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REGULAR PAPER

Yanxin Wang · Yihan Liu · Lingyun Yu · Chengtao Ji · Yu Liu

A comparative study of table-sized physicalization and digital visualization

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Abstract Data physicalization is gaining popularity in public and educational contexts due to its potential to make abstract data more tangible and understandable. Despite its growing use, there remains a significant gap in our understanding of how large-size physical visualizations compare to their digital counterparts in terms of user comprehension and memory retention. This study aims to bridge this knowledge gap by comparing the effectiveness of visualizing school building history data on large digital screens versus large physical models. Our experimental approach involved 32 participants who were exposed to one of the visualization mediums. We assessed their user experience and immediate understanding of the content, measured through tests after exposure, and evaluated memory retention with follow-up tests seven days later. The results revealed notable differences between the two forms of visualization: physicalization not only facilitated better initial comprehension but also significantly enhanced long-term memory retention. Furthermore, user feedback on usability was also higher on physicalization. These findings underscore the substantial impact of physicalization in improving information comprehension and retention. This study contributes crucial insights into future visualization media selection in educational and public settings.

Keywords Visualization · Physicalization · Digitization · Memorability

1 Introduction

In an era characterized by an overwhelming abundance of information, the role of visualization has become pivotal in ensuring the effective comprehension and retention of data. As individuals and organizations generate and consume vast volumes of data, the transformation of this data into accessible and memorable formats is crucial for cognitive development and adaptive capabilities (Manyika et al. 2011). Visualization,

Y. Wang · Y. Liu · L. Yu · C. Ji · Y. Liu (✉)
School of Advanced Technology, Xi'an Jiaotong-Liverpool University, 111 Ren'ai Road, Suzhou 215123, Jiangsu Province, People's Republic of China
E-mail: Yu.Liu02@xjtlu.edu.cn

Y. Wang
E-mail: yanxin.wang20@student.xjtlu.edu.cn

Y. Liu
E-mail: yihan.liu17@student.xjtlu.edu.cn

L. Yu
E-mail: Lingyun.Yu@xjtlu.edu.cn

C. Ji
E-mail: Chengtao.Ji@xjtlu.edu.cn

as a unique method of representing data, plays a central role in this process, enabling a deep and intuitive understanding of complex datasets (Manovich 2010; Wijk 2005).

Recent technological advancements, such as 3D printing and laser cutting (Ang et al. 2019; Djavaherpour et al. 2021), have enabled the creation of physicalization with greater precision and speed, thus enhancing the accessibility of physicalization in visualization. Physicalization, which involves the presentation of data on tangible physicalization, has been increasingly explored and applied in visualization fields. This medium has shown potential to complement or even surpass digital forms in certain scenarios. For instance, Swedish global health specialist Hans Rosling used physical commonplace items (LEGO blocks, toilet paper rolls, etc.) to illustrate data regarding global development issues in a TED talk (Dragicevic et al. 2020), which allows the audience to capture and understand these professional data in a short period of time. Also, physicalization was used to show four-dimensional blood flow data (Ang et al. 2019) and the findings revealed that physicalization enhanced the audience's understanding of the data in a more lucid and straightforward manner, enabling them to swiftly compare data relationships among various segments.

Despite the growing prevalence of physicalization, we still identified several research gaps that need to be addressed. First, there are a limited number of studies that explore large-scale physicalizations to represent complex real-world data. Prior studies have mainly focused on small- to medium-sized physicalizations (Jansen et al. 2013; Stusak et al. 2015; Ren and Hornecker 2021; Teng et al. 2024; Herman et al. 2024), as well as simple visual forms such as bar charts (Stusak et al. 2015; Ren and Hornecker 2021) and maps (Kirshenbaum et al. 2020). Second, past experiments comparing different visualization media have typically relied on only two metrics-response time and immediate memory. Such evaluations are not always consistent with the intention of the visualization.

This study aims to bridge this gap by investigating the efficacy of large-sized physicalizations compared to screen-based digital forms. It is challenging to find a well-recognized definition of large physicalizations. However, based on previous studies, we observed that screens larger than typical displays are often referred to as large screens (Liu et al. 2023). The term "large screen" encompasses various types, including standard 85-inch displays as well as wall-sized screens. Drawing from this concept, and referring to prior research on physicalizations (López García et al. 2021), we note that dimensions exceeding those of regular computer displays are commonly classified as large sized. To provide greater clarity in this study, we refer to our physicalization as "table-sized", representing a specific form of large-scale physicalization. We also used complex datasets and visual designs that integrate both spatial and temporal data in 3D annual ring shapes. Additionally, our research compared two table-sized visualizations across four metrics: response time, user experience, immediate comprehension, and memory retention which are highly relevant to the intent of a large sized visualization. Through this comprehensive comparative experiment, we seek to provide valuable insights for designers and developers in selecting appropriate visualization and display mediums. Ultimately, this research aims to enhance the public's ability to acquire information and learn in communal spaces (see study overview in Fig. 1). Our contributions to the field of data visualization are multifaceted. Firstly, our research provides a robust comparative analysis of digital and physical data representations. We conducted a comprehensive evaluation on four dimensions-response time, user experience, information comprehension, and memory retention-employing both qualitative and quantitative methods. This multifaced approach allows us to draw nuanced insights into how different mediums affect the comprehension and recall of information, providing a detailed understanding of the cognitive and perceptual dynamics at play. Additionally, the reflections from our study also represent our major contribution. These recommendations offer practical guidance for future designers and developers on choosing the most effective mediums for data visualization. By outlining the strengths and limitations observed in our experiments, we equip practitioners with the knowledge to enhance the efficacy of educational and public displays, thereby improving public learning and information dissemination in various settings. These contributions collectively advance the field of data visualization, pushing forward the boundaries of how data is represented and interacted with in both digital and physical forms.

