome sound beeping every 5 seconds. We dumped and synchronised the RB-KAIROS+ RGB camera mages during the sessions in a ROS bag at 30 fps. Post-hoc, we fed the collected RGB images to the ARUCOs and human detectors, obtaining 112800 data points composed by 2 features human detected (0=detected, 1=not detected) and aruco detected (0=no aruco, 1=unpopulated, 2=populated). Based only on the last perception, we labelled each data point as TASK-ORIENTED, ATTENTIVE, or HUMAN-ORIENTED. To simulate the working memory, we kept the last assigned label in the non-deterministic case, in which no humans nor ARUCOs are detected (i.e., when the robot has to rely on memory). The resulting dataset is slightly unbalanced with 41% TASK-ORIENTED, 19% ATTENTIVE and 40% HRI-ORIENTED data points. 2) GRU training: To train and validate the GRU-based model, we segmented the dataset in time windows of size 500 (overlapped with stride 1). Humans' and ARUCOs' detections were generated at 30Hz (the same frame rate of the robot camera); hence 500 data points corresponded to a time window of 16.6 seconds, retention consistent with humans' working memory [36]. The resulting dataset comprises 120000 segments. Finally, we trained our model considering 80% as training and the remaining 20% as the test set. 3) WorkMATe training: The WorkMATe model was trained via Reinforcement Learning (RL) over small batches of data points as per the network design. We segmented our dataset in non-overlapped windows of size 100 (i.e., 3.3 seconds). The resulting dataset comprises 1128 segments. In our RL task, for each perception data point (i.e., a human and ARUCO observation), the agent can undertake three possible actions (i.e., the behaviour modalities). Then, the agent was positively rewarded (r = +1 for ATTENTIVE, r = +0.6 for TASK-ORIENTED and HUMAN-ORIENTED) if the selected modality matched our label; otherwise, it was negatively rewarded r = −1. The reward for the ATTENTIVE modality is higher than the others to counter the unbalancing of our dataset as in [37]. As before, we trained our model considering 80% as training and the remaining 20% as the validation set.

3.1.3 Design

HRI with an RB-KAIROS robot with WorkMate (vs. GRU) vs. no memory between-subjects design.

3.1.4 Spatial Memory Task with LEGO bricks

We aimed to test participants' memory performance during HRI with the RB-KAIROS robot. To force participants to cross the robot's trajectory, participants must perform an active task like participants in Study 1 to Study 3. We thus created a spatial memory task by adapting the digit span memory test (Werheid et al., 2002). To increase human-robot interaction and to have greater similarity to an industrial working setting, two participants perform the memory task at the same time. Participants must recreate models of LEGO bricks from memory. Each participant has to recreate the same models. To do so, each participant has her or his own work cell (cell, because it should be protected from the eyes of the other participant in each case) and two brick stations. The work cells are placed opposite each other in the centre of the room. The two work cells are separated by a dark curtain. Participants' brick stations are placed diagonally left and right from a participant's work cell. This way, one participant performs the task in the left corner of the room and the other in the right corner. Therefore, each participant can do the task at his or her own pace without being distracted by the other participant. At the same time, however, the robot is moving around participants' work cell and a non-crowded room similar to Study1 to Study 3. This allows us to investigate the effect of a robot on participants' memory performance, while keeping effects of the "co-worker" low (see Figure 2for participants' working stations).

Figure 2: The two participant working areas within the crowded room

By pressing a button, the LEGO models are presented on a screen for a limited time (via Webapp). In the digit span test (see Werheid et al., 2002), each digit is presented for a second. As participants must memorise two features of the LEGO bricks, namely their colour and size, we opted to show each model two seconds per number of bricks. After having watched a model, participants must collect the bricks they need from two working stations. This way, participants are forced to cross the robot's path. To balance participants' walking direction (left vs. right), each brick station contains the same number of bricks (58 bricks each). However, one brick station contains "hot" colours (i.e., yellow, red) and one brick station contains "cold" colours (i.e., blue, green). In addition, each brick station contains six white bricks, which were considered neutral in terms of colour (see Table 1:). These were needed to balance the number of "hot"- and "cold"-coloured bricks in models with an odd number of bricks. After having recreated a model, participants must place the final model into a box on their work cell. In order not to be distracted by viewing a former model when having to recreate another, the box must be closed after a model has been placed into it. In addition, participants must press a button to indicate that they finalised and stored a model into the box. Then, they had to press a button again to get the next model presented on a screen. Participants are not competing. Therefore, it is important to ensure that a participant does not get distracted when the other participant finishes the task. The termination of a session should thus be done discreetly.

