Invisible, Inaudible, and Impalpable: Users' Preferences and Memory Performance for Digital Content in Thin Air

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We address in this work novel interfaces that enable users to access digital content "in thin air" in the context of smart spaces that superimpose digital layers upon the topography of the physical environment. To this end, we collect and evaluate users' preferences for pinning digital content in thin air, for which we report medium to high agreement levels (from 0.245 to 0.622, measured on the unit scale) and up to 80% success rates for recalling the locations of invisible, inaudible, and impalpable regions in space with no assistive feedback. Informed by our empirical findings, we elaborate a set of guidelines for practitioners to assist the design of novel user interfaces that implement digital content superimposed on the physical space.

As we enter the ubiquitous computing era, next-generation user interfaces that will support our new visions to access, manipulate, and share digital content fluidly and seamlessly will compulsorily need to capitalize on the particularities of the physical environment that we will inhabit.[1–3] Physical–digital spaces possess an unprecedented potential to offer their users a natural interactive experience with digital content by superimposing digital layers upon the topography of the physical surroundings. In such spaces, digital content "floats" unconstrained, free to be consumed and manipulated in ways that feel natural and intuitive, already built-in into the user's behavior.[1,3,4]

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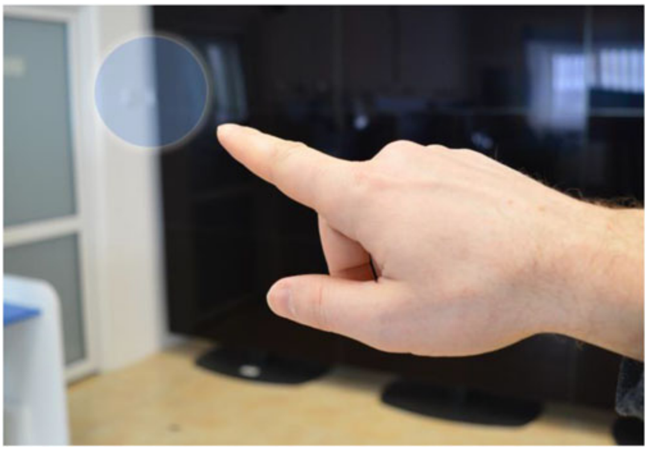

Figure 1. Repurposing "thin air" for novel interactions opens up new opportunities for smart environment to overlay digital content upon the topography of the physical space. Our empirical results show that people can accurately recall and point to locations in thin air, even in the absence of any assistive feedback.

The "spatial metaphor" for user interfaces[5] and "spatial data management"[6] were among the first attempts to connect digital content with the physical space, and they were soon followed by a variety of work that blurred even stronger the boundary between the physical and the digital, such as "imaginary interfaces,"[7] "radical atoms,"[3] "ZeroN,"[4] or "digital vibrons."[8] Further efforts to connect the physical and the digital brought even more concepts to light, such as "spatial electronic mnemonics,"[9] "physical loci,"[10] or "spatial shortcuts."[11] To elaborate on just one example, Perrault *et al.*[10] applied memorization techniques for a long-term recall of cognitive links between individual commands and physical objects in a room, and reported 90% recall rates for a set of 48 items when the users' object, spatial, and semantic memory were involved.

However, despite exciting results, there is still a lack of empirical data that prevent a thorough understanding of fundamental aspects of interacting with digital content in thin air. Moreover, designing smart environment that intertwines the services of the digital space with the material and tangible attributes of our physical world is still challenging, despite impressive progress in technology to render spatial augmented reality fast and credibly to its users [1,2] as well as advances in tangible and embedded computing to create the physicality of touching and grasping objects from our digital reality.[3,8] Despite breakthrough advances in technology, what has been missing in the community are fundamental and diligent investigations of human performance for physical–digital spaces as well as practical guidelines to assist the design of user interfaces for mixed reality environment in which digital content takes over the physicality of the space.

In this work, we address the problem of designing novel interfaces that enable users to access digital content pinned "in thin air" in the digital layer of the smart environment (see Figure 1). We are interested in people's preferences for good locations in space where to pin digital content. Moreover, we aim to understand human performance pushed at its limits, which we examine by quantifying and reporting the accuracy of memory recall in the absence of any form of assistive feedback, i.e., users access content by referring to invisible, inaudible, and impalpable regions in thin air. Our fundamental exploration of the ability of the human brain to recall precise locations of incorporeal objects enables us to recommend practical design guidelines for such novel interfaces and smart environment.

