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Two distinct neural pathways for mechanical versus digital technology

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ABSTRACT

Technology pervades every aspect of our lives, making it crucial to investigate how the human mind deals with it. Here we examine the cognitive and neural foundations of technological cognition. In the first fMRI experiment, participants viewed videos depicting the use of mechanical tools (e.g., a screwdriver) and digital tools (e.g., a smartphone) compared to simple object movements. Results revealed a key dissociation: mechanical tools extensively activated the dorsal and ventro-dorsal visual streams, which are motor- and action-oriented brain systems. Conversely, digital tools largely engaged the ventral visual stream, associated with conceptual and social cognition. A second behavioral experiment showed a pronounced tendency to anthropomorphize digital tools. A third experiment involving a priming task confirmed that digital tools activate the social brain. The discovery of two different neurocognitive systems for mechanical versus digital technology offers new insights into human-technology interaction and its implications for the evolution of the human mind.

1. Introduction

On July 20, 1969, Neil Armstrong left his footprint on the moon and forever etched his name in the annals of human history. The Apollo 11 mission remains one of the defining moments in the evolution of human technology, demonstrating our extraordinary ability to push beyond the limits of Earth's surface. Unsurprisingly, investigating how the human mind may generate *technological cognition* is one of the most important scientific questions of our time (Kennedy and Norman, 2005).

Technology is ubiquitous and varies significantly in form and complexity. For instance, during the Apollo 11 mission, Armstrong used advanced digital navigation systems to pilot the spacecraft. However, we may assume that he also used mechanical tools such as screwdrivers, hammers, or levers when adjusting something on the spacecraft. This dichotomy exemplifies how, at a more *tangible* level, mechanical artifacts allow individuals to manipulate the world physically (Adibpour

and Hochmann, 2023; Allen et al., 2020). On a more *abstract* level, digital tools, like smartphones or computers, may extend cognitive and social capabilities (Risko and Gilbert, 2016; Sparrow et al., 2011).

The distinction between tangible and abstract tools is subtle yet fundamental in understanding how individuals interact with technology. On the one hand, mechanical tools are inherently *transparent*, requiring practical understanding for their use (e.g., grasping a hammer by its handle and using it to drive a nail) (Goldenberg and Spatt, 2009). On the other hand, digital tools remain *opaque*, as their underlying mechanisms (e.g., electronics, electromagnetism) are not immediately evident to users (Keil, 2003). For example, we use a remote control without considering how it turns on a TV. Conversely, using a hexagonal key to screw a nut and assemble a wardrobe is straightforwardly linked to the key's mechanical properties. Therefore, the spatial congruency between the action and the tool, inherent in mechanical tasks, is not mandatory for digital tools, where the connection between user actions

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and tool functions is less immediately apparent.

These observations prompt an intriguing question: does the distinction between tangible and abstract technological knowledge reflect differences in brain function? In other words, does interacting with different technologies engage distinct neural systems? By following the examples mentioned earlier, one can hypothesize that interacting with mechanical technologies might be more closely linked with neurocognitive mechanisms responsible for action and motor control, given their tangible and practical nature. Conversely, interacting with digital technologies might produce stronger engagement of neurocognitive systems tied to conceptual and social cognition, given their abstract and pro-communicative nature.

To explore these aspects, we employed functional magnetic resonance imaging (fMRI) to scrutinize the brain activity of participants ($N = 29$; female/male/non-binary gender: 23/6/0; mean age = 20.45 \pm 2.68 years) while they watched 5-second videos depicting interactions with either mechanical tools (e.g., using a screwdriver) or digital tools (e.g., setting the program on a washing machine). These interactions were compared to a control condition involving videos of simple objects movements. This condition aimed to subtract the brain activations associated with reaching, grasping/touching, and moving actions common to both types of tools. Additionally, the extent of arm-hand movements required to use the tools was matched as closely as possible across pairs to ensure further experimental control. For instance, the arm-hand interaction of swiping on a tablet was paired with the analogous mechanical action of using a brush to remove dust. In all videos, both the arm and the hand were visible, and the speed and kinematics of the movements were kept constant. Participants were tasked with deciding whether the video depicted a tool-use action, producing the same positive answer in both the mechanical and digital tool conditions and a negative answer in the control condition.

Along with the fMRI experiment, we devised a second and third experiment to investigate differences in mechanical versus digital technology at a behavioral level (Hutzler, 2014). In the second experiment, new participants ($N = 36$; female/male/non-binary gender: 35/1/0; mean age = 23.00 \pm 10.38 years) rated mechanical and digital tools based on a series of anthropomorphic traits (Gray et al., 2007). We expected a different level of anthropomorphism for digital tools compared to mechanical ones, assuming that digital tools have a greater social affinity. In the third experiment, we used specific frames from the fMRI experiment videos as priming stimuli. Hence, new participants ($N = 30$; female/male/non-binary gender: 22/8/0; mean age = 22.83 \pm 4.20 years) were presented with target images depicting distinct social situations and were asked to indicate whether these stimuli were communicative or not. We anticipated that if digital tools activate the conceptual/social brain, participants would be faster at discriminating communicative stimuli.

2. Methods

2.1. Ethics

The study was in accordance with the Declaration of Helsinki and approved by a French Ethics Committee (IRB: 2020-A02115–34). Written informed consent was obtained from all participants.

2.2. Participants

The *fMRI Experiment* was conducted in the Lyon Neuroimaging Department (CERMEP, Lyon, France). The *Anthropomorphic Traits Behavioral Experiment* and the *Priming Task Behavioral Experiment* were conducted in the Laboratory for the Study of Cognitive Mechanisms at the University of Lyon (Lyon, France). Participants were randomly recruited through advertisements posted on social media websites. For the *fMRI Experiment*, one week before the neuroimaging session, the participants were interviewed by a medical doctor to confirm their

eligibility for the neuroimaging session. In all experiments, participants were right-handed, had normal or corrected-to-normal vision, and reported no neurological or psychiatric disorder history. Participants in the fMRI experiment were offered a monetary incentive for their time (€ 60,00). No participant took part in more than one of the present experiments. Twenty-nine participants took part in the *fMRI Experiment* ($M_{age} = 20.45$, $SD = 2.68$, range: 18 to 27; female/male/non-binary gender: 23/6/0). Inclusion in the final sample required that head motion during scanning did not exceed 0.5 mm displacement (i.e., framewise displacement) between consecutive volumes on 90 % of volumes. All participants were included based on this criterion. Thirty-six participants took part in the *Anthropomorphic Traits Behavioral Experiment* ($M_{age} = 23.00$, $SD = 10.38$, range: 18 to 59; female/male/non-binary gender: 35/1/0) and 30 in the *Priming Task Behavioral Experiment* ($M_{age} = 22.83$, $SD = 4.20$, range: 18 to 31; female/male/non-binary gender: 22/8/0). Finally, 10 additional participants were included as a jury to assess the communicativeness of the stimuli used in the *Priming Task Behavioral Experiment* ($M_{age} = 31.40$, $SD = 6.85$, range: 23 to 46; female/male/non-binary gender: 5/5/0).

2.3. Power analyses

fMRI Experiment. Python scripts based on *neurodesign* were used to determine the optimal design and sample size, aiming to improve the results' generalizability, reliability, and validity (Durnez et al., 2018). The selected sample size is consistent with those in similar studies (Bosch et al., 2023; Federico et al., 2023; Seidel et al., 2023).

Anthropomorphic Traits Behavioral Experiment. A power analysis was performed using the *pwr* package in R (<https://www.r-project.org>) (Champely et al., 2020) to test the difference between two paired samples using a one-tailed test, a medium effect size ($d = 0.50$), a power of 0.80, and an alpha of 0.05. We used a one-tailed test because we predicted that participants should rate digital tools as showing more anthropomorphic characteristics than mechanical tools. We chose a medium effect size as proposed by Cohen (Cohen, 2013) when no justification to expect a different effect size is available. The result showed that a sample of 27 participants was required. We rounded this number to 30. We recruited six more participants than planned because of their willingness to participate.