Table 1: Details of the Brick Task

Task details
Brick Stations
Each work cell is equipped with the same number of bricks that are arranged in the following order (see also Cold_colors_1, Cold_colors_2, Hot_colors_1, Hot_colors_2 images displaying each single brick station).
Hot colors:
2 x 2 bricks: 14 yellow, 14 red, 6 white
2 x 4 bricks: 8 yellow, 6 red
2 x 6 bricks: 6 yellow, 3 red
= 58 bricks in total
Cold colors:
2 x 2 bricks: 12 dark blue, 12 light blue, 15 dark green, 6 white
2 x 4 bricks: 8 dark blue, 5 dark green
= 58 bricks in total

Models: In total, participants must recreate twelve models. In adaptation of the digit task (see Werheid et al., 2002), the models' complexity increases by increasing the number of bricks every second model. That is, the first two models contain three bricks, while the last two models contain eight bricks each. Each model contains the same number of "hot"- and "cold"-coloured bricks. For models with an odd number of bricks, a white brick is added. The bricks of a model differ in colour and size (i.e., 2x2, 2x4, and 2x6), while the orientation of the bricks is always the same. This way, the bricks are arranged in a vertical order. To avoid any biases due to the saliency of a colour or experimenters' preferences, the models were created by using a Python script which balanced the number of "hot"- and "cold"- numbers within models (see Teams folder for the final models).

Task evaluation: To evaluate the memory task, we calculated the percentage of errors per participant. To do so, we calculated Levenshtein distance for each model feature that is, for colour and for size (see Levenshtein, 1966). More precisely, Levenshtein distance is calculated by counting the number of replacements, additions, and removals that are needed to turn the model that participants provided into the original correct model. Replacements, additions, and removals are counted per colour and per size of the bricks. Their sum is then divided by the number of bricks within a respective model, which results in an error ratio per colour and per size. Error ratios for colour and for size are finally averaged so that an overall error rate is calculated per participant.

To illustrate, Figure 3 shows one of the models as it should be recreated (left) and a model that a participant provided (right) in our pilot testing of the task.

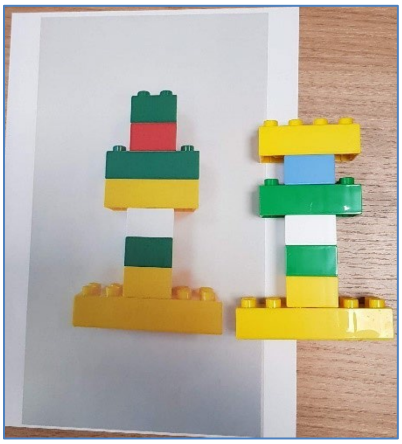

Figure 3: Actual model (left) and participant's recreation from memory (right)

To calculate the participant's error rate for this model, Levenshtein distance (Levenshtein, 1966) needs to be calculated for each of the two features (color and size of the bricks) first. Let's start with the calculation of the error rate for color (see Figure 4). To do so, we check whether the color of bricks in participant's model matches the color of bricks in the actual model starting from bottom to top. Therefore, for the first four bricks, the color in participant's model matches the color of the actual model. The fifth brick in participant's model, however, needs to be replaced because it is blue though it was supposed to be yellow to match the actual model. The sixth brick in participant's model is light blue, though it should have been green. The seventh brick in participant's model is yellow, though it should have been red, while the eighth brick is missing in participant's model. That way, we have three bricks that need to be replaced and one brick that needs to be added to match the actual model in color.

$$\text{Error rate for color} = \frac{4\ (3\ replacements + 1\ addition)}{8\ (number\ of\ bricks\ in\ the\ actual\ model)} = 0.5$$

Figure 4: Formula for the calculation of the error rate for colour

The error rate for size is calculated analogously (see Figure 5). To match the actual model in brick size, the sixth brick needs to be replaced by a 2x8 brick, while the seventh brick needs to be replaced by a 2x2 brick and the eighth brick needs to be added. Therefore, error rate for size is:

$$\text{Error rate for size} = \frac{3\ (replacements + additions)}{8\ (number\ of\ bricks\ in\ the\ actual\ model)} = 0.38$$

Figure 5: Formula for the calculation of the error rate for size

To get the total error score, we simply average the error rate for color and size. That is, for this model, the participant gets a total error rate of 0.44%. Alternatively, the total error rate could be calculated by summing replacements and additions (and if you have, removals) for color and size divided by twice the number of bricks.