The contributions of this work are

1) we conduct a user elicitation study to collect and understand people's preferences for pinning digital content in thin air, for which we report an average agreement rate of 0.344 for a set of 12 referents;

2) we conduct an empirical evaluation of people's memory performance to recall precise locations of digital content in the absence of any feedback, for which we observe 60% success rates for trials with accuracy rates better than $200\ \mathrm{mm}$ and 80% success rates when error offsets can be tolerated with up to $500\ \mathrm{mm}$ from the actual location; and
3) informed by our findings, we elaborate guidelines to assist practitioners to design novel user interfaces for environment that expose digital content in thin air. We hope that our practical results will inspire and assist new designs of interactive experiences for our next generation physical–digital spaces.

EXPERIMENT

We conducted an elicitation experiment to collect users' *performance* and *preferences* for anchoring digital content into a physical space.

Participants

A total of twenty (20) participants (10 female) were involved in our experiment. Participants' ages ranged between 19 and 40 years ($M = 21.0,\ \ \mathrm{SD} = 4.9$ years). A total of ten participants had a technical background, such as Computer Science, Electronics, and Automatics, while the other ten were nontechnical, with backgrounds in Social and Educational Sciences.

Apparatus

Localization data in three dimensions were collected with a Vicon Motion Capture system (www.vicon.com) with six Bonita cameras ($1\ \mathrm{Mp}$ resolution and $100\ \mathrm{fps}$ for each camera) in a volume of space of approximately $48\ \mathrm{m}^3$($4\ \mathrm{m}$ length $\times$ $4\ \mathrm{m}$ depth $\times$ $3\ \mathrm{m}$ height). Participants wore a glove with IR reflective markers attached. We set up a custom mise-en-scène in this space consisting of common furniture and household items, such as a bookshelf, an indoor plant, a table and a tea set, an armchair, a lamp, a picture frame, and a TV set; see Figure 2.

Task

The experiment consisted of three phases. In the first phase, participants were asked to pin digital objects (e.g., music files) into the environment by moving to a particular location in the room and

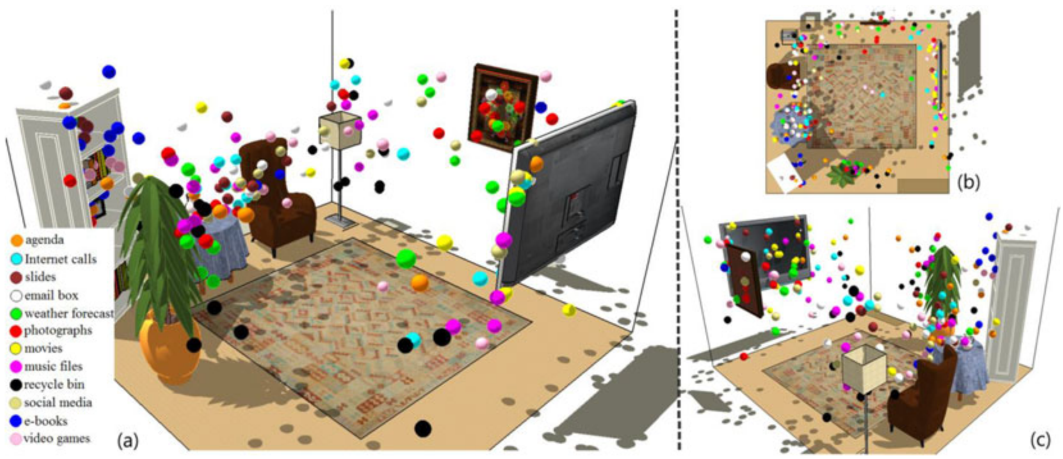

Figure 2. Virtual recreation of our physical space $(4\ \mathrm{m} \times 4\ \mathrm{m} \times 3\ \mathrm{m})$ with participants' preferences for locations of digital content shown as colored circles (a). A top-view (b) and a view from the opposite angle (c) are also shown to better understand the spatial organization of clusters of common preferences.

pointing to that location, knowing that they would have to recall locations later as fast and accurately as possible. We imposed no constraint on how pointing was to be performed (e.g., using the index finger, the whole hand, pinching or tapping, etc.), but most participants used the index finger to indicate to locations in space. The order of digital objects was randomized per participant. In the second phase, which took place after a 10-min break, participants were asked to point again to the locations where they placed objects during the first phase. Objects were presented to participants in a random order with three repetitions, which enabled us to collect multiple measurements of participants' memory recall and pointing accuracy. The third phase took place 24 h later and followed the same procedure. Participants completed the CAS++ Spatial Orientation test (www.cognitrom.ro) after the first phase, and rated the perceived difficulty of the recall tasks after the second and third phases.