Priming Task Behavioral Experiment. A power analysis was conducted using *G*Power* (Faul et al., 2007). Based on a desired power of 0.80, an alpha level of 0.05, and a medium effect size ($f \approx 0.25$), the analysis indicated a sample size of 28 participants was required. We rounded this number to 30.

2.4. Materials and procedure

Materials and Stimuli. The materials and stimuli used for all the experiments described below are available online at <https://osf.io/9dpjb>.

fMRI Experiment. The experiment aimed at examining brain activity in participants as they watched 5-second videos showing interactions with either mechanical or digital tools. This was compared to a control condition, where videos depicted simple object movements. The degree of arm-hand movement required to use the tools was matched across pairs to ensure experimental consistency. The task for participants was to decide whether the video depicted a tool-use action, requiring a positive answer for both mechanical and digital tool conditions and a negative answer for the control condition. The stimuli consisted of 10 video sequences each for mechanical tools, digital tools, and control movements, balanced and randomized across six runs to ensure equal presentation and reduce potential order effects. The stimuli are available online at <https://osf.io/9dpjb>. The experiment was programmed using PsychoPy 2021.2.3 (Peirce et al., 2019). Participants were instructed to lie still inside the MRI scanner while they viewed the videos. Each run began with a fixation cross (“+”) displayed for 2 s, followed by a series of 5-second video clips, with a randomized inter-trial interval of 3 to 5 s.

Participants responded using a button box, indicating whether the video depicted a tool-use action.

Priming Task Behavioral Experiment. The priming task was devised using PsychoPy 2021.2.3 (Peirce et al., 2019). Specific frames from videos used in the fMRI experiment, depicting the use of mechanical and digital tools, were utilized as priming stimuli. The target images depicted either communicative (e.g., people drinking and speaking) or non-communicative situations (e.g., an individual gazing alone at the sea). These images were previously evaluated by a jury of 10 individuals ($N = 10$; female/male/non-binary gender: 5/5/0; mean age = 31.40 ± 6.85 years) to assess their communicativeness. The stimuli are available online at <https://osf.io/9dppjb>. At the beginning of the experiment, investigators collected participants' demographic information, including participant number, age, and gender, through a graphical user interface dialogue box that appeared on the screen. Each participant provided responses using designated keys on a keyboard, balanced 50 % with "a" for communicative responses and "p" for non-communicative responses. The experiment was conducted in full-screen mode on a monitor set to 1920×1080 resolution. The priming stimuli consisted of 10 images of mechanical tools and 10 of digital tools. Target stimuli included 10 images depicting communicative situations and 10 depicting non-communicative situations. The experiment followed a 2 (prime type: mechanical vs. digital) × 2 (target type: communicative vs. non-communicative) within-subjects design. A custom Python script was used to randomize and pair prime images with target stimuli, ensuring a balanced presentation across conditions. The generated stimuli pairs were saved into a CSV file for subsequent presentation during the experiment. Participants read the instructions on the screen and initiated the experiment by pressing the spacebar. A fixation point ("+") was displayed for a random duration between 0.75 and 1 second to focus the participant's attention. A prime image depicting mechanical or digital tool usage was shown for 1 second. The fixation point was displayed again for a random duration between 0.75 and 1 second. The target stimulus image was then presented for up to 3 s. Participants responded by pressing the designated key corresponding to their perception of the image (communicative or non-communicative). A blank screen was displayed for 2 s to minimize carry-over effects between trials. The trial sequence was repeated for each participant, with the number of repetitions set to three. The order of the stimuli presentation within each block was randomized to prevent order effects. Response accuracy and reaction times were recorded for each trial. Detailed logs were saved, including start and stop times for each stimulus presentation and participant responses. Upon completing all trials, participants were given a thank-you message and instructed to press the spacebar to end the experiment. All data were automatically saved in CSV for data analysis.

Anthropomorphic Traits Behavioral Experiment. This experiment was conducted online using LimeSurvey and is available at <https://enquetes.univ-lyon2.fr/index.php/349641>. Participants were asked to assess ten mechanical tools and ten digital tools on five anthropomorphic traits (Gray et al., 2007): communication, consciousness, emotion, memory, and personality. The tools were the same as those used in the fMRI experiment, except we used specific frames depicting the central tool-use action instead of the videos. For each item, the participants could see the picture of the tool at the top of the screen and the anthropomorphic trait question at the bottom. Their task was to rate the tool based on the anthropomorphic trait using a five-point scale going from "not at all" to "very much". The participants had to rate the 20 tools on these five traits, i.e., 100 ratings per participant. There were five blocks of items, each block corresponding to one trait. Said differently, the participants rated the 20 tools on a trait, then on another trait, and so on. The order of blocks and the order of the items within each block were fully randomized across the participants. The participants had to respond by clicking on the graduation of their choice with a computer mouse. There was no time limit. The questions were as follows:

Communication. Is [name of the tool] able to communicate its

thoughts or feelings to others?

Consciousness. Is [name of the tool] able to be conscious?

Emotion. Is [name of the tool] able to feel or express emotions?

Memory. Is [name of the tool] able to memorize information?

Personality. Is [name of the tool] able to have its own personality?

2.5. Behavioral analyses

Priming Task Behavioral Experiment. Data analysis was conducted using the statistical software Jamovi (version 2.5.1.0; <https://www.jamovi.org>). The study employed a 2 (prime type: mechanical vs. digital) × 2 (target type: communicative vs. non-communicative) within-subjects design. Only correct responses were included in the analysis. Response times (RT) were filtered to include only those within the range of 0.55 to 1.10 s. This range was selected to capture deliberate and accurate responses while excluding extremely fast or slow outliers that might indicate inattentiveness. A repeated measures ANOVA was performed to assess the main effects of prime type and target condition, as well as their interaction, on participants' RTs. Post hoc comparisons were conducted to explore further the significant interaction between prime type and target condition. To control for multiple comparisons, the Holm-Bonferroni correction was applied. An alpha level of 0.05 was used for the analysis.

Anthropomorphic Traits Behavioral Experiment. For each anthropomorphic trait (Communication, Consciousness, Emotion, Memory, and Personality), we employed regression modeling in R using the *lmerTest* package (Kuznetsova et al., 2017). We fitted a linear mixed-effects model with the anthropomorphic trait as the dependent variable, technology type (mechanical vs. digital) as a fixed effect, and participant identity as a random effect. To control for multiple comparisons, the Holm-Bonferroni correction was applied. Additionally, we computed a total anthropomorphism score by averaging the five anthropomorphic trait scores for each participant. We then fitted a linear mixed-effects model with the total score as the dependent variable, technology type (mechanical vs. digital) as a fixed effect, and participant identity as a random effect. An alpha level of 0.05 was used for the analysis.