Instructions for participants:

“Your task is to memorise and rebuild a set of models. In total, you will be presented with 12 models of LEGO bricks that differ in color and shape. The complexity of the models will increase over time. Each model will be displayed only once for a limited time. So please first watch the model carefully. What matters is to rebuild the models correctly, no time constraints will be given for the reconstruction.”

3.1.5 Results

We computed five metrics for each loop of the collected evaluation data to verify our expectations. As a metric related to comfort, we measured the average distance from obstacles (from laser data); whilst for smoothness of navigation, we measured the frequency of acceleration anomalies as the percentage of data samples that lies 3σ away from their average value. In addition, we estimated the robot energy consumption, loops’ average duration and traveled distance as indexes of efficiency in industrial scenarios. See the caption of Figure 8 for more details on the computed features. Pursuing a more comfortable and efficient navigation, we expected the RBKAIROS+ robot to preserve a higher distance from obstacles, and to generate a smoother velocity profile and lower energy consumption when equipped with the memory modules with respect to the not adaptive counterpart. In addition, we expected the robot to travel a higher distance and take more time on completing each loop due to the lack of holonomicity and reduced speed in the populated areas. Regarding the Big and Small rooms, we were not interested in directly comparing them but rather in (i) proving that our working-memory-based system can adapt the robot’s behavior in slightly different (Big room) and novel (Small room) scenarios and (ii) to explore whether effects on the five metrics mentioned above would be present in both rooms. Some preliminary analyses on the small room evaluation have been previously presented in [38].

In this study, we developed and evaluated a working memory-based robot architecture for adaptive navigation, fostering comfort, naturalness, and efficiency during human-robot collaboration in dynamic industrial settings. Indeed, the optimal behavior (i.e., trajectory and speed) a robot would adopt could not be suitable when the area is shared with human workers. At the same time, always behaving cautiously would be counterproductive from a cost/benefit point of view. Hence, we speculated industrial robots should be enabled with context awareness - i.e., spatial and human awareness - adopting the policy best suited for each case. Furthermore, we advocated that such a module would benefit from working memory, enabling the robot to keep its awareness and optimal behavior, even if perception is prevented. After collecting data in a mocked-up industrial environment, we trained the WorkMATe - a biologically plausible model - and a GRU-based model - the state-of-the-art for working-memory networks. Finally, we evaluated such models in comparison with a non-adaptive robot architecture. Our results suggest that adopting a Working Memory module, either GRU- or WorkMATe-based, guiding the navigation strategies of a robot can improve HRI in a collaborative industrial setting. When pursuing a working-memory-based adaptive behavior, the robot kept a higher distance from obstacles, which workers might perceive and thus deem comfortable; it also produced a lower number of abrupt accelerations and breaking, making its trajectory smoother and less alarming. Moreover, energy consumption was also reduced. Finally, our system functioned and showed the same effects in two environments of different sizes and shapes, supporting its generalisability. Hence, we speculate our system would benefit from both a performance and a human-robot interaction point of view. Since navigation with working memory exposes those beneficial assets, we may expect that the workers sharing the room with the moving robot might interact more pleasantly with it, improving their working conditions and performance. We plan to undertake a follow-up user-study in a real industrial environment to test such claims.

For this purpose, a few system limitations should be addressed. We relied on ARUCO markers to identify the two areas of our setup, requiring only RGB images to let our system work. ARUCO placement offers reliable landmarks when other relevant key points are absent; also meant to be detected even in low-light conditions. However, this would require to physically change the industrial setting, which is not always feasible or convenient. We speculate ARUCOs could be used to semi-supervise the training of a dedicated system based on other environment features or absolute spatial awareness and removed afterward. In addition, in this study, we focused on the robot's behavior without defining a specific industrial task for it (other than reaching a spatial goal) or requiring direct human-robot interaction between the robot and the workers. In the follow-up study, we plan to evaluate the effect of the robot's adaptive navigation on workers' performance when performing a memory-based realistic task (e.g., assembling); furthermore, we plan to involve a direct interaction and active robot task (e.g., making the robot delivering components and fetching assembled object to/from the workers). In addition, such a future study could be suited to test other interesting effects that emerged from this manuscript, like the different collision avoidance styles produced by our system. The study may point out whether human partners would prefer a robot that avoids collision with them by stopping or following alternative trajectories. We speculate that it is likely that, in the latter case, the trim of holonomicity can help the human partner forecast robot path planning more easily [40], especially when human-robot interaction is required. Another limitation regards the simplicity and discretisation of the behavioral modalities. Even if simple, the difference between modalities is already visible in our data hence, we speculate human workers would also perceive it, but this is subject to ongoing research (see Bernotat et al., pre-registered at AsPredicted, 125198). Furthermore, based on the same collected data, our system could be easily retrained to foster more complex and customised adaptive policies. Finally, it would be crucial to evaluate workers' perception of our working-memory-based navigation via questionnaires and, if feasible, via implicit measures like gaze, electrodermal activity, heart rate, or direct contact. The combination of user perspective and technological aspects will be the core of the developmental process of future steps, answering the call for a holistic technological, user-centred, empirically driven approach to human-robot interaction [41] applied to navigation.