Design

Our experiment was a within-subject design with two main independent variables.

1. Digital content, nominal variable with 12 conditions representing digital content frequently accessed by users: agenda, Internet calls, presentation slides, email box, movies, music files, weather forecast, photographs, recycle bin, social media, e-books, and video games.
2. Recall time, ordinal variable with two conditions: immediate and 24 h after the first phase.

In this work, we analyze performance overall, but we also pay attention to differences determined by participants' gender (nominal variable with two conditions), technical background (nominal variable with two conditions: technical and nontechnical participants), and spatial-orientation abilities [ordinal variable with three conditions: *poor* (3 participants), *fair* (10), and *good* (7)].

Measures

To understand participants' preferences and performance, we employed the following four measures.

1. Agreement rate reports the consensus between participants' preferences for pinning objects in the physical space, which we computed with a variant of the agreement rate formula of Vatavu and Wobbrock[12] (p. 1327):

$$\mathrm{AR}(r) = 1 - \frac{1}{\lambda}\frac{\sum_{i=1}^{n}\sum_{j>i}^{n}\delta(p_i,p_j)}{n(n-1)/2}, \qquad (1)$$

where r is the referent (i.e., the digital object), n is the number of participants, $\delta(p_i, p_j)$ is the Euclidean distance between two points p_i and p_j where object r was anchored by *both* the *i*th and *j*th participants, and λ is a coefficient that normalizes distances $\delta(p_i, p_j)$ to the size of the space. A back-of-the-envelope calculation with points p_i placed at the maximum distance from each other (i.e., at the opposite ends of the longest diagonal of the 4 m $\times$ 4 m $\times$ 3 m cuboid) gives an estimation of 6403.1 mm for λ. However, λ needs to be more carefully chosen than that, because a value that is too large will over-optimistically inflate agreement rates, while a value that is too small might cause a pessimistic interpretation of agreement, overlooking consensus where it actually exists. To find a realistic value for λ, we ran repeated Monte Carlo simulations to compute the largest average distance between $n = 20$ points placed at random locations in a cuboid of size 4 m $\times$ 4 m $\times$ 3 m. Our results, from over 10^8 runs, informed the value 2605.8 mm for λ.

2. Offset reports participants' inaccuracy of pointing into thin air, computed with the Euclidean distance between the original (first phase) and recalled locations (second and third phases). Offset is expressed in millimeters.
3. Accuracy, computed from offset measurements, with six levels: *highly accurate* (for offsets less than 100 mm), *accurate* (offsets between 100 and 200 mm), *moderately accurate* (less

than 300 mm), *marginally accurate* (less than 400 mm), *inaccurate* (less than 500 mm), and *off-target* (for offset distances larger than 500 mm).

4. Perceived difficulty represents a rating of the difficulty perceived by participants regarding the recall tasks, which we measured with a 5-point Likert scale with ratings from 1 (very easy to recall) to 5 (very difficult to recall).

RESULTS

We analyze in this section participants' preferences and memory recall performance for digital objects in the physical space, and we point to strategies developed for effective recall.

Pinning Digital Objects in the Physical Space

Figure 2 shows the spatial distribution of the digital objects for all the 240 trials (= 20 participants × 12 objects), as they were placed by participants during the first phase of the experiment. Different colors indicate different types of digital objects, e.g., movies are shown in yellow. Before diving into the numerical analysis of quantified levels of consensus among participants, the visual illustration of this distribution already offers valuable information about our participants' preferences and strategies to pin digital objects in the physical space in order to maximize their recall performance later. For instance, physical objects, such as the table or the bookshelf, acted as powerful attractors for digital objects, creating regions around them with high densities of digital content. Also, many connections can be observed between digital and physical objects with similar characteristics, e.g., *e-books* were mostly anchored around the bookshelf, *movies* around the TV set, while *weather forecasts* were pinned around the plant.