2 Related work

Our work builds upon previous research on data physicalization and its comparison with other visualization methods.

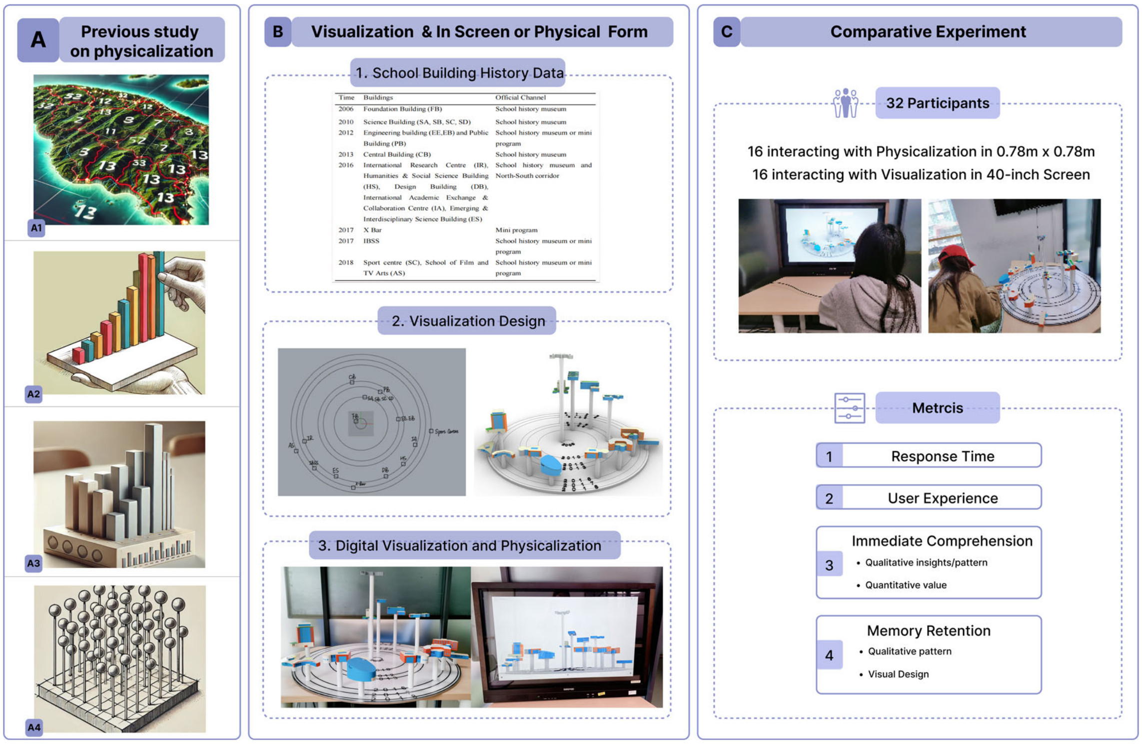

Fig. 1 Overview of the experiment: **A** Experiment trigger: Previous research on physicalization (**A1** Projected 2D surface versus 3D terrain (Kirshenbaum et al. 2020) **A2** Physical Visualization versus Digital Visualization (Stusak et al. 2015) **A3** Physicalization versus On-screen Visualization (Jansen et al. 2013) **A4** Physicalization versus Virtualization (Ren and Hornecker 2021); **B**. the process of achieving visualization; **C** experimental design and evaluation metrics

2.1 Data physicalization

Data physicalization transforms abstract data into tangible forms, enhancing haptic exploration and problem-solving (Hull and Willett 2017). This method is widely used across various fields. For instance, in manufacturing, General Motors head engineer Kevin Quinn uses a customized Lego-based board to monitor and update the progress of the manufacturing line, motivating engineers by making their work visible (Jansen et al. 2015). In the medical field, physicalization help patients understand their conditions better, such as using physical visualizations to describe hip pain or to analyze four-dimensional blood flow data from cardiac MRI (Thudt et al. 2018; Ang et al. 2019). In education, physical visualizations enhance students' creative and structural thinking, allowing them to demonstrate lifestyle habits like sleep duration and running routes through tangible physicalization (Perin 2021; Anderson 2017; Menheere et al. 2021).