3.2 Showcase in Relevant Environment UPM

This experimental scenario simulated a relevant real-world environment. The designed protocol describes a non-interventional experimental setup aimed at measuring the perceived behaviour of a mobile robot by naive subjects (defined as individuals that have never interacted with robots before) while performing collaborative tasks. The aforementioned memory-inspired modules trigger a different robot's behaviour as a function of how the motor command is directed by different types of memory. The different memory-based models aim to foster a mutual understanding between machines and humans and enhance the trust and acceptance. In lab tests performed at IIT (previous experiment), we have evaluated how the robot autonomously completes a predefined task in the presence of humans, but without directly implementing how to avoid human collaborators upon task onset and adapt to changes in humans' conduct. In this showcase (UPM), we executed a similar study, leveraging a wider space with fewer experimental constraints and adding surveillance and sensors.

Recruitment of naïve participants is often a challenge but essential to address safety and efficacy. Human safety and privacy considerations have been addressed and approved by the corresponding ethical committees at UPM. These efforts also expand the project's impact in future applications, since they are typically a big concern in the companies who implement such solutions. Nevertheless, the envisioned outcomes and changes in the behaviour need to be further explored and validated in controlled real scenarios, to be fine-tuned and released into a real use case (ROB, described in the next chapter).

3.2.1 Research Aims

To compare the behaviour of the KAIROS robot using two different implementations: (1) The working memory configuration and (2) the absence of a working memory model. That is, to compare the WorkMate module developed within the HBP versus a no-memory architecture. The comparison is studied with naïve participants who interact with the robot in a real-world simulation environment.

The main objectives of the experiment in relevant environment were:

- Evaluate the behaviour, adaptation capabilities, and performance of the robot in the presence of naive human pairs while changing from an environment devoid of people and another in the presence of humans.

- Evaluate the behaviour, adaptation capabilities, and performance of the robot depending on its configuration: either cognitive-inspired using WorkMate or without a memory module.
- Investigate the effects of robot working memory configuration (WorkMate vs. no memory) on participants' evaluation of the robot in terms of robot appearance.
- robot movements.
- perceived robot memory functions.
- and on participants' behavior during HRI in terms of
- memory performance (using the LEGO task)
- cognitive load, arousal (using sensor data)

At the same time, examine the effects of participants' positive and negative attitudes toward robots, social desirability, evaluation of the experimental situation, perceived task load, experience with technology and robots, and demographics are controlled for analogous to User Study 1 and User Study 2.

3.2.2 Research questions

1) Does the WorkMate memory module enhance the robot's performance when collaborating with humans in a shared environment?
2) Does the WorkMate memory module vs no memory module affect the user experience during human-robot collaboration tasks?
3) Does the subjects' impression of the robot's appearance and behaviour have an effect on how they performed the task?
4) What psychological aspects (e.g., attitudes toward robots, experience level with robots and technology, perceptions of the experimental situation, cognitive load, and demographic background) affect participants' a) memory performance, b) evaluations of the robot

The initial hypothesis was assuming that the version with WorkMATe memory implementations would lead to:

1) Smoother robot navigation
2) More positive overall evaluations/opinions of the robot
3) A better memory performance during the LEGO task
4) Lesser arousal and cognitive load during the LEGO task

Results of the experimental study are shown in section 3.2.6.

3.2.3 Experimental Design and Overview of the procedure

The study took place at LifeSpace (formally known as Smart House Living Lab by LifeSTech) at UPM. Participants had to solve a memory task using LEGO constructions to test their cognitive performance while the RB-KAIROS robot was moving around, equipped with either WorkMATe or with no memory module. During the LEGO task, participants were equipped with wearable sensors (I.e., a Fitbit wristband) while 360º surveillance cameras captured the scenery and potential factors that might affect HRI complementary. After finishing the LEGO task, participants were asked to complete a questionnaire (see descriptions below for further details). Every experiment was performed simultaneously by two participants, and it took an average time of 20 minutes to complete the LEGO task. The robot was stopped once the participants completed the last LEGO construction.