2.6. fMRI analyses

fMRI Data Acquisition. fMRI data were obtained using a 3T Siemens Prisma Scanner (Siemens, Erlangen, Germany) equipped with a 64-channel head coil. Blood-Oxygen Level Dependent (BOLD) images were captured through T2*-weighted echo-planar imaging (EPI) utilizing a multiband sequence. All functional images were acquired as oblique-axial scans aligned with the anterior-posterior commissure (AC-PC) line. The imaging parameters were as follows: 57 slices, TR/TE = 1400/30 ms, flip angle = 70°, field of view = 96×96 mm², slice thickness = 2.3 mm, voxel size = 2.3 × 2.3 × 2.3 mm³, multiband factor = 2. Structural T1-weighted images were obtained using an MPRAGE sequence with the following specifications: 224 sagittal slices, TR/TE = 3000/2.93 ms, inversion time = 1100 ms, flip angle = 8°, field of view = 224×256 mm, slice thickness = 0.8 mm, voxel size = 0.8 × 0.8 × 0.8 mm³.

fMRI Univariate Analyses. Univariate analyses were performed using the FMRIB Expert Analysis Tool (FEAT) version 6, part of FSL (FMRIB Software Library; <https://fsl.fmrib.ox.ac.uk>). Preprocessing steps included slice timing correction, linear motion correction (Jenkinson et al., 2002), high-pass temporal filtering (sigma = 25 s), brain extraction (Smith, 2002), and linear co-registration to the corresponding T1-weighted image followed by linear registration to the MNI152 standard space (Jenkinson and Smith, 2001). Spatial smoothing was applied using a Gaussian kernel with a full-width at half-maximum (FWHM) of 5 mm, and grand-mean intensity normalization of the entire 4D dataset was achieved using a single multiplicative factor. The preprocessed time series data were modeled using FMRIB's Improved Linear Model (FILM) with local autocorrelation correction (Woolrich

et al., 2001), incorporating all experimental conditions of interest (Control, Mechanical, Digital) and confounds such as motion parameters. The analyses involved thresholding the Z (Gaussianized T) statistic using clusters determined by $Z > 3.1$ and a corrected cluster significance threshold of $P < 0.05$ at the participant level. A fixed effects model was employed at the group level using FMRIB's Local Analysis of Mixed Effects (FLAME), with the random effects variance set to zero (Beckmann et al., 2003; Woolrich, 2008; Woolrich et al., 2004). Both stages 1 and 2 of FLAME were implemented. Group-level analyses were conducted using a cluster-correction method with a Z-statistic threshold of 3.1, defining clusters based on contiguous voxels. Multiple comparisons were controlled through Gaussian Random Field Theory, with a family-wise error rate threshold of $P < 0.001$. The following contrasts were performed: Mechanical vs Control, Digital vs Control, Mechanical vs Digital, and Digital vs Mechanical.

Task-Based Functional Connectivity Analyses. Functional connectivity analyses were performed using the Functional Connectivity Toolbox (Whitfield-Gabrieli and Nieto-Castanon, 2012) version 22a in MATLAB version R2024a. Preprocessing was conducted using the standard CONN preprocessing pipeline, which included the following steps: (i) functional realignment and unwarping; (ii) slice-timing correction; (iii) outlier detection via ART-based scrubbing; (iv) direct segmentation and normalization to the Montreal Neurological Institute (MNI) reference space; and (v) Gaussian smoothing with an 8-mm full-width at half-maximum (FWHM). The data were then denoised using CONN's default procedures, which involve linear detrending, de-spiking, and bandpass filtering within a 0.008 Hz to 0.09 Hz range. Psychophysiological interaction (PPI) analyses were used to study changes in functional connectivity between experimental conditions (i.e., mechanical vs. digital). Regions of Interest (ROI) included 10 Harvard-Oxford atlas: Left Angular Gyrus (AG), Left Frontal Orbital Cortex (OFC), Left Inferior Lateral Occipital Cortex (iLOC), Left Inferior Frontal Gyrus (*pars opercularis*; IFG), Left Middle Temporal Gyrus (anterior division; aMTG), Left Middle Temporal Gyrus (posterior division; pMTG), Left Middle Temporal Gyrus (temporooccipital part; toMTG), Left Supramarginal Gyrus (anterior division; aSMG), Left Supramarginal Gyrus (posterior division; pSMG), and Left Temporal Pole (TP). For each pair of ROIs, a generalized psychophysiological interaction model (McLaren et al., 2012) (gPPI) was defined with ROI BOLD signals as physiological factors, boxcar signals characterizing each individual task condition convolved with an SPM canonical hemodynamic response function as psychological factors, and the product of the two as psychophysiological interaction terms (Cisler et al., 2014). Functional connectivity changes across conditions were characterized by the multivariate regression coefficient of the psychophysiological interaction terms in each model. Group-level analyses were performed using a General Linear Model (GLM). A separate GLM was estimated for each connection, with first-level connectivity measures at this connection as dependent variables (one independent sample per participant and one measurement per experimental condition) and groups as independent variables. Connection-level hypotheses were evaluated using multivariate parametric statistics with random effects across participants and sample covariance estimation across multiple measurements. Inferences were performed at the level of individual clusters (groups of similar connections). These inferences were based on parametric statistics within and between each pair of networks (Functional Network Connectivity), with networks identified using a complete-linkage hierarchical clustering procedure based on ROI-to-ROI anatomical proximity and functional similarity metrics. Results were thresholded using a combination of a $P < 0.01$ connection-level threshold and a familywise corrected p -FDR < 0.05 cluster-level threshold (Jafri et al., 2008).

3. Results and discussion

The results of the first fMRI experiment revealed bilateral activations in brain regions encompassing the dorsal, ventro-dorsal, and ventral

streams (Milner and Goodale, 2008; Rizzolatti and Matelli, 2003). Both the univariate analyses of the Blood-Oxygen-Level-Dependent (BOLD) time-series data (Figs. 1-2; Tables 1-4) and task-based functional connectivity (Fig. 3; Tables 5-6) highlighted the recruitment of distinct brain regions for the two experimental conditions (Huang et al., 2024; Parker et al., 2002). Different technological knowledge appeared associated with distinct neural circuits: Mechanical tools extensively engaged the dorsal and ventro-dorsal streams. Conversely, digital tools strongly activated the ventral stream. Participants in the fMRI experiment were instructed to merely detect whether a tool-use action was shown on the screen, producing the same response for both digital and mechanical tool-use actions. Yet, this recruited distinct neural networks, suggesting the spontaneous, implicit recruitment of different cognitive resources depending on the type of technology. Finally, the two behavioral studies highlighted that we anthropomorphize digital technology more than mechanical technology (Fig. 4A) and that digital technology primes communicative content, thereby activating the conceptual/social brain (Fig. 4B-D).

3.1. Mechanical technology recruits the action brain

Mechanical tools primarily recruited dorsal and ventro-dorsal regions of the so-called *action observation network* (Karakose-Akbiyik et al., 2023). The pattern of BOLD activations included the primary and secondary somatosensory, premotor, and supplementary motor cortex, suggesting that participants may have mentally rehearsed the motor actions required for using these tools. This idea aligns with the principle of *motor simulation* (Jeannerod, 2001), which posits that observing an action can activate neural circuits similar to those used in actually performing the action. These activations may also be attributed to the "here and now" motor control (Pisella et al., 2000) inherent in the practical nature of mechanical tasks. A complementary hypothesis that justifies such specific action-related activations involves the so-called *mirror neurons* (Rizzolatti and Sinigaglia, 2010), which are assumed to be present in these brain regions. These neurons fire when an individual performs a specific action and, most importantly, when they observe someone else performing the same action, indicating a potential neural basis for action understanding.

Both cerebral hemispheres appeared engaged in processing mechanical tools, suggesting a more integrated and distributed neural network than previously proposed by studies emphasizing primarily left-lateralized activation for tool-related cognition (Sakreida et al., 2016; Seidel et al., 2023). This discrepancy could be due to variations in experimental design, task demands, or the nature of stimuli across studies. However, the bilateral engagement observed here may also indicate the necessity of integrated sensorimotor processing when interacting with mechanical tools. As stimulus complexity increases, interhemispheric communication mechanisms may indeed play a more significant role (Gazzaniga, 2000; Lewis, 2006). Thus, the results of this study may serve as an impetus for future research on hemispheric lateralization in processing different types of technology and tools.