To quantify these strategies, we counted the number of associations between digital and physical objects (see Table 1), which amounted to 222 (92.5% of all trials), a result that reveals the importance of physical cues to inform pinning of digital content. For instance, 85% of participants connected digital *e-books* with the physical bookshelf, while 80% pinned *movies* to various locations around the TV set. *Internet calls* were associated with the TV set as well (45%), but also with the table (25%), physical locations where

Table 1. Frequency matrix showing associations between digital and physical objects for which physical distances were less than 500 mm.

	Plant	Shelf	Table	Chair	Lamp	Picture	TV	Other
Photogarphs	3	4	3	0	1	8	1	0
Music files	4	1	4	0	4	0	7	0
Movies	0	0	1	1	1	0	16	1
e-books	0	17	0	2	0	1	0	0
Agenda	3	5	7	0	0	1	3	1
Presentation slides	0	4	5	2	2	1	6	0
E-mail box	0	5	3	4	3	2	3	0
Video games	0	6	0	5	0	2	5	2
Social media	0	0	5	5	1	3	5	1
Internet calls	0	0	5	1	2	0	9	3
Recycle bin	2	0	2	3	4	0	0	9
Weather forecast	7	1	1	0	0	6	4	1
Total	**19**	**43**	**36**	**23**	**18**	**24**	**59**	**18**

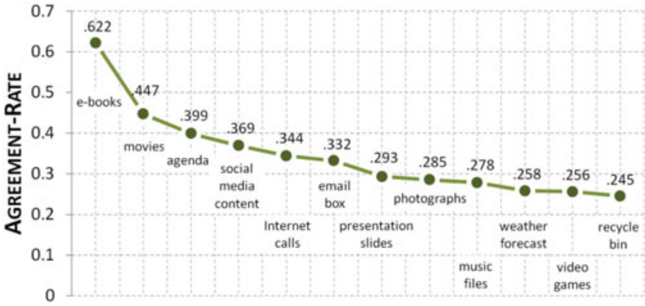

Figure 3. Agreement rates for our participants' preferences for pinning digital content in the physical space. Average agreement was 0.344 (SD = 0.106).

participants usually performed such calls. *Photos* were pinned to the picture frame (40%), bookshelf (20%), and the table (15%), and *weather forecasts* were associated with nature-like objects, such as the plant (35%) and the painting, which pictured a flower (30%). The TV set was the most "attractive" physical object (it attracted 24.5% of all the digital objects), probably due to the flexibility of smart TVs to render multimedia of various types and genres. At the opposite end, the lamp and the plant fostered the smallest number of associations with digital content (only 7.5% and 7.9%, respectively).

Figure 3 shows agreement rates computed from participants' preferences for pinning digital objects in the physical space. Average agreement was 0.344 (SD $= 0.106$) showing medium to high consensus according to the interpretation recommendations of Vatavu and Wobbrock[12] (p. 1332). Some digital objects reached high agreement, such as *e-books* (0.622) and *movies* (0.447), while others received less, e.g., the *recycle bin* only reached 0.245 agreement in the absence of a correspondent in the physical space. Agreement rates were 0.302 for male and 0.385 for female participants ($+27\%$ more agreement for females), and 0.327 for technical and 0.360 for nontechnical participants ($+10\%$ more agreement for nontechnical people), respectively, but Mann–Whitney U tests did not detect any statistically significant effects of gender or background on the agreement rate ($p > 0.05$).

Recall Performance

We evaluated memory recall by asking participants to point to the locations where they had pinned digital objects during the first phase. Results showed that 32% of all trials were *highly accurate* (i.e., offset distances from the actual locations were less than 100 mm), followed by 27% trials that were *accurate* (offsets between 100 and 200 mm); see Table 2. However, we also found that one in

Table 2. Recall accuracy (%) function of participants' gender, background, spatial orientation abilities, and the moment of recall.