3.2.4 Infrastructure

LifeSpace (formally known as Smart House Living Lab by LifeSTech), is an environment relevant both for companies and the healthcare sector as it consists of a controlled and interactive ecosystem that combines advanced technologies to simulate real-life scenarios, offering innovative and personalised solutions. This ecosystem also serves to generate new knowledge, acquire home-similar data from individuals, and promote the creation of new products and services. Smart living environments can contribute to the premarket validation of new products and have beneficial effects on self-perceived quality of life, perception of physical health status, and social engagement, advancing the active and healthy ageing and frailty domains (Tannou et al., 2022). Specifically, more than 50 sensors and actuators, iterative robots, the Internet of Things (IoT), and smart devices and other emerging technologies such as blockchain are distributed in the LifSpace. This ubiquitous device distribution is designed to allow monitoring and testing of ICT applications, which capture data both within the controlled environment and associated users who actively participate and live at home in the city itself. The LifeSpace is designed to capture measurements of gait and further quantification of a person's frailty, early detection of worsening trends due to disease progression, and even lacks in pharmacological treatment, to better adjust interventions to every person's needs. LifeSpace is thus an ideal scenario to test human-robot interaction settings and gain new insights into how these interactions affect human performance and improve human-robot relations under controlled conditions.

The LifeSpace hosted the activities of the experiment in relevant environment, aiming to scientifically contribute not only to the creation of innovative technology services but also to the open experimentation methodologies in realistic environments, tailored to the needs of end users (the companies),but also health professionals, patients and general society.

3.2.5 Spatial Memory Task with LEGO bricks description

We aimed to test participants' memory performance during HRI with the RB-KAIROS robot because memory performance was considered a good proxy of working performance in a realistic setting. At the same time, we aimed to force participants to cross the robot's trajectory. Therefore, participants had to perform an active task similar to the ostensible workers that were displayed in Study 1 to Study 3. We thus created a spatial memory task by adapting the digit span memory test (Werheid et al., 2002). To increase human-robot interaction and to have greater similarity to an industrial working setting, two participants performed the memory task at the same time. Participants had to recreate models of LEGO bricks from memory. Each participant had to recreate the same models. To do so, each participant had her or his own work cell (cell, because it should be protected from the eyes of the other participant in each case) and two brick stations. The work cells were placed opposite each other in the centre of the room. The two work cells were separated by a dark curtain. Participants' brick stations were placed diagonally left and right from a participant's work cell. This way, one participant performed the task in the left corner of the room and the other in the right corner. Therefore, each participant could do the task at his or her own pace without being distracted by the other participant. At the same time, however, the robot was moving around participants' work cell and a non-crowded room. This procedure was deliberately kept similar to User Study 1, User Study 2 and the Lab Study at IIT to make findings comparable across studies. This setup furthermore allowed us to investigate the effect of a robot on participants' memory performance, while keeping effects of the "co-worker" low (see Figure 1 for participants' working stations).

By pressing a button, the LEGO models were presented on a screen for a limited time. In the digit span test (see Werheid et al., 2002), each digit is presented for a second. As participants must memorise two features of the LEGO bricks, namely their color and size, we opted to show each model two seconds per number of bricks. After having watched a model, participants had to collect the bricks they needed from two working stations. This way, participants were forced to cross the robot's path. To balance participants' walking direction (left vs. right), each brick station contained the same number of bricks (58 bricks each). However, one brick station contained "hot" colors (i.e., yellow, red) and one brick station contained "cold" colors (i.e., blue, green). In addition, each brick station contained six white bricks, which were considered neutral in terms of color. These were needed to balance the number of "hot"- and "cold"-colored bricks in models with an odd number of bricks. After having recreated a model, participants had to place the final model into a box on their work cell. In order not to be distracted by viewing a former model when having to recreate another, the box had to be closed after a model had been placed into it. In addition, participants had to press a button to indicate that they finalised and stored a model into the box. Then, they had to press a button again to get the next model presented on a screen. Participants were not competing. Therefore, it was important to ensure that a participant did not get distracted when the other participant finished the task. The termination of a session thus had to be done discreetly.