Alongside motor-based activations, areas within the parietal and frontal lobes were recruited, notably the rostral part of the inferior parietal lobule—including the anterior supramarginal gyrus—and the inferior frontal gyrus. These regions, especially the left anterior supramarginal gyrus (Federico et al., 2022), are involved in understanding objects' mechanical properties, enabling individuals to engage with the physical world through a cognitive process recently termed *technical reasoning* (Osieurak et al., 2023). Such a form of *causal understanding* is essential for using tangible, practical tools. For instance, when Armstrong was tasked with maintaining the vessel's structural integrity during the Apollo 11 mission, using a wrench to secure a loose bolt on the spacecraft represented an optimal *technical solution* to prevent malfunctions. Convergent evidence from clinical neurology highlights that damage to the regions of the technical reasoning network may result in *tool-use apraxia*, a condition characterized by the inability to use

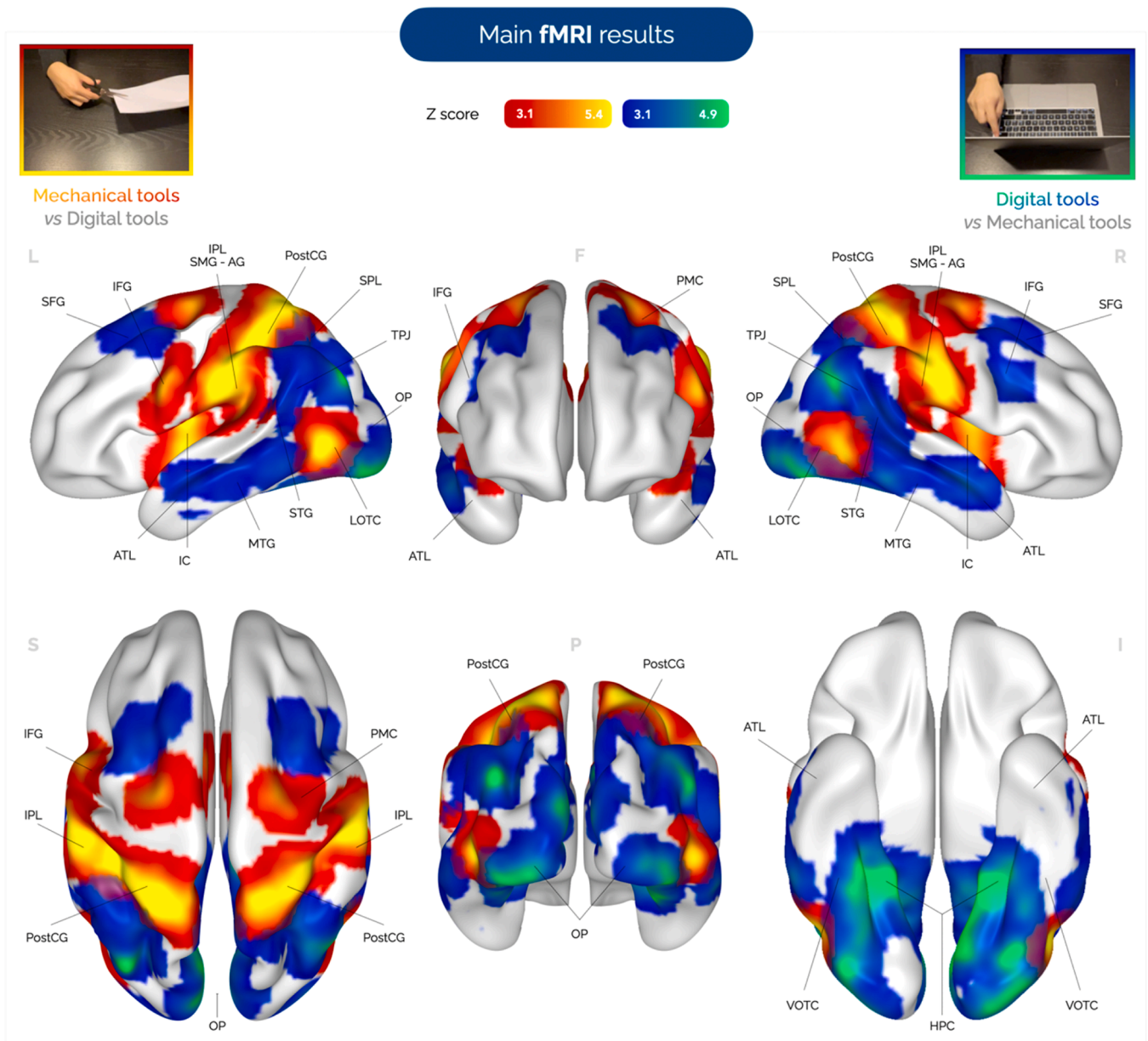


Fig. 1. Main results. This figure displays brain activation maps contrasting mechanical tools with digital tools. Activations favoring mechanical tools over digital tools are represented in warm colors (red and yellow), whereas activations favoring digital tools over mechanical tools are shown in cool colors (blue and green). *Acronyms:* L = Left view of the brain, F = Frontal view of the brain, R = Right view of the brain, S = Superior view of the brain, P = Posterior view of the brain, I = Inferior view of the brain, IFG = Inferior Frontal Gyrus, IPL = Inferior Parietal Lobule, SMG = Supramarginal Gyrus, AG = Angular Gyrus, PostCG = Postcentral Gyrus, SPL = Superior Parietal Lobule, TPJ = Temporoparietal Junction, OP = Occipital Pole, PMC = Premotor Cortex, SFG = Superior Frontal Gyrus, STG = Superior Temporal Gyrus, MTG = Middle Temporal Gyrus, LOTC = Lateral Occipitotemporal Cortex, ATL = Anterior Temporal Lobe, IC = Insular Cortex, HPC = Hippocampus, and VOTC = Ventral Occipitotemporal Cortex. The images illustrate the distribution and intensity of activation clusters. The color bar indicates Z-scores, with 3.1 as the threshold for significant activations ($P < 0.001$). The cluster list is reported in [Tables 1-2](#).

mechanical tools and reason about their physical properties (Goldenberg, 2009; Metaireau et al., 2024).

The lateral occipitotemporal and insular cortex were also engaged when looking at mechanical tools. These regions are involved in perceiving biological motion, processing physical laws such as gravity, and analyzing dynamic aspects of actions, including movement direction (Indovina et al., 2005; Lingnau and Downing, 2015; Rousseau et al., 2021). The lateral occipitotemporal cortex is organized around a posterior-anterior gradient, encapsulating visual information from perceptual action precursors to conceptual action representations (Wurm and Caramazza, 2022). This process allows for integrating various action-related visual elements, such as tools, body parts, and

their movements, in a single perceptual/conceptual entity. Consequently, these regions may collectively contribute to a comprehensive and consistent neural representation of tangible tools, integrating sensorimotor and visual information with higher-level action-related knowledge (Federico et al., 2023).

3.2. Digital technology recruits the conceptual and social brain

Despite displaying similar kinematics and movement modalities and necessitating the same task response (*i.e.*, “yes, it is a tool-use action”), the neural response to digital tools, as compared to mechanical ones, revealed a distinctly different landscape. This response involved