Accuracy [%]	Gender		Background		Orientation			Recall time	
	Male	Female	Technical	Nontechnical	Poor	Fair	Good	Immediate	24 h
Highly accurate	32	30	32	30	19	31	36	32	30
Accurate	26	27	29	25	23	27	28	27	26
Moderately accurate	12	15	16	11	13	16	11	13	14
Marginally accurate	6	6	6	5	2	8	4	5	6
Inaccuarte	3	3	4	3	4	4	2	3	3
Off target	20	20	14	26	40	15	19	20	20

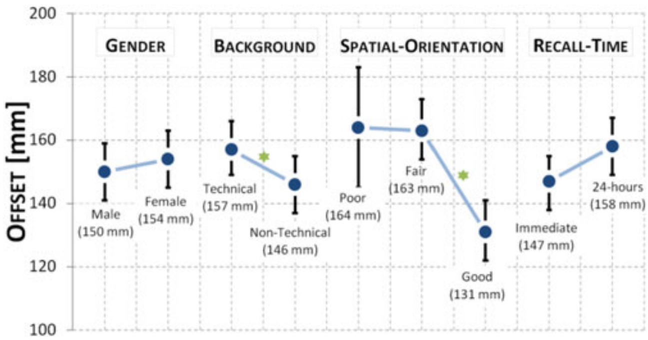

Figure 4. Average offset values function of participants' gender, background, spatial orientation abilities, and the moment of recall. Error bars show 95% CIs. A green asterisk $\star$ denotes a significant difference $(p < 0.01)$.

five trials was *off-target* (offsets larger than 500 mm), because participants forgot the original locations where they placed objects, as reported in their questionnaires. Thus, we decided to use the 500 mm threshold to discriminate between valid and failed attempts. Next, we examine participants' recall performance in detail using the Offset measure.

Figure 4 illustrates offsets from targets computed for valid trials only. Overall, the average offset was 152 mm (SD $= 108$ mm), showing a good level of accuracy for recalling exact locations in space without any feedback. A Wilcoxon signed-rank test revealed that Recall-Time had a marginally significant effect on Offset ($Z_{(N=40)} = -1.867, p = .06, r = .295$): more accurate recalls occurred right after the pinning phase than 24 hours later (147 mm versus 158 mm). We found no significant effects of Gender (150 mm versus 154 mm, $U = 50.000$, $Z_{(N=20)} = 0.000, p > .05$), Background ($157$ mm versus 147 mm, $U = 30.000$, $Z_{(N=20)} = -1.512, p > .05$), or Spatial-Orientation (164 mm and 131 mm, respectively, for participants with poor and good spatial-orientation abilities) on Offset.

Perceptions of Recall Difficulty

Figure 5 illustrates the average ratings of the participants' perceived difficulty of the recall tasks, which was low overall ($M = 1.68, SD = 1.07$). A Wilcoxon signed-rank test revealed that Recall-Time had no significant effect on Difficulty ($Z_{(N=40)} = -0.552, p > .05, r = .087$) even though recall felt easier 24 hours after the experiment than immediately after. Gender and Spatial-Orientation did not have a significant effect on Difficulty ($p > .05$), but Background did, with technical participants perceiving tasks easier than nontechnical people (1.52 versus 1.84, $U = 28.500$, $Z_{(N=20)} = -2.009$,

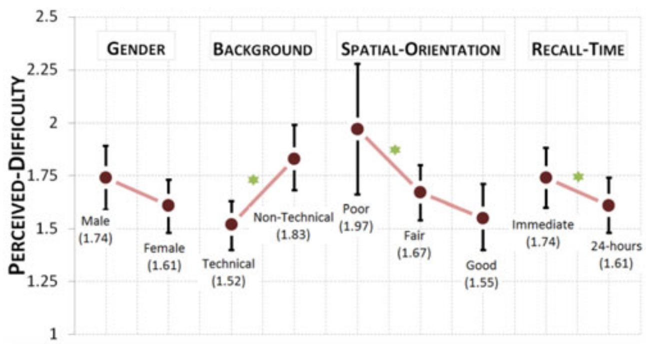

Figure 5. Average perceived difficulty of the recall tasks rated from 1 (very easy) to 5 (very difficult to recall). Error bars show 95% CIs; a green asterisk $\star$ denotes a statistically significant difference $(p < 0.01)$.

$p < .05, r = .449$). The average perceived difficulty was 1.68, in between "very easy" (1) and "easy" (2). This result suggests likely adoption of such interfaces, given that users find tasks easy to perform. However, it is important to note that even participants with poor spatial abilities that were off-target for 40% of all trials (see Table 2) rated the difficulty of the recall tasks as "easy" (average 1.97). This result indicates a poor judgment of the actual difficulty of a task for some users, which may generate contradictions during system usage between expected and actual performance. We believe that situations like these need to be handled on a per user basis, by adapting the system to the recall capacity and abilities of each user; see guideline #5, the next section.