The trial simulates a situation where a person is engaged in the task in one part of the working area and in parallel, the interaction with the robot is forced, which navigates between the workers' and the non-crowded area (see Figure 6 and Figure 7). For example, the robot avoided collisions and its aimed to adapt its behavior in the presence of humans. In the case of the RB-KAIROS with the WorkMate, the memory module is installed and compared with other working memory models. The working memory should guarantee the movements will be smoother. The robot will sense and avoid the participants moving in the room, as it is equipped with a real-time Human Detection system based on YOLO (You Only Look Once). The OpenCV-based library ArUco is used for the robot to sense recognisable features of the environment. We will compare the impression of participants with the two models of working memory through validated questionnaires. Our hypothesis was that participants would feel more comfortable and have a better working experience in presence with the robot with the WorkMate working memory model robot. During the procedure, participants are provided with a wrist-wearable device to track their heart rate variability in two stages: First, without the presence of the robot, to calibrate for 5-10 minutes their relaxed frequency rate, while the coordinator finishes the experiment explanation. Second, during the human-robot interaction to detect reactivity or alterations related to the presence and movement of the KAIROS-RB. Any alterations will be cross-checked with the camera recordings to evaluate if they coincide with a particular event (i.e., participants crossing the robot trajectory) while mean heart rate frequencies will serve to assess the influence or stress that the presence of the robot may cause to participants. We expect to validate quantitatively that participants will feel more comfortable and have a better experience with the WorkMate module robot.

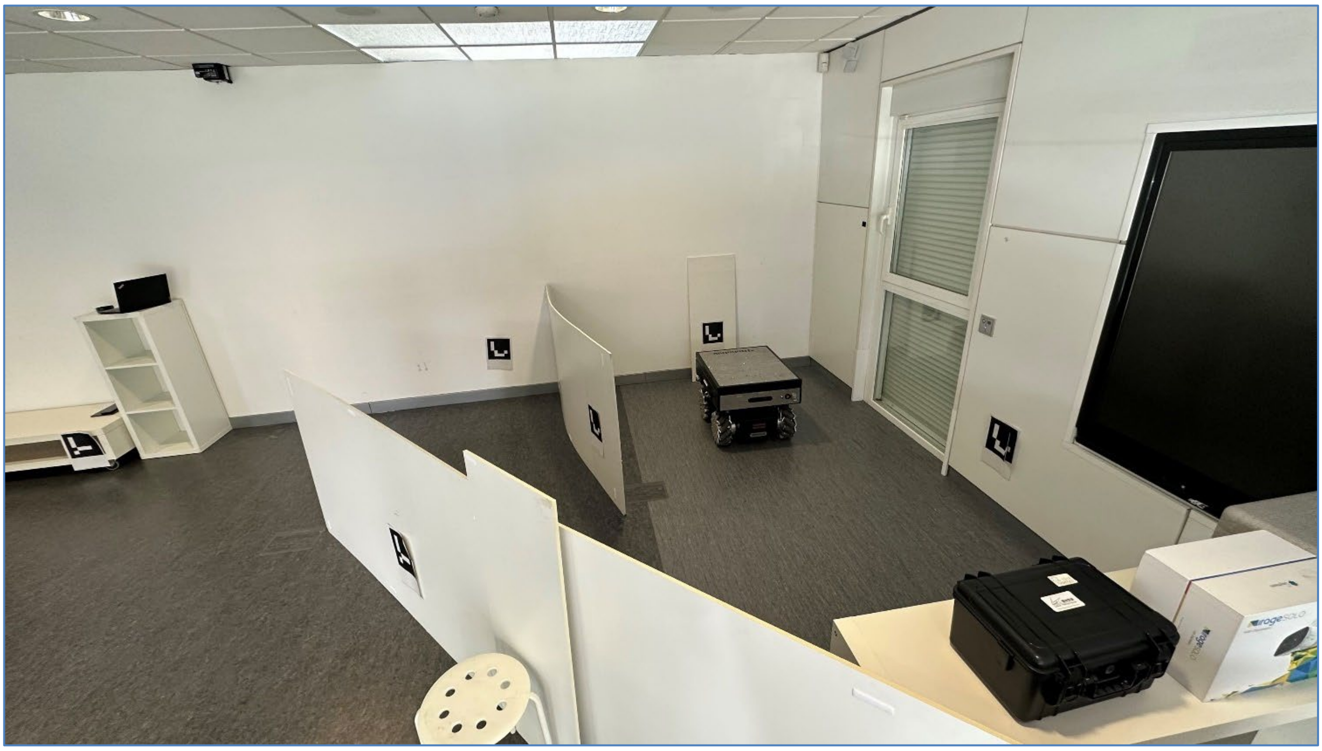

Figure 6: Experimental setup at UPM displaying the two working areas

Figure 7: Experimental setup displaying the workers' area at UPM

3.2.6 Results of the UPM study

44 participants (22 per No Memory vs WorkMATe condition) took part in the study. Most of them were professionals with a university degree or PhD. Although most participants knew robots from other studies, only a few participants indicated to have known the RB-KAIROS robot before from media or other studies. When the experimental situation was perceived as positive robot movements and robot memory were more positively evaluated.