Physical visualizations can be static or dynamic. Static physicalization, such as bar charts, is straightforward and simple, while dynamic physicalization offer more interactive experiences. For example, the EMERGE bar chart includes push-pull operations and RGB data output, providing a more immersive experience through direct haptic interaction (Taher et al. 2015, 2017). Dynamic microrobots, like Zooids, represent data points that can move and be manipulated in real time, aiding in tasks like selecting job applicants or tourist destinations (Le Goc et al. 2019). Effective design of physical visualizations involves using representative and symbolic materials (e.g., pencils for study time, forks for meals) (Perin 2021), adding color to enhance comprehension (Gwilt et al. 2021), and ensuring readability and engagement while minimizing user interaction (Bhargava and D'Ignazio 2017; Wijk 2005). Medium-sized visualizations are particularly effective for capturing data, while larger sizes leave a lasting visual impact (López García and Hornecker 2021). This comprehensive approach to design makes data physicalization a powerful tool for conveying complex information and engaging users in a meaningful way.

Table 1 Previous literature on physicalization comparison

Author	Visualization type	Comparison content	Size of physicalization	Testing metric	Result
Jansen et al. (2013)	Bar chart	Physical visualizations Stereo Mono 2D	$8cm \times 8cm$	(a) Error rate; (b) Time on task.	Physicalization performs best at time on task.
Stusak et al. (2015)	Bar chart	Physical Visualizations Digital Visualizations	$28cm \times 17cm$	(a) Correctness rate; (b) Memorability score.	Less memory loss in physicalization.
Ren and Hornecker (2021)	Scatter plot	Physical Visualizations Virtualization	$60cm \times 40cm$ $\times 50cm$	(a) Response time; (b) Correctness rate.	(a) Lower response times in physicalization; (b) Differences of correctness rates are marginal.
Chettaoui et al. (2023)	Annotated image	Tangible user interface (TUI) Classic method with non-augmented objects	$52cm \times 70cm$	(a) System Usability Scale (SUS) score; (b) Completion time;	TUI performs better at short-term retention time.
Teng et al. (2024)	Map	Projection Augmented Relief Maps (PARM) Traditional Digital Maps (DM)	$36cm \times 24cm$	(a) Effectiveness; (b) Efficiency; (c) Memory retention; (d) User engagement.	Neither PARM nor DM consistently outperforms the other across all tasks.
Herman et al. (2024)	Digital Elevation Model	Physical visualizations Virtualization Digital visualizations	$15cm \times 15cm$	(a) Completion time; (b) Error;	Physicalizations have performance similar to or better than their digital counterparts in most conditions.

2.2 Comparative study on data physicalization

In recent years, the performance of physicalization in practical applications has emerged as a major topic of investigation in the field of visualization research. Researchers have devoted their efforts to comparing physicalization with various visualization methods across multiple dimensions (Table 1), aiming to comprehensively understand its performance and effectiveness in practical applications.

2.2.1 Task completion time

Jansen et al. (2013) compared a 3D physical visualization with multiple on-screen models, including VR. Their findings indicated that physical visualization significantly outperformed the on-screen models in terms of task completion time. This was attributed to the direct hand interaction between participants and the physical visualization, which facilitated quicker task execution. However, the physical visualization used in this experiment was limited in size, measuring only 8 cm, which posed constraints in displaying multiple bar chart data. Also, Ren and Hornecker (2021) compared physical visualizations with VR counterparts and found that physical visualizations significantly outperformed VR in terms of task completion time due to the tangible interactions they afford.

2.2.2 Memorability

Stusak et al. (2015) provided insights into the comparative memorability of physical and digital visualizations using bar charts. The study found that physicalization exhibited higher memorability for long-term memory tasks, showing lower forgetting effects. However, physicalization performed relatively poorer in immediate memory tasks. Stusak suggested that the size limitation of the physical visualization (28 cm) used in the experiment could be a contributing factor. The handheld physical visualization reduced the extent of haptic engagement and interaction, potentially impacting immediate recall.

2.2.3 Interactivity and usability

Kirshenbaum et al. (2020) extended the comparison to topographic maps, evaluating geographical information projections on 3D and 2D map models. They found that 3D visualizations demonstrated greater advantages in terms of interactivity due to the enhanced engagement afforded by the physical medium. However, in terms of usability, 2D representations were clearer and more comprehensible for users. This highlights the trade-off between the enhanced interactivity of 3D physical visualizations and the clarity provided by 2D digital visualizations.

2.3 Research Gaps

While the related work has provided many valuable insights, it has also revealed several research gaps that need to be addressed. First, previous studies primarily focus on relatively small-scale physicalizations Ren et al.Jansen:2013:EEP,Stusak:2015:EMP,Teng:2024:EGI,Herman2024), typically not exceeding dimensions of 0.4 square meters. However, these findings are difficult to apply directly to larger-scale physicalizations, as previous research has indicated that size significantly affects user perception and experience of data Ren et al.Gramazio:2014:RVS). Therefore, the effectiveness of large-scale physicalization still requires further investigation. Although there are a few studies on table-sized physicalizations, they have primarily focused on simple and singular visual forms, such as bar charts (Jansen et al. 2013; Stusak et al. 2015) and maps (Kirshenbaum et al. 2020), while those that are closer to the complexity of real-world data and visual forms have been largely unexplored. However, exploring complex data through large-scale physicalization is necessary, as research has shown that a larger physical scale allows for more immersive experiences compared to small-scale physical representations (López García and Hornecker 2021). Whether this sense of immersion can enhance audience comprehension is a question worth exploring—and is precisely what this paper aims to investigate. Lastly, most prior studies have relied on only two metrics—response time and immediate memory (Jansen et al. 2013; Stusak et al. 2015; Ren and Hornecker 2021; Chettaoui et al. 2023) —when comparing different visualizations. This evaluation approach can be improved by incorporating additional metrics, such as memory retention on not only data but also visual design and underlying insights and user experience data, to assess satisfaction.