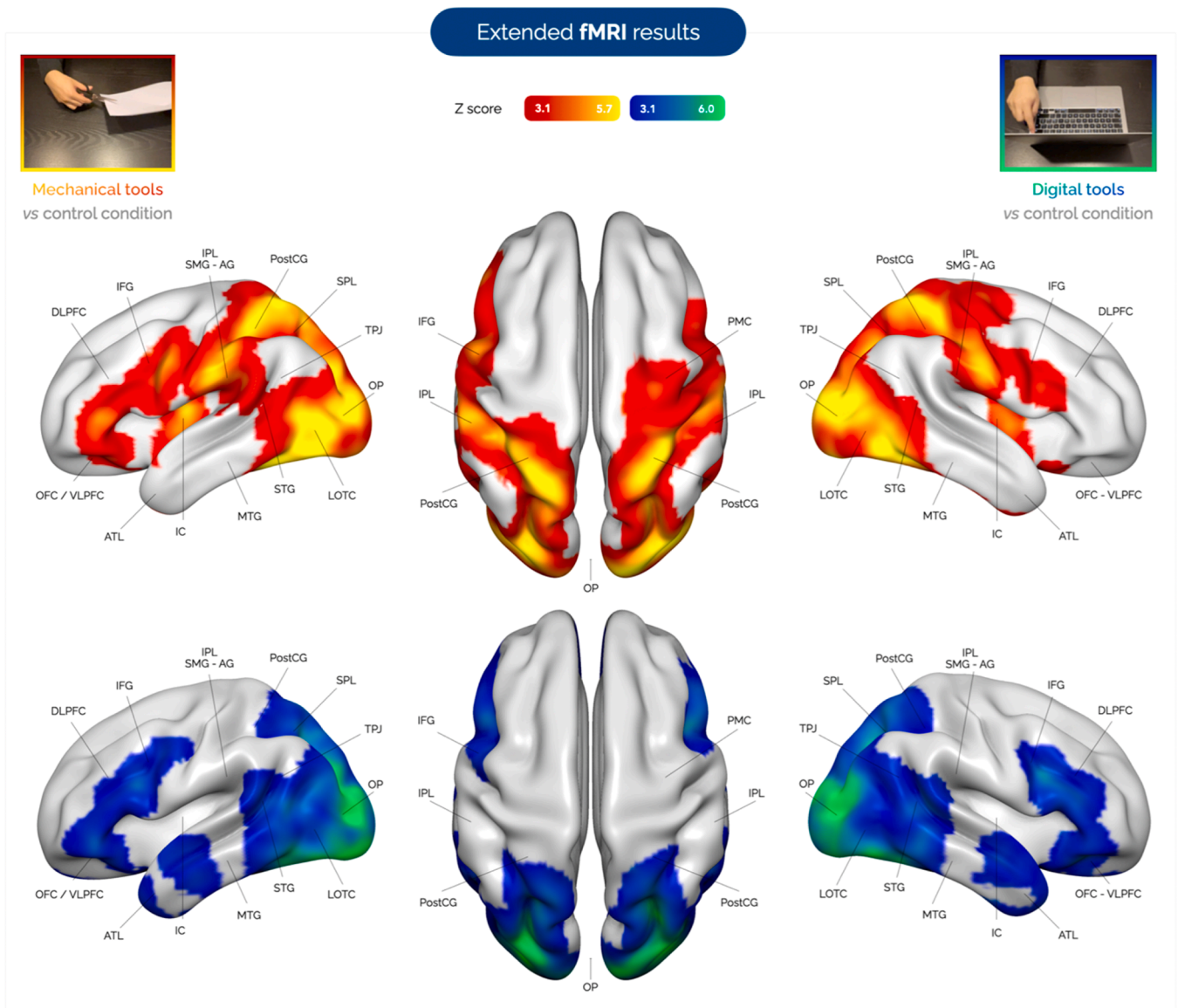


Fig. 2. Brain Activation Patterns for Mechanical and Digital Tools (vs Control Condition). This figure presents brain activation maps contrasting mechanical and digital tools with the control condition. The upper row displays activation patterns associated with mechanical tools, as detailed in Table 3. The lower row shows activation patterns related to digital tools, with cluster information provided in Table 4. The activation intensity is represented by color scales indicating the Z scores ($P < 0.001$). *Acronyms:* DLPFC = Dorsolateral Prefrontal Cortex, IFG = Inferior Frontal Gyrus, IPL = Inferior Parietal Lobule, SMG = Supramarginal Gyrus, AG = Angular Gyrus, PostCG = Postcentral Gyrus, SPL = Superior Parietal Lobule, TPJ = Temporoparietal Junction, OP = Occipital Pole, PMC = Premotor Cortex, OFC = Orbitofrontal Cortex, VLPFC = Ventrolateral Prefrontal Cortex, STG = Superior Temporal Gyrus, MTG = Middle Temporal Gyrus, LOTC = Lateral Occipitotemporal Cortex, ATL = Anterior Temporal Lobe, IC = Insular Cortex.

Table 1
fMRI Univariate Analysis: Mechanical tools > Digital tools (cluster list).

Cluster Index	Voxels	P value	Z max	MNI Coordinates (X, Y, Z)
9	4762	< 0.001	7.32	-38, -40, 50
8	3991	< 0.001	6.84	36, -36, 52
7	1089	< 0.001	5.84	-40, -6, 12
6	844	< 0.001	6.38	-44, -68, 0
5	683	< 0.001	5.98	44, -60, 0
4	584	< 0.001	5.25	-22, -12, 54
3	503	< 0.001	5.54	24, -8, 62
2	490	< 0.001	5.7	38, -2, 14
1	289	< 0.001	5.4	-2, 4, 36

Table 2
fMRI univariate analysis: digital tools > mechanical tools (cluster list).

Cluster Index	Voxels	P value	Z max	MNI Coordinates (X, Y, Z)
9	10,394	< 0.001	7.13	-22, -50, -10
8	1741	< 0.001	5.53	46, -66, 28
7	1325	< 0.001	5.66	-36, -76, 32
6	865	< 0.001	5.19	2, -38, 36
5	468	< 0.001	4.12	-66, -46, -4
4	355	< 0.001	4.25	-26, 10, 48
3	287	< 0.001	4.66	32, 12, 58
2	237	< 0.001	4.27	34, 10, 26
1	231	< 0.001	4.42	56, -6, -18