In addition, participants made fewer errors during the memory task regarding the memory of the brick's color of the bricks, $F(1,40) = 5.29$, $p = .027$ and the total error score across color and shape of the bricks $F(1,40) = 4.94$, $p = .032$.

Participants' Task load was low which led to more positive evaluations of robot appearance ($F(1,40) = 20.10$, $p < .001$). All this, however, applied for No Memory and WorkMATe equally ($ps > .05$). That is, the experimental condition (WorkMATe vs. No Memory) did not affect participants' task performance, nor their overall evaluations of the robot. Evaluations of robot appearance and robot movements were moderate (means around 4) confirming findings of User Study 1 and User Study 2. However, robot memory was fairly positive evaluated in both experimental conditions (WorkMATe: $M = 5.30$, no memory: $M = 5.15$).

To sum up, none of the robot memory configurations (WorkMATe vs. no memory) were decisive for more positive evaluations of the robot and better task performance. A positively perceived HRI setting and perceived low task load were crucial for a comfortable and efficient HRI in the working context. In addition, as in User Study 1 and User Study 2, our measures on robot appearance, robot movements, and robot memory were found to be highly reliable which means they are well suitable for further HRI research.

Figure 8: Experimental setup in UMP: the KAIROS moves towards the area without humans

3.3 Showcase Demonstration in a realistic environment ROB

3.3.1 Research Aims

To test the adaptive memory-based robot navigation in an industrial working environment, porting the HBP model contribution named WorkMATE on the RB-KAIROS. Here, the operation of the RB-KAIROS robot was performed in the working area of an SME such as ROB during working hours with real users.

3.3.2 Infrastructure

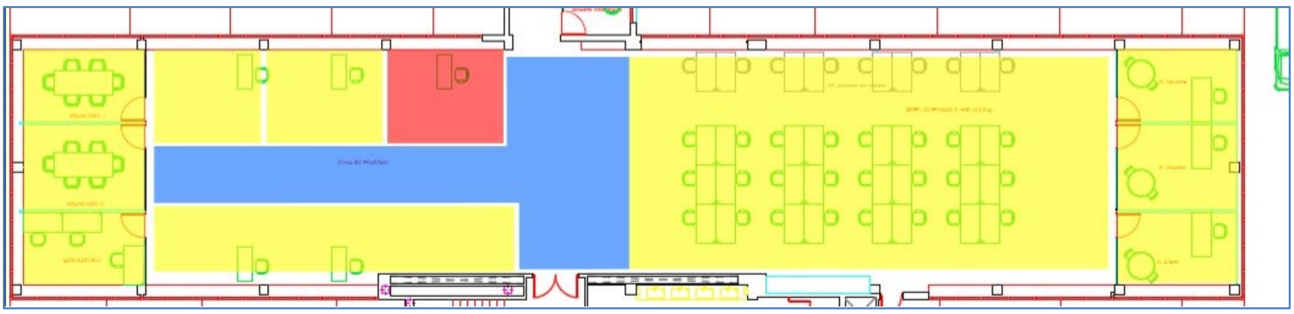

Figure 9: Layout of the experiment in ROB working facilities

The selected environment consists of an entire floor of the ROB company, to prove the adaptive capabilities of the robot with working memory. The robot is programmed to fulfil a particular task in an area shared with naïve workers performing their daily routines. The floor is subdivided into three areas potentially visible with the sensors incorporated in the robot. The red area (Figure 9) is not accessible by people and therefore no human will be detected by the robot's sensors. This simulates a storage area where the robot can freely move. When the robot detects the features of a void-of-people room, it prioritises speed and shortest routes to finish the programmed tasks or activities. In the blue area, both workers and the KAIROS-RB robot cohabit. In this area, the safety and comfortability of humans interacting with the robot are prioritised, avoiding collisions and smoothing motor behaviours when required. The yellow area is an area where the workers are located but where the robot is not admitted. The yellow area does not have perimetric walls, which imply that workers are perceived by the robot's sensors.