This paper aims to address the aforementioned research gaps by shifting the focus to large-scale physicalization and exploring real-world data that integrates both temporal and spatial dimensions. A comprehensive evaluation was conducted based on four metrics: response time, user experience, immediate comprehension, and memory retention.

3 Data and visualization design

This section provides an overview of the data selected for visualization and the design choices made for both physical and digital representations. The aim of this study is to evaluate how different visualization mediums affect response time, user experience, information comprhension and memory retention. We used publicly available data on our university buildings' completion dates due to their intrinsic interest and relevance to our participants. By utilizing both physical and digital visualization methods, we extend previous research focused on simpler forms like bar charts (Jansen et al. 2013; Stusak et al. 2015) and maps (Kirshenbaum et al. 2020), enabling a deeper exploration of more complex data visualizations.

Table 2 Year of initial building utilization

Time	Buildings
2006	Foundation building (FB)
2010	Science building (SA, SB, SC, SD)
2012	Engineering building (EE,EB) and public building (PB)
2013	Central building (CB)
2016	International research centre (IR), humanities and social science building (HS), design building (DB), international academic exchange and collaboration centre (IA), emerging and interdisciplinary science building (ES)
2017	X Bar
2017	International business school suzhou (IBSS)
2018	Sport center (SC), School of film and TV arts (AS)

3.1 Data Collection

We selected the completion dates of various buildings on our university campus as the content for visualization. This data choice was guided by several key considerations:

- *Relevance to participants:* Our primary user group consists of students who are readily accessible and have a vested interest in the university's history. By selecting data that they find interesting yet may not easily obtain themselves, we aimed to increase their engagement and motivation.
- *Educational value:* Understanding the chronological and spatial development of campus buildings helps students and long-term faculty better connect with the university's history and evolution. Even experienced campus community members often lack detailed knowledge of these aspects, making this data both informative and engaging. By visualizing the development of the university's infrastructure, we can provide a meaningful educational experience that strengthens participants' connection to the institution.
- *Complexity of data:* Unlike previous studies that focused on either purely spatial information (Teng et al. 2024) or simple numerical data represented in bar charts (Jansen et al. 2013), our data combines temporal and spatial elements, making it more complex. This complexity provides a richer, more detailed understanding of the effectiveness of different visualization media.

We collected the completion years for these buildings (Table 2) through three official sources: the school history museum, the exhibition map in the North–South corridor, and the official WeChat mini-program.

3.2 Visualization design

The visualization media served as the sole independent variable in our experiment, focusing on both three-dimensional (3D) physical and digital visualizations to assess their impact on response time, user experience, information comprehension, and memory retention.

3.2.1 Physicalization

We adopted the "tree ring" format to visualize the completion years of the 14 university buildings (as seen in Fig. 1B2). Each ring represents a specific year (from 2006 to 2018), and the positions of the buildings on the rings maintain their relative spatial relationships. For instance, buildings on the same side of a ring belong to the same campus area (either the North or South Campus). To avoid issues with displaying multiple buildings at the same height, we also encoded the historical duration of each building using the length of the cylindrical supports beneath them. Thus, from Fig. 2A, we can see the overall visualization encodes the building's history through the distance from the physicalization's center and the cylinders' height. The positioning on each ring approximately preserves the original relative locations of the buildings.

Our design leverages a familiar time representation format (tree rings) and effectively uses two encoding channels to display the buildings' completion sequence and relative positions. The primary design goal is to enhance user engagement and interest, enabling a quick and intuitive understanding of the campus's architectural history while meeting the aesthetic requirements common in artistic installations.

Regarding size, we chose a large scale (diameter of 0.78 ms, height of 0.39 ms) commonly seen in museum and exhibition settings. This table-sized format balances the advantages of both large and small-scale visualizations, allowing users to view the entire visualization and inspect details easily (López García and Hornecker 2021). The physicalization consists of a circular base with cylindrical supports and miniature