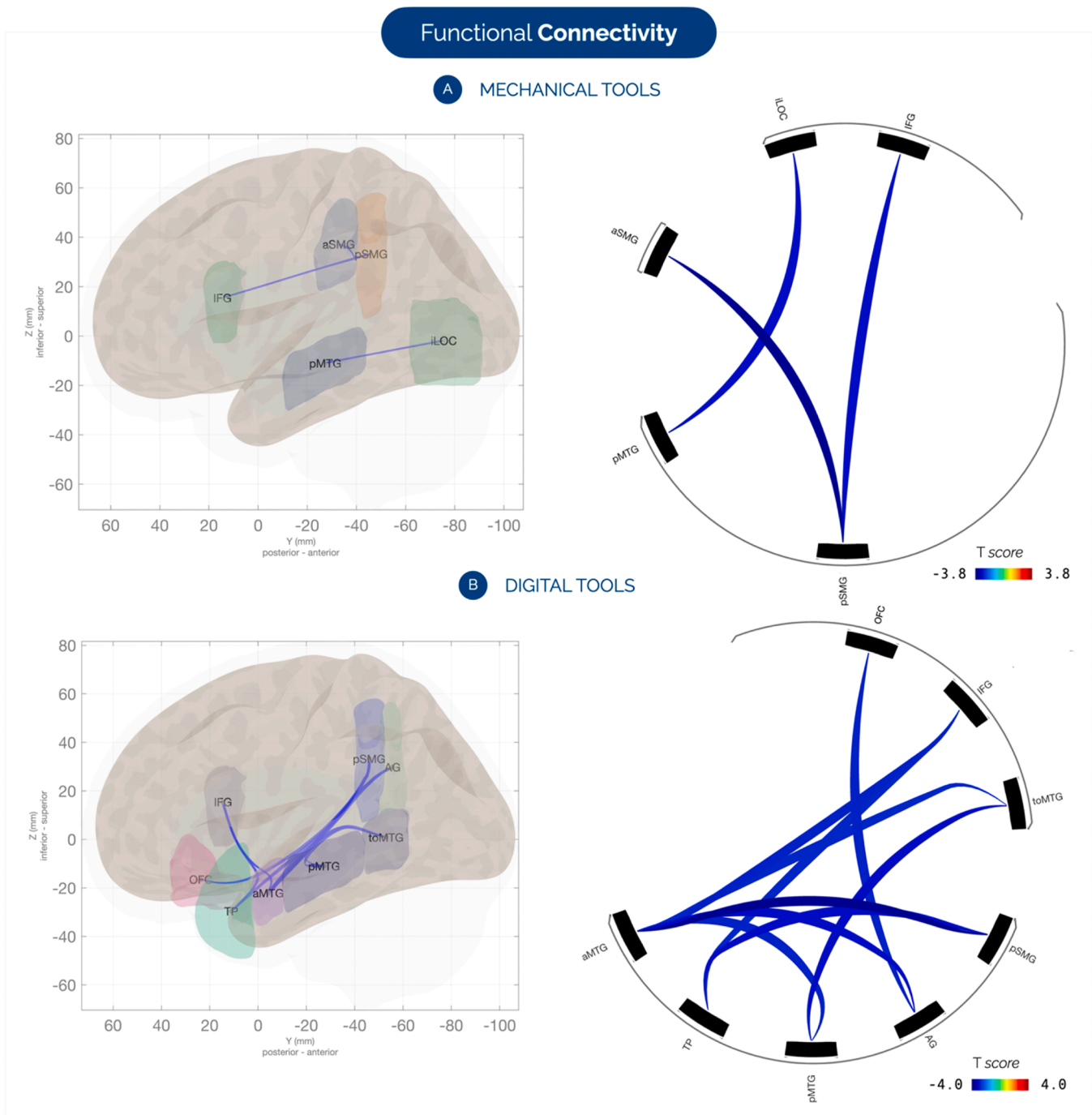


Fig. 3. Functional Connectivity. This figure recaps the results of the task-based functional connectivity analysis comparing mechanical and digital tools, including 10 regions of the left hemisphere. **(A)** The left panel depicts the functional connectivity associated with mechanical tools, visualized on a sagittal view of the left brain. Cluster-level statistics revealed a functional network comprising the anterior division of the supramarginal gyrus (aSMG), inferior frontal gyrus *pars opercularis* (IFG), inferior lateral occipital cortex (iLOC), posterior middle temporal gyrus (pMTG) and posterior division of the supramarginal gyrus (pSMG). The right panel presents a circular plot detailing the strength and direction of task-based ROI-to-ROI connectivity modulation, with color-coded edges representing *T*-scores. See [Table 5](#) for the extended statistics of each connection. **(B)** The left panel depicts the functional connectivity associated with digital tools, visualized on a sagittal view of the left brain. Cluster-level statistics revealed a functional network comprising the anterior division of the supramarginal gyrus (aSMG), anterior middle temporal gyrus (aMTG), inferior frontal gyrus *pars opercularis* (IFG), orbitofrontal cortex (OFC), posterior division of the supramarginal gyrus (pSMG), posterior middle temporal gyrus (pMTG), temporal pole (TP), and temporo-occipital middle temporal gyrus (toMTG). The right panel presents a circular plot detailing the strength and direction of task-based ROI-to-ROI connectivity modulation, with color-coded edges representing *T*-scores. See [Table 6](#) for the extended statistics of each connection.

bilateral activation of specific occipital, frontal, and temporal regions within the ventral stream, potentially indicating how participants may have relied on visual processing and object recognition strategies that engaged higher-order cognitive functions (Wang et al., 2020; Wurm and Caramazza, 2019).

A notable activation pattern emerged along a gradient of visual information processing in the ventral occipitotemporal cortex, progressing bilaterally from posterior to anterior regions. This gradient suggests that digital tools, being opaque and abstract, are processed in more anterior, a-modal regions of the occipitotemporal cortex (Patterson et al., 2007).

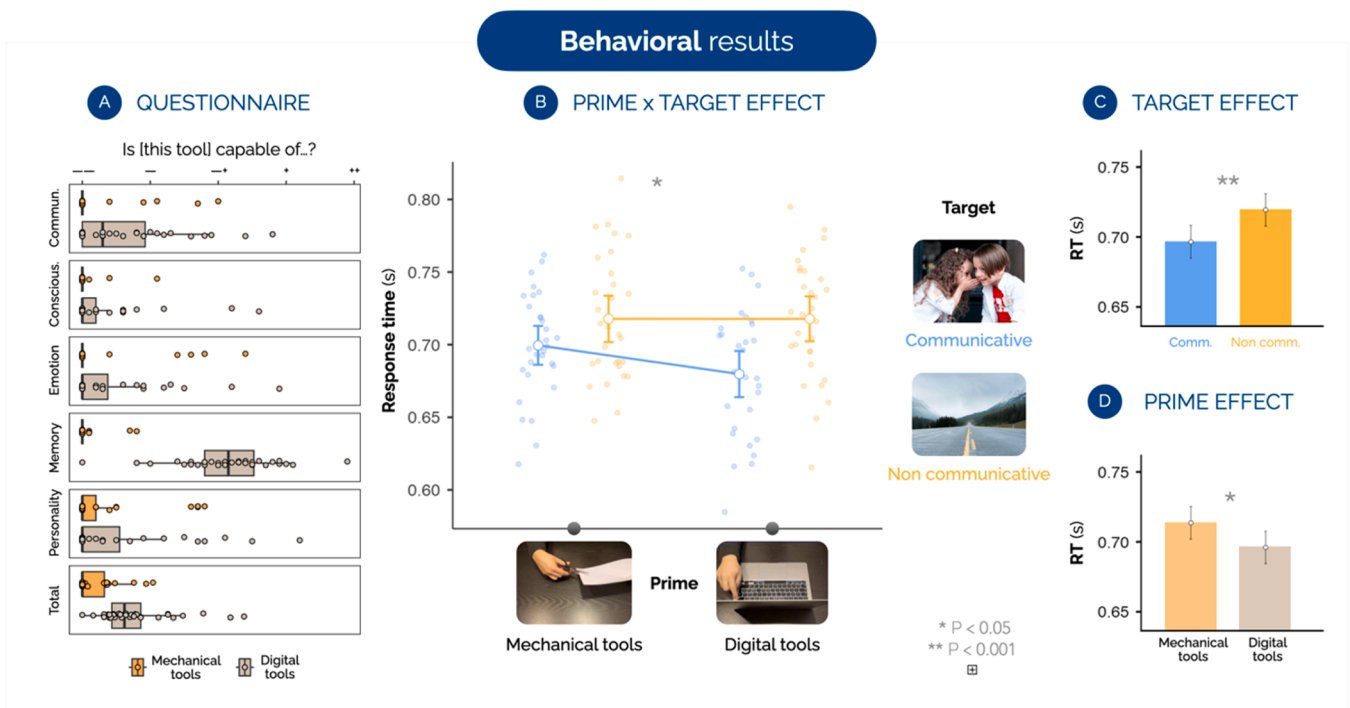


Fig. 4. Behavioral results. This figure recapitulates the results of the behavioral experiments. (A) *Questionnaire*: Participants were asked if the tools (mechanical and digital) were capable of various functions (Communication, Consciousness, Emotion, Memory, Personality). The box plots display the responses for mechanical tools (orange) and digital tools (gray). (B) *Prime x Target Effect*: Response times (RT) are shown for targets following primes of mechanical tools (orange) and digital tools (blue). The scatter plot illustrates individual response times with mean RTs represented by the horizontal lines. The error bars indicate the standard error of the mean (SEM). (C) *Target Effect*: Comparison of RTs for communicative (Comm.) and non-communicative (Non comm.) targets. The bar graph shows mean RTs with error bars representing SEM. (D) *Prime Effect*: RTs for primes of mechanical tools versus digital tools. The bar graph presents mean RTs with error bars indicating SEM. (A–D) Significant differences are indicated by * ($P < 0.05$) and ** ($P < 0.001$).