DESIGN GUIDELINES

Informed by our empirical results, we elaborated a set of practical guidelines to assist user interface design for smart spaces with digital content pinned at physical locations.

1. *Prefer anchoring digital content to physical objects with stable locations in the environment*, e.g., furniture or appliances, *to foster accurate recall*. Our empirical results showed that a large percent (95%) of all the pinning tasks performed by our participants involved a physical object. Moreover, placing digital content in the space around a physical object determines a low perceived difficulty of the recall task as well. The fact that 78% of all the recall tasks were perceived as "very easy" and "easy" is an encouraging result, indicating that physical–digital spaces could become second nature for user behavior.
2. *Associate digital and physical objects by exploiting characteristics common to both types of objects.* For instance, 85% of our participants associated *e-books* with a physical bookshelf, while 80% preferred to pin *movies* in regions around the TV set. Such intuitive connections mediated by characteristics shared by both physical and digital objects play a key role for the usability of digital content pinned in the physical space and can be very effective for creating cognitive links by employing specialized learning techniques, such as physical loci.[10] Moreover, our results show that even when the physical correspondent object is missing, people search for potential locations where the physical counterpart could be located (e.g., the case of the recycle bin).
3. *Use associations between digital and physical objects for which high consensus can be reached easily.* Our results for a group of 20 participants show medium to large agreement rates (between 0.245 and 0.622) for pinning digital content in a physical space, with some associations showing higher agreement than others. We recommend relying on such preferences that involve common and intuitive associations between digital and physical objects by implementing them during design as *a priori* knowledge,[16] while we recommend expert design[2,13,14] for associations that score low consensus between users. Where possible, user-defined associations should be preferred, as previous work found that user-defined gestures are easier to remember than designer gestures[13] and, overall, have high recall rates,[14] while specialized learning techniques can be very effective to help users recall tens of cognitive associations between commands and physical loci.[10]
4. *Design for tolerant offsets for users' pointing actions in thin air.* Our results showed that 500 mm represents a reasonable upper threshold to filter out imprecise pointing to physical locations in the space, yet still be confident in detecting correctly users' intentions for referring to digital objects in space. Because our results showed that some users are more accurate than others at recalling and pointing to specific locations (e.g., 32% of trials were accurate under 100 mm and another 27% were better than 200 mm), we recommend adapting the granularity of the physical–digital space to each user to foster effective memory recall.
5. *Design for the recall capacity of the human memory.* Our results showed that the *short-term memory* capacity of our participants followed the upper limit predicted by Miller's law,[15] i.e., on average, 9 out of the 12 locations were recalled accurately during the second phase of the experiment. However, results obtained (with no memory reinforcement) after 24 h, much beyond the time span of short-term memory, showed a similar accuracy performance of our participants (see Table 2), which suggests the potential to increase the number of locations that can be learned and retrieved accurately from the *long-term memory*. Evidence from the literature and practice of gesture user interfaces supports this hypothesis: it is a known fact that people develop with practice very good memory skills, including the ability to learn tens of gesture commands (see successful products, such as the Swype gesture

keyboard, www.swype.com, where geometric shapes are associated with words that people learn in time and reproduce directly from memory), as well as the ability to learn tens of physical locations in space.[10] However, people also have different learning abilities and, consequently, we recommend a design that adapts to the recall capacity and abilities of each user. For instance, we can recommend starting off with a small set of digital objects distributed in the physical space and, in time, update the set by adding more objects according to the application demands or users' capacity to recall locations effectively. Also, because our participants were less accurate at recalling the precise locations of digital objects as more time had passed (with offsets increasing from 147 to 158 mm on average), reinforcement strategies are likely to be needed to keep success rates high enough for real-world practical scenarios.

6. *Design associations that speak to users' technical abilities.* Our results showed that these factors influence memory recall significantly, e.g., a technical background favors better performance. Adapting the granularity and density of the physical–digital space to each user's abilities (a step that can be easily performed during setup, for instance, by asking users a few questions to determine their profile) will foster better recall performance and, consequently, better user experience.

CONCLUSION

We examined in this work people's preferences for pining digital content in a physical space and their performance at recalling locations later. Our results are promising, showing that intuitive associations are being formed consistently across users and that recall rates can be high, given proper design. Several interesting aspects could be explored for future work in terms of technical design and human studies. For instance, it seems that good spatial orientation skills lead to better recall accuracy for digital content pinned in a physical environment. However, the opposite implication could also be true: more practice with applications exposing digital content that co-inhabits the physical space could have the positive effect of increasing users' spatial abilities for other real-world tasks. Future work will also explore effective interaction techniques to consume content hovering in thin air, once it has been correctly retrieved. While we leave these interesting explorations for future work, we believe that this first examination of users' preferences and memory recall performance for objects in thin air opens the way toward a better understanding of designing interactions with digital content co-inhabiting the physical world.