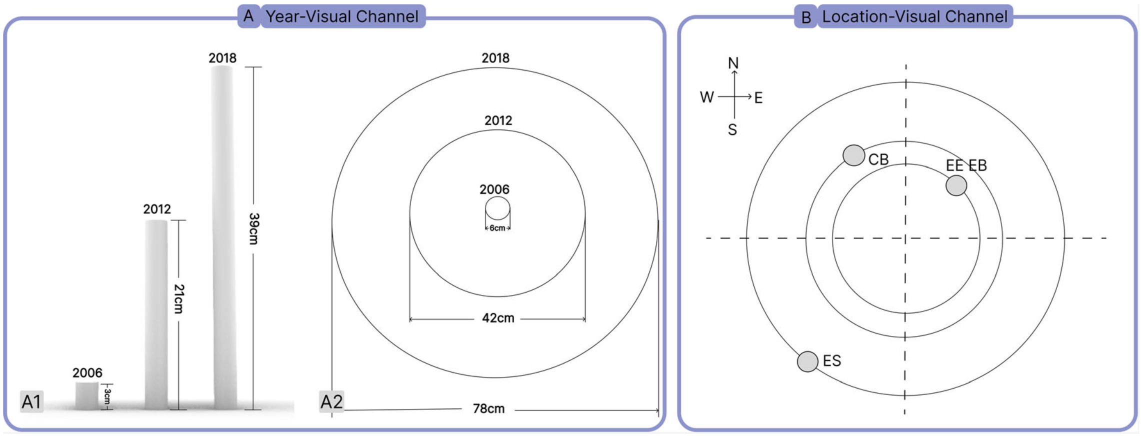

Fig. 2 Encoding details in our visualization: **A** Two channels for encoding the year-visual (**A1** Height of buildings: the smallest height is 3 cm and the highest is 39 cm. It increases by 3 cm with each additional year **A2** Diameter of the tree rings: the smallest diameter is 6 cm and the largest is 78 cm. It increases by 6 cm with each additional year); **B** one channel for encoding the location-visual (Position placed on the tree rings)

building physicalization on top. The buildings' colors closely matched their real-life counterparts on campus, enhancing the physicalization's authenticity and visual appeal (Gwilt et al. 2021).

3.2.2 Digitalization

For digital visualization, we used Rhino software to ensure consistency with the physical one's colors and design (Gwilt et al. 2021). The Rhino-rendered digital model provides a 3D multi-perspective view (as shown in Fig. 3A), maintaining the same spatial relationships and color schemes as the physicalization.

To ensure an equitable comparison, we displayed the digital visualization on a touch-enabled electronic screen of similar size (40-inch; $0.88m \times 0.49m$) to the physicalization. We also keep the display view the same as the physical visualization size. This setup included two common interaction methods in museums and art exhibitions: direct touch interaction on the screen and interaction via a smaller connected touch-screen device. For this study, we connected a 10.9-inch tablet to allow users to experience different interaction modes and choose their preferred method. Participants were allowed to observe from any angle and height for physicalization, ensuring consistent viewing experiences.

Fig. 3 **A** Multiple perspectives of our visualization; **B** two mediums of visualization: **B1** screen-based digital visualization **B2** Physicalization

4 Experiment

4.1 Participant and experimental design

In our study, we had 32 participants, with each participant assigned to one of the two conditions in a between-subjects design. Using G-power (Serdar et al. 2021) for an independent two-sample t-test with an effect size of 0.8, an alpha level of 0.05, and a power of 0.85, the required sample size was approximately 29 participants. Our sample size of 32 participants (16 per condition) is adequate and slightly exceeds the required number, ensuring sufficient power to detect significant effects. We employed the convenience sampling. And they were reached through multiple social media at our university, ranging in age from 19 to 26 years, with an average age of 22. The group included 1 doctoral student, 1 graduate student, and 30 undergraduate students. These participants are mainly from five different backgrounds, including computer science (18), business (10), engineering (2), mathematics (1), and environment (1) (Fig. 4).

The participants were divided into two equal groups, each consisting of 8 males and 8 females. Both groups of participants were conducted within the same laboratory setting, where the individuals had unrestricted access to engage with visualization in the designated area, allowing for free interaction during the experiment.

Group A This group observed the digital visualization displayed on a 40-inch LCD touch screen (Fig. 3B1). To control for the variable of interest—the type of visualization—participants were only allowed to rotate the model but not zoom in or out directly or using an iPad. This ensured that any differences in memorability could be attributed to the visualization method rather than variations in visualization size.

Group B Participants in this group were tasked with observing the physical visualization (Fig. 3B2). They were given complete freedom to interact with the physicalization, including touching it and moving around to view it from different angles. This unrestricted interaction was intended to provide a comprehensive understanding of the physicalization's impact on memorability.

4.2 Metrics

The specific metrics of our experiment included response time, user experience, immediate feedback, and long-term memory retention measured seven days later.

4.2.1 Response time

To effectively evaluate the impact of two different media on participants' memorability regarding questions of varying difficulty levels, the duration spent contemplating each participant's responses to different levels of questions was documented. A timer was used to track how long participants spent on each question.

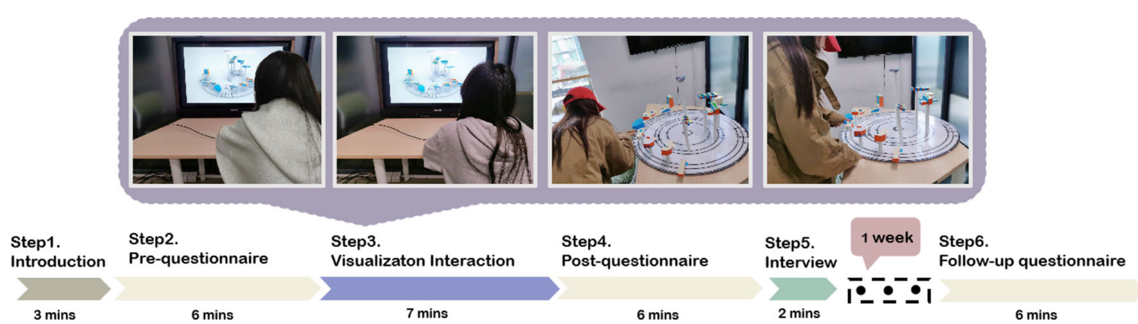

Fig. 4 Overview of the entire experimental procedure

4.2.2 *Quantitative data comprehension and recall*

The quantitative assessment of data comprehension and recall was divided into three task-based categories inspired by map-related tasks (Roth 2013; Shneiderman 2011), as our data combines temporal and spatial elements. These tasks were designed to measure different levels of cognitive engagement (see details in Table 4):

(1) *Identification (Easy)*: Participants were asked to identify and recognize individual buildings based on their location and completion year.
(2) *Comparison (Moderate)*: Participants were required to compare two buildings, determining which one was completed first or relative position.
(3) *Ranking (Difficult)*: Participants were tasked with ranking three buildings according to their completion dates or ranking their relative position from north to south or from east to west.