Accordingly, the anterior regions of the temporal lobe exhibited activations for digital tools, suggesting their integration within neural frameworks that handle abstract information (Simmons and Martin, 2009). The anterior temporal lobe has recently been considered a neural hub (Patterson and Lambon Ralph, 2016) for the cross-modal integration of abstract conceptual knowledge (Lambon Ralph et al., 2016). In addition, activations in the posterior regions of the middle temporal gyrus likely may signal specific object-related semantic information processing, which is crucial for understanding complex associations between actions and meanings (Kalénine et al., 2010; Lesourd et al., 2023). Collaterally, clinical neurology studies have documented that patients with lesions in these regions may experience a profound deficit in their ability to recognize the functions associated with objects while maintaining the capacity to manipulate them, a condition known as *semantic dementia* (Hodges et al., 1999). Thus, the temporal circuitry recruited when engaging with digital tools may indicate the need to rely on conceptual reasoning and analogy to interpret how these tools work. This process likely involves the anterior temporal lobe, as it helps synthesize abstract ideas and apply them to novel contexts, like digital interfaces (Lambon Ralph et al., 2016; Patterson and Lambon Ralph, 2016; Simmons and Martin, 2009; Visser et al., 2012; Weiller et al., 2021). In contrast, mechanical tools automatically engage brain pathways specialized for well-known actions and tool use, activating regions related to well-practiced actions (Hamzei et al., 2016; Sakreida et al., 2016). Digital tools, however, may lack these ingrained patterns, prompting the brain to draw on more abstract knowledge systems. This difference suggests that the anterior temporal lobe may play a critical role not just in understanding meaning but also in adapting to new kinds of tools and interfaces (Federico et al., 2023; Lesourd et al., 2023; Seidel et al., 2023).

Along with the ventral occipitotemporal circuitry, digital tool-related brain activations prominently involved the temporo-parietal

junction, as well as the inferior, middle and superior frontal gyri, the hippocampus, and the parahippocampal regions. The recruitment of such neural circuitry is particularly insightful when considering the role of digital tools in *social cognition* (Herrmann et al., 2007). Indeed, these tools facilitate social learning, networking, and connectivity, fundamentally shaping how we interact and communicate in the digital age. Nowadays, this connectivity is often facilitated by the Internet, which enhances the cognitive processes associated with social cognition (Firth et al., 2019). The pattern of activated brain regions we found is well-known for their association (Amodio and Frith, 2006; Gangopadhyay et al., 2021) with communication abilities, action monitoring, social skills, and, more generally, with the set of capabilities we have to understand others, known as *mentalizing* (Quesque et al., 2024) and *theory of mind* (Frith and Frith, 2005). Therefore, on the one hand, the engagement of the neural circuitry recruited by digital tools may serve as a neural interface for higher-level semantic cognition, reflecting the abstract nature of these tools. On the other hand, this circuitry may also suggest that digital technological knowledge is deeply embedded within the social brain (Thye et al., 2024). In a way, digital tools may share a fundamental quality with other minds: their inherent opacity, which calls on the social brain to construct theories about their functioning.

3.3. Task-Based functional connectivity

The broad picture of the BOLD activations reveals that distinct brain regions are engaged when interacting with different types of technology. Mechanical technology principally activates ventro-dorsal regions, while digital technology is more associated with the activity of ventral regions. To further explore this, we conducted a second-level task-based functional connectivity analysis (McLaren et al., 2012), examining the interactions between specific brain regions based on the type of tool. Building on the insights gained from the univariate analyses of each

Table 3
fMRI univariate analysis: mechanical tools > control condition (cluster list).

Cluster Index	Voxels	P value	Z max	MNI Coordinates (X, Y, Z)
8	28,367	< 0.001	7.26	-44, -50, -20
7	824	< 0.001	5.66	-54, 6, 34
6	400	< 0.001	5.06	-46, 36, 4
5	342	< 0.001	4.33	52, 14, 22
4	303	< 0.001	6.55	-16, -34, -2
3	300	< 0.001	5.42	22, -32, 0
2	275	< 0.001	4.28	-36, 32, -18
1	250	< 0.001	5.02	38, -2, 0

Table 4
fMRI univariate analysis: digital tools > control condition (cluster list).

Cluster Index	Voxels	P value	Z max	MNI Coordinates (X, Y, Z)
5	29,017	< 0.001	8.05	(32, -50, -14)
4	1137	< 0.001	5.74	(40, 12, 24)
3	564	< 0.001	4.44	(-6, 14, -16)
2	474	< 0.001	5.18	(32, 30, -18)
1	342	< 0.001	4.44	(-18, -80, -38)

Table 5
ROI-to-ROI functional connectivity: mechanical tools.

Cluster 1 $F(2,27) = 10.45$ ($p\text{-FDR} = 0.002$)			
Seed	Target	T (28)	p-FDR value
IFG	pSMG	-3.28	0.024
iLOC	pMTG	-3.22	0.029
Cluster 2 $F(2,27) = 4.09$ ($p\text{-FDR} = 0.046$)			
aSMG	pSMG	-3.80	0.006

Acronyms: aSMG: Left Anterior Supramarginal Gyrus, iLOC: Left Inferior Lateral Occipital Cortex, pMTG: Left Posterior Middle Temporal Gyrus, pSMG: Left Posterior Supramarginal Gyrus. Parametric multivariate statistics (cluster-level inferences) were used with a cluster threshold of $P < 0.05$, familywise error corrected (MVPA omnibus test), and a connection threshold of $P < 0.01$ (Jafri et al., 2008).

Table 6
ROI-to-ROI functional connectivity: digital tools.

Cluster 1 $F(2,27) = 8.56$ ($p\text{-FDR} = 0.006$)			
Seed	Target	T (28)	P value
pSMG	aMTG	-4.05	0.003
pSMG	TP	-3.39	0.009
aMTG	pSMG	-3.34	0.015
aMTG	AG	-3.21	0.015
TP	AG	-2.44	0.048
TP	pSMG	-2.33	0.048
Cluster 2 $F(2,27) = 7.63$ ($p\text{-FDR} = 0.006$)			
aMTG	IFG	-2.89	0.016
aMTG	toMTG	-2.89	0.016
toMTG	pMTG	-3.32	0.022
TP	IFG	-2.89	0.048
TP	OFC	-2.67	0.048
TP	toMTG	-2.34	0.048

Acronyms: AG: Left Angular Gyrus, aMTG: Left Anterior Middle Temporal Gyrus, aSMG: Left Anterior Supramarginal Gyrus, IFG: Left Inferior Frontal Gyrus, *pars opercularis*, OFC: Left Frontal Orbital Cortex, pMTG: Left Posterior Middle Temporal Gyrus, pSMG: Left Posterior Supramarginal Gyrus, TP: Left Temporal Pole, toMTG: Left Middle Temporal Gyrus, temporooccipital part. Parametric multivariate statistics (cluster-level inferences) were used with a cluster threshold of $P < 0.05$ familywise corrected (MVPA omnibus test) and a connection threshold of $P < 0.01$ (Jafri et al., 2008).

condition compared to the control condition (Fig. 2; Tables 3-4), we instrumentally analyzed the functional connectivity of 10 left-brain regions (see **Material and Methods**, Fig. 3 and Tables 5-6).

Interaction with mechanical tools engaged a functional network involving the inferior frontal gyrus, anterior and posterior divisions of the supramarginal gyrus, inferior segment of the lateral occipital cortex, and posterior middle temporal gyrus (see Table 5 and Fig. 3A). As we discussed above, these regions are integral to action processing and sensorimotor integration. In this context, the inferior frontal gyrus is associated with motor planning, timing and execution; thus, it might play a key role in integrating action-related information of diverse nature to facilitate the interaction with mechanical objects (Bortoletto and Cunnington, 2010; Federico et al., 2023; Koehlin and Summerfield, 2007; Stadler et al., 2011). The left supramarginal gyrus plays a key role in technical reasoning and mechanical tool use (Bosch et al., 2023; Federico et al., 2022). The lateral occipital cortex and the posterior middle temporal gyrus contribute to the visual processing of object features, aiding in the recognition and utilization of mechanical tools by processing motion and action-related visual information, thereby supporting the understanding of tool use dynamics (Lesourd et al., 2023). Collectively, these regions may support the interaction with mechanical tools, emphasizing the importance of sensorimotor processing in such tasks.