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REFERENCES

1. B. Jones *et al.*, "RoomAlive: Magical experiences enabled by scalable, adaptive projector-camera units," in *Proc. 27th Annu. ACM Symp. User Interface Softw. Technol.*, 2014, pp. 637–644.
2. R.-D. Vatavu, "There's a world outside your TV: Exploring interactions beyond the physical TV screen," in *Proc. 11th Eur. Conf. Interact. TV Video*, 2013, pp. 143–152.
3. H. Ishii, D. Lakatos, L. Bonanni, and J.-B. Labrune, "Radical atoms: Beyond tangible bits, toward transformable materials," *Interactions*, vol. 19, pp. 38–51, Jan. 2012.
4. J. Lee, R. Post, and H. Ishii, "ZeroN: Mid-air tangible interaction enabled by computer controlled magnetic levitation," in *Proc. 24th Annu. ACM Symp. User Interface Softw. Technol.*, 2011, pp. 327–336.
5. W. P. Jones and S. T. Dumais, "The spatial metaphor for user interfaces: Experimental tests of reference by location versus name," *ACM Trans. Inf. Syst.*, vol. 4, no. 1, pp. 142–163, Jan. 1986.

6. G. Robertson, M. Czerwinski, K. Larson, D. C. Robbins, D. Thiel, and M. Van Dantzich, “Data mountain: Using spatial memory for document management,” in *Proc. 11th Annu. ACM Symp. User Interface Softw. Technol.*, 1998, pp. 153–162.
7. S. Gustafson, D. Bierwirth, and P. Baudisch, “Imaginary interfaces: Spatial interaction with empty hands and without visual feedback,” in *Proc. 23nd Annu. ACM Symp. User Interface Softw. Technol.*, 2010, pp. 3–12.
8. R.-D. Vatavu, A. Mossel, and C. Schönauer, “Digital vibrons: Understanding users' perceptions of interacting with invisible, zero-weight matter,” in *Proc. 18th Int. Conf. Hum.-Comput. Interact. Mobile Devices Serv.*, 2016, pp. 217–226.
9. Y. Ikei, H. Ota, and T. Kayahara, “Spatial electronic mnemonics: A virtual memory interface,” in *Proc. Symp. Hum. Interface Manage. Inf.*, 2007, pp. 30–37.
10. S.T. Perrault, E. Lecolinet, Y.P. Bourse, S. Zhao, and Y. Guiard, “Physical loci: Leveraging spatial, object and semantic memory for command selection,” in *Proc. 33rd Annu. ACM Conf. Hum. Factors Comput. Syst.*, 2015, pp. 299–308.
11. M. Uddin, “Use of landmarks to design large and efficient command interfaces,” in *Proc. 2016 ACM Companion Interact. Surf. Spaces*, 2016, 13–17.
12. R.-D. Vatavu and J. O. Wobbrock, “Formalizing agreement analysis for elicitation studies: New measures, significance test, and toolkit,” in *Proc. 33rd Annu. ACM Conf. Hum. Factors Comput. Syst.*, 2015, pp. 1325–1334.
13. M. A. Nacenta, Y. Kamber, Y. Qiang, and P. O. Kristensson, “Memorability of pre-designed and user-defined gesture sets,” in *Proc. SIGCHI Conf. Hum. Factors Comput. Syst.*, 2013, pp. 1099–1108.
14. R.-D. Vatavu and I.-A. Zaiți, “Leap gestures for TV: Insights from an elicitation study,” in *Proc. ACM Int. Conf. Interact. Experiences TV Online Video*, 2014, pp. 131–138.
15. G. A. Miller, “The magical number seven, plus or minus two: Some limits on our capacity for processing information,” *Psychol. Rev.*, vol. 63, no. 2, pp. 81–97, Mar. 1956.
16. R.-D. Vatavu, “Characterizing gesture knowledge transfer across multiple contexts of use,” *J. Multimodal User Interfaces*, vol. 11, no. 4, pp. 301–314, 2017.

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