The assessment questionnaires for both the year and geographical location data included 12 questions each, with four questions per difficulty level. This structure allowed us to evaluate accuracy and response time across different levels of complexity.

4.2.3 *Qualitative pattern comprehension and recall*

In addition to quantitative tasks, participants were asked to provide qualitative feedback on the patterns or trends they noticed in the visualizations. We recorded these observations immediately after the visualization session and revisited them during the long-term memory test seven days later. Participants were also required to describe or sketch their memory of the visualization, helping to capture the depth and persistence of their recall.

4.2.4 *User experience*

The user experience was assessed using the User Experience Questionnaire (UEQ) (Rauschenberger et al. 2013; Schrepp et al. 2014), which is normally used to evaluate interactive products based on various criteria such as attractiveness, perspicuity (shown in Table 5), efficiency, dependability, stimulation, and novelty. Participants completed this questionnaire immediately after interacting with the visualization, capturing their immediate reactions and experiences.

4.3 Experiment Process

To comprehensively understand how visualization methods affect immediate comprehension and long-term memory retention, we divided the evaluation into three key stages: pre-test, immediate, and long-term (a week later). This design allowed us to assess participants' instant memory of the data and observe memory decay over time, aligning closely with numerous previous studies on the memorability of visualizations (Chettaoui et al. 2023; Saket et al. 2016; Shneiderman 2011; Stusak et al. 2015). A 7-day interval for long-term testing is considered appropriate and has been validated in prior research as an effective timeframe for assessing long-term memory retention (He et al. 2024; Zdanovic et al. 2022). Our study was approved by the school's ethical board before its initiation.

(1) **Introduction and consent**
   - *Project Introduction:* The experiment began with an introduction of the project, explaining the study's objectives, methodology, and significance.
   - *Informed consent:* Participants were provided with an information sheet and consent form to ensure they understood the study and their rights.
   - *Pre-test questionnaire:* Participants completed a background information and knowledge questionnaire, similar to Chettaoui et al. (2023); He et al. (2024). This included questions about their background information and prior knowledge of the subject matter to ensure a baseline understanding before the experiment.

(2) **Observation and interaction:** Participants were assigned to either the digital or physical visualization group, with 7 min to explore their assigned visualization. This duration was determined through

multiple rounds of testing among the authors, ensuring it was an optimal time for most participants to engage with and remember the information effectively.

- *Digital group:* Interacted with the digital model on a large touch screen or small iPad, rotating it to view different angles.
- *Physical group:* Touched and viewed the physicalization from various perspectives, moving around it freely.

(3) **Immediate testing:** Participants completed a questionnaire to assess their understanding and memory after a 7-minute interaction.

- *Questionnaire structure:* The survey was divided into six sub-sections, covering year and location data across three difficulty levels.
- *Insight and pattern recognition:* Participants wrote down approximately three insights or patterns they observed.
- *User experience questionnaire:* Participants also completed a User Experience Questionnaire (UEQ).

(4) **Long-term memory testing:** One week later, participants took a similar test to assess long-term memory retention.

- *Questionnaire Consistency:* The questionnaire content was identical, with the question order shuffled.
- *Visualization recall:* Participants were asked to draw or write down their recollection of the visualization.
- *Offline/online options:* Participants could complete the test offline or online.

4.4 Analysis method

To examine significant differences between the data from different visualization, we employed the t-test method. Additionally, to investigate memory retention over different time points within the same group, we conducted repeated-measure ANOVA. This approach allowed us to assess whether memory retention significantly impacted the data across the three testing sessions.

5 Results

Our comparative study examined the effectiveness of digital and physical visualizations across four key metrics: response time, user experience, immediate comprehension, and long-term memory retention of information. We used a t-test to compare the two types of media, with effect size measured using Cohen's d. The thresholds for interpreting the magnitude of Cohen's d are: small effect (0.2), medium effect (0.5), and large effect (0.8) (Goulet-Pelletier and Cousineau 2018). For the comparison within a single medium across three different time points, we conducted a one-way repeated-measures ANOVA and calculated the effect

Table 3 Overview of the Average Accuracy of Two Visualizations: average accuracy rates across three different stages - pre-test, immediate testing, and long-term testing, as well as three levels of difficulty (E-Easy, M-Moderate, and D-Difficult) in Year and Location information

		Pre-test E|M|D	Immediate Comprehension E|M|D	Memory Retention E|M|D
Physicalization	Overall	35.16%	84.90%	73.96%
		46.88%|32.03%|26.56%	92.19%|83.59%|78.13%	88.28%|78.13%|55.47%
	Year	20.83%	88.54%	76.04%
	Location	49.48%	81.25%	71.88%
Digitalization	Overall	31.25%	78.13%	58.85%
		37.50%|25.00%|31.25%	84.38%|74.22%|75.78%	66.93%|66.67%|40.36%
	Year	27.08%	84.38%	63.02%
	Location	35.42%	71.88%	54.69%

size using partial eta squared (η_p^2). The thresholds for η_p^2 are: small effect (0.01), medium effect (0.06), and large effect (0.14). Below, we summarize and analyze our findings based on the metrics.