Digital tools elicited functional connectivity involving the inferior frontal gyrus, orbitofrontal cortex, anterior temporal lobe, various divisions of the middle temporal gyrus, posterior supramarginal gyrus, and angular gyrus (see Table 6 and Fig. 3B). The inferior frontal gyrus, beyond the above-mentioned role in motor functions, is implicated in language processing, abstract reasoning and social cognition (Diveica et al., 2023; Grecucci et al., 2013). For instance, processing artificial grammar rules in foreign languages activates the IFG even when participants are unaware of the unnatural structure, suggesting the IFG's role in processing complex, non-natural information, as with digital tools (Musso et al., 2003). This region has direct connections with the temporal pole as well as with the left angular gyrus, supramarginal gyrus, and orbitofrontal cortex (Heather Hsu et al., 2020; Weiller et al., 2021). The orbitofrontal cortex is implicated in social behavior and its engagement suggests that digital tool interaction may involve the integration of social information, possibly due to the interactive nature of digital technologies (Beer et al., 2006; Hodson, 2018; Rolls, 2004). The anterior temporal lobe may signal the integration of distinct types of semantic knowledge when using digital tools (Patterson and Lambon Ralph, 2016; Simmons and Martin, 2009; Visser et al., 2012). The middle temporal gyrus, supramarginal gyrus, and angular gyrus are part of the temporoparietal junction, a region involved in social cognition, including theory of mind and empathy (Saxe and Kanwisher, 2003). Their involvement suggests that digital tool use may require understanding and predicting user interactions, akin to social cognitive processes. In sum, the functional connectivity associated with digital tools supports the idea that these tools require a greater degree of conceptual and social cognitive engagement than mechanical tools.

Finally, it should be noted how functional connectivity analyses revealed the co-activation of the left inferior frontal gyrus in both mechanical and digital tool conditions. Along with the above-mentioned specificities of this region, the role of the inferior frontal gyrus in action and conceptual/social processing could be effectively explained by the dual-loop model, positioning the inferior frontal gyrus as a convergence hub for both dorsal and ventral stream (Weiller et al., 2022). Therefore, in the context of mechanical tools, the inferior frontal gyrus may support motor planning and technical reasoning, potentially facilitating action-oriented processing. Conversely, with digital tools, the IFG might integrate inputs from the ventral stream, enabling conceptual and social processing as well as analogical reasoning, essential for navigating the abstract and interactive nature of digital technology. This dual-loop system may thus allow the brain to flexibly and integratively process action-driven, conceptually demanding tools.

3.4. Behavioral findings

To substantiate reverse cognitive inference from the neuroimaging data (Hutzler, 2014), that is, to demonstrate that observed differences in the brain correspond to actual differences in cognition, we conducted a second behavioral study. New participants were asked to complete a questionnaire in which they rated mechanical and digital tools based on various anthropomorphic traits, including *communication, consciousness, emotion, memory, and personality* (Gray et al., 2007). The results revealed that participants tended to anthropomorphize digital tools more than mechanical ones. This intriguing tendency to attribute human-like qualities to digital tools suggests a link to social cognition, as the cognitive processes involved in recognizing these anthropomorphic traits are closely related to those used in social interactions. Subsequently, we utilized specific frames from the videos employed in the fMRI experiment—depicting the use of mechanical and digital tools—as priming stimuli in a third behavioral study. In this study, distinct target images depicted either communicative (e.g., people drinking and speaking) or non-communicative situations (e.g., an individual gazing alone at the sea). A jury previously evaluated these images to assess their communicativeness. New participants were instructed to indicate whether these stimuli were communicative.

We hypothesized that if mechanical versus digital tools used as primes pre-activate distinct neural networks, as indicated by the fMRI experiment, these activations should influence participants' reaction times. Specifically, if digital tools (primes) pre-activate social brain regions more than mechanical tools, participants should be quicker at discriminating communicative stimuli (targets) when primed with digital tools. Behavioral results supported this hypothesis, indicating a significant main effect of prime ($F(1, 29) = 4.99, P < 0.05, \eta^2p = 0.147$; Fig. 4D) and target ($F(1, 29) = 26.58, P < 0.001, \eta^2p = 0.478$; Fig. 4C) on reaction times. Thus, participants were faster at distinguishing communicative stimuli than non-communicative, regardless of the prime type. However, when primed with digital tools, participants processed social information more efficiently, leading to quicker reaction times. Most importantly, there was a significant interaction between primes and targets ($F(1, 29) = 4.40, P < 0.05, \eta^2p = 0.132$; Fig. 4B), suggesting that the type of tool used as a prime influenced participants' reaction times in the communicative versus non-communicative conditions. Post-hoc tests crucially revealed that participants were significantly faster at discriminating communicative stimuli when primed with digital tools compared to mechanical tools ($P < 0.05$; see **Material and Methods**).

4. Conclusion

This study demonstrates the existence of two distinct neural pathways for digital and mechanical technology, highlighting how our cognition adapts to different technological demands. Mechanical artifacts engage action-oriented functional brain networks, whereas digital technologies activate conceptual and social-cognition brain circuits. In an era where technological advancement shapes the very fabric of society, investigating the cognitive and neural processes driving humanity's technological mastery can reveal essential insights into our potential for future innovation and adaptation in an ever-evolving technological landscape. The focus here is on understanding the neurocognitive foundations of cumulative technological culture—a phenomenon in which technology becomes increasingly complex and efficient across generations, impacting human genetics (Laland et al., 2010) and cognition (Shipton and Nielsen, 2015). As technologies evolve, their manufacture becomes more and more opaque to non-experts. This increased opacity necessitates advanced social learning modes, such as teaching, which in turn fosters new cognitive abilities (Csibra and Gergely, 2011). Our results indicate that the complexity of human technology also transforms our interactions with these tools. Namely, we no longer merely manipulate tools to alter our

physical environment; we communicate with them as if they were social partners. From an evolutionary standpoint, digital technologies may present a novel challenge for modern brains, distinct from the tangible tools humans have used for millions of years. Just as the socialization around stone tools is believed to have catalyzed exceptional technological potential in early humans (Stout and Hecht, 2017), the use of digital tools may be reorganizing the brain in ways that propel humanity into its next evolutionary phase. Future research may build on these findings to explore the broader impacts of cumulative technological culture, particularly how technology shapes our skills, knowledge, social interactions, and cognitive processes, potentially driving a significant evolutionary trajectory in our species. Additionally, future studies should focus on how elements like tangibility, motor complexity, and task specificity contribute to the unique cognitive demands posed by different types of technologies.

Data and code availability

The data and codes supporting this study's findings, including all the methods described below, are available on the Open Science Framework (OSF) at <https://osf.io/9dpjb>.

CRediT authorship contribution statement

Giovanni Federico: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. **Mathieu Lesourd:** Formal analysis, Funding acquisition, Methodology, Writing – review & editing. **Arnaud Fournel:** Formal analysis, Writing – review & editing. **Alexandre Bluet:** Investigation, Writing – review & editing. **Chloé Bryche:** Investigation, Writing – review & editing. **Maximilien Metaireau:** Data curation, Formal analysis, Investigation, Software, Writing – review & editing. **Dario Baldi:** Resources. **Maria Antonella Brandimonte:** Writing – review & editing. **Andrea Soricelli:** Resources. **Yves Rossetti:** Funding acquisition, Writing – review & editing. **François Osiurak:** Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing.

Declaration of competing interest

The authors declare that there are no financial or non-financial competing interests.

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