3.3.3 Procedure

For this study, we employed a RB-KAIROS+ robot (see Figure 12) [28] (weight 115Kg, size 978 × 776 × 690mm), a rover robot equipped with four holonomic wheels, enabling it to move in any direction (holonomic), a frontal RGB-D camera (resolution 640x480, 30 fps) and a pair of SICK S300 laser scanners spanning 360 degrees, placed at the top right and bottom left corners of the base at a height of 30cm from the ground. The robot is equipped with a Kinova Jaco2 assistive robotic arm (see Figure 12) that was never put into action during the experiment; we kept it to preserve the robot's appearance over multiple studies with the same platform. While the workers performed their pick-and-place task, the RB-KAIROS+ navigated between the populated and the unpopulated areas following a predefined sequence of waypoints (see Figure 11). During the route, the robot was expected to adapt its behaviour depending on its (i) spatial awareness (i.e., by recognising the room it was in and hence the potential presence of humans) and (ii) human awareness. In particular, the robot should navigate following one of three modalities, TASK-ORIENTED (TO), ATTENTIVE (ATT), and HRI-ORIENTED (HO), affecting its speed and possibility to move holonomically. Fostering co-workers' comfort [2], the robot slowed down as soon as it sensed being in the populated area (see Figure 10 and Figure 11). In addition, to improve the naturalness and legibility of its movement, as soon as humans were sensed, the robot imitated their non-holonomic behaviour [29], switching to a differential planner. We opted for this solution to match the expected behaviour given the robot car-like shape. The combination of these adaptations was expected to generate less abrupt acceleration and breaking along with lower energy consumption and more comfortable and predictable trajectories, allowing the co-workers to evade the robot if needed Notably, if the robot is unaware of being in any of the two areas and unable to perceive any human, its behaviour is non-deterministic. Here, working memory could be beneficial. A working-memory-enabled robot could remember its past perception, keeping the correct behaviour until spatial and/or human awareness was restored.

Figure 10: Area available for the robot where the absence of human workers was guaranteed

Figure 11: Set-up for the experiment in ROB where the two experimental areas are visible

Figure 12: RB-KAIROS robot in ROB performing arm motor action based on working memory

3.3.4 *Results*

The results of this showcase are promising, though we have a fairly small sample of robot experts. The analysis provided in the ROB showcase is mainly qualitative. In the real experimental setting, we found that participants in the no memory condition shared less positive evaluations of robot movements (F(1,10) = 8.83, p = .014) and experience with robots (F(1,9) = 11.97, p = .007) than participants in the WorkMATe condition. Participants' lower levels of experience with robots did not affect participants' evaluations of the robot (ps > .05). The effects of experimental condition on participants' evaluations of robot appearance and robot memory were not statistically significant (ps > .05). Overall evaluations of the robot were fairly positive. Participants' open response indications about their ideas of robot memory revealed that expert opinions about robot memory were not that different from the ideas of a heterogeneous sample in User Study 1. Robot memory was associated with data storage, capacity, and processing amongst the robot's capability to "learn" in terms of autonomous adaptation to new settings and changing situations automatically.

Complementary to overall positive evaluations of the robot, most participants described the robot movements as safe, precise, and dynamic. Some participants just remarked the robot could make less abrupt movements and that it could stop earlier when detecting humans, but these participants.

To sum, robot movements were more positively evaluated when the robot was shown with no memory vs. WorkMATe while participants' overall evaluations of the robot were fairly positive in both experimental conditions. Despite the small sample size, again, our measures were proved reliable which makes them well suitable for further HRI research in online settings, lab settings, and in real industrial settings (α = .79 – .93). Complementary to participants' suggestions in User Study 1, participants' Participants' suggestions for improvements of the robot movements might help to further develop the RB-KAIROS (and any other industrial) robot's navigation. Overall, our research findings were fruitful regarding the technological developments of memory-based robot navigation as well as regarding the perspective of potential users that collaborate with an industrial robot at work.

3.4 Emerging Collaborations

In addition to the above, a number of productive collaborations have emerged from the work described. In particular, activities related to motor control constitute a natural extension of those on motor control models exploited in Task 3.4. A roadmap is being defined to provide Task 3.4 contributors with models developed for the present demonstrator, supporting embodiment and motor control strategies.

The opportunity of extending this collaboration will be investigated, with the long-term perspective of developing cognitive models able to use memory (not only working memory but also other typologies of memory) and reuse memory to create adaptive motor behaviours with applications to the industrial and healthcare robotics.

Finally, discussions are emerging on the possibility of merging (relevant aspects of) these showcases in WP3 with other showcase; for instance, including the anthropomorphic manipulator considered in Showcase 5 (and corresponding dextrous manipulation capabilities) with the working memory component that has been presented and demonstrated in this Deliverable.

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