5.1 Response time

We measured and recorded participants' time to complete quantitative information comprehension questions. A t-test revealed no statistically significant differences in response times between the two visualizations, with p-values of 0.605 and Cohen's d = 0.095. Participants who observed the digital visualization (Group A) had an average response time of 149.91 s ($SD = 73.58$), and participants who observed the physical visualization (Group B) had an average response time of 143.06 s ($SD = 70.41$).

5.2 User experience

We conducted an analysis of the user experience with a confidence interval set at 95%. The findings (see Fig. 5) indicated a significant difference between the two types overall (p = 0.011, Cohen's d = 0.967), particularly in terms of pragmatic quality (p = 0.030, Cohen's d = 0.812). However, no significance was observed in hedonic quality. These results suggest that while both visualizations were similarly enjoyable, participants found the physical visualization more practically useful.

5.3 Information comprehension

Quantitative results: Before analyzing accuracy, participants' questionnaire responses were encoded: correct answers were coded as 1, while incorrect answers and "I don't know" responses were coded as a 0. 95% confidence interval was applied.

We assessed participants' comprehension of information three times: before using the visualizations, immediately after use, and seven days later. The same set of questions was used for each test, with the order randomized. The repeated-measure ANOVA revealed significant differences in accuracy rates across the three different times for each medium (p = 0.001, η_p^2 = 0.708 for physicalization, p = 0.007, η_p^2 = 0.634 for digitalization). For the digital visualization group, the average pre-test accuracy was 31.25% ($SD = 0.148$), which increased to 78.13% ($SD = 0.163$) immediately after use and retained a rate of 58.85% ($SD = 0.141$) after seven days. For the physical visualization group, the average pre-test accuracy was 35.16% ($SD = 0.149$), which improved to 84.90% ($SD = 0.115$) immediately after use, and retained a rate of 73.96% ($SD = 0.157$) after seven days. The detailed results can be seen in Table 3. We conducted t-tests to compare the accuracy rates between the two visualizations at each time point. The pre-test accuracy differences were not statistically significant (p = 0.089, Cohen's d = 0.263), indicating that both groups started with similar levels of knowledge. However, significant differences were found in the accuracy rates

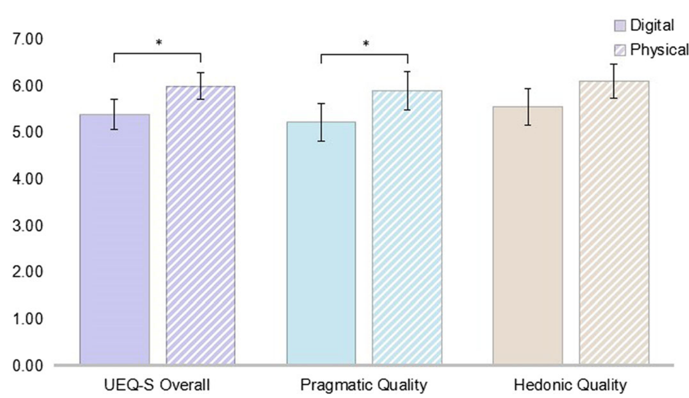

Fig. 5 Results of the mean score of the two visualizations on user experience. (* indicates a significant difference)

immediately after using the visualizations (p = 0.042, Cohen's d = 0.480) and seven days later (p = 0.028, Cohen's d = 1.014), with the physical visualization group consistently outperforming the digital group.

Further analysis was conducted to examine the accuracy for different types of data (year and location) and across different difficulty levels (Fig. 6):

- *Year:* The average pre-test accuracy was 27.08% ($SD = 0.227$) for the digital visualization and 20.83% ($SD = 0.149$) for the physical visualization, showing no significant difference initially. After using the visualizations, the immediate memory accuracy increased to 84.38% ($SD = 0.185$) for the digital group and 88.54% ($SD = 0.085$) for the physical group, with a significant difference between the two (p = 0.023, Cohen's d = 0.290). Seven days later, the retention accuracy was 63.02% ($SD = 0.204$) for the digital group and 76.04% ($SD = 0.187$) for the physical group, with a significant difference (p = 0.025, Cohen's d = 0.667).
- *Location:* The average pre-test accuracy was 35.42% ($SD = 0.171$) for the digital visualization and 49.48% ($SD = 0.252$) for the physical visualization. Immediate memory accuracy improved to 71.88% ($SD = 0.211$) for the digital group and 81.25% ($SD = 0.181$) for the physical group. Seven days later, the retention accuracy was 54.69% ($SD = 0.209$) for the digital group and 71.88% ($SD = 0.172$) for the physical group, with a significant difference (p = 0.041, Cohen's d = 0.899).
- *Difficulty levels:* Analysis of specific recall questions at different levels showed significant differences in the moderate questions (p = 0.026). Seven days later, the retention accuracy showed significant differences across easy, moderate and difficult questions (p = 0.043, p = 0.032 and p = 0.038, respectively).

Qualitative results: Participants were asked to summarize the patterns they observed from the visualizations immediately after usage (see details in Table 6 and Table 9 in Appendix). Among the digital visualization group, only 5 participants mentioned relevant patterns, while 8 participants from the physical visualization group identified these patterns. The main patterns observed included: (1) a closer proximity between buildings correlates with a shorter duration until they are put into use, (2) the North campus was initially operationalized, followed by the subsequent utilization of the South campus, and (3) the buildings in the South campus were occupied at a faster pace compared to the North campus.

Seven days later, participants were again asked to recall the patterns. Consistently, participants who used the physical visualization could recall more patterns accurately. Additionally, they were asked to accurately sketch the visualization they had used (see Fig. 7). In the digital group, only 8 participants could provide a rough depiction of the tree-ring visualization and spatial distribution, whereas 14 participants in the physical group successfully completed the drawing task satisfactorily.

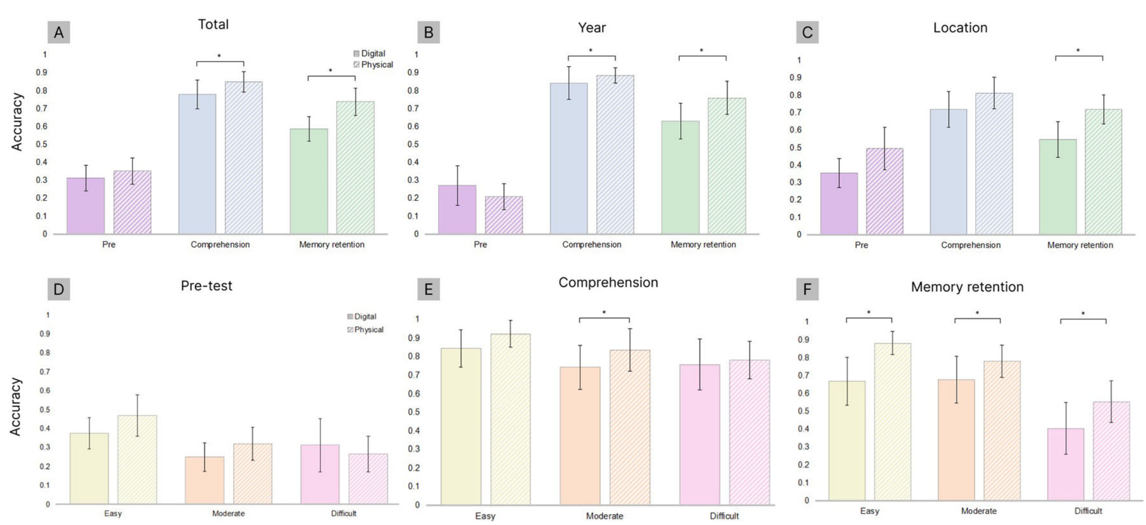

Fig. 6 Average accuracy of the two visualizations at different test time and problem levels: **A** Total average accuracy; **B** average accuracy of the year; **C** average accuracy of the location; **D** average accuracy of three-level questions in pre-test; **E** average accuracy of three-level questions in comprehension; **F** average accuracy of three-level questions in memory retention. (* indicates a significant difference)

5.4 Summary

Our results indicate that while there are no significant differences in response times between digital and physical visualizations, physical visualizations offer a better user experience and significantly improve immediate comprehension and long-term memory retention of information. The main differences between the two visualizations are evident in more difficult tasks, where physical visualizations show a clear advantage. Additionally, in terms of visual recall, physical visualizations are more effective at helping users remember the visualization itself. Furthermore, in qualitative feedback, users of physical visualizations are more likely to uncover underlying patterns within the whole dataset. These findings support the use of physical visualizations in settings where understanding and retaining complex information are critical.

6 Discussion

In this section, combining the previous literature findings related to materialization, we analyze, discuss and reflect the data results.

6.1 Discussion on results

- *Response Time.* Our study found no significant difference in response time between the two visualization media. This finding contrasts with Jansen's study, which reported faster task completion times for small-sized ($8cm \times 8cm$) physical visualizations compared to on-screen models (Jansen et al. 2013). When the medium comes to the table size, there is no significant difference in effectiveness between the screen and physical forms.
- *User Experience.* The user experience analysis showed that physicalization outperformed digital visualization. This aligns with findings from previous studies, such as Stusak et al. (2015), which found that physical visualization demonstrated superiority over the tablet to provide a more enjoyable reading experience for participants when presenting bar chart-related data.
- *Immediate Comprehension.* Our analysis revealed a significant effect of display media on immediate comprehension, with physical visualizations demonstrating higher accuracy compared to digital ones. We attribute this outcome to two main factors. First, physical visualizations enable participants to directly interact with the data, engaging in a more immersive exploration through tactile means and examining the data from multiple perspectives. This direct interaction likely enhances the capture and memorization of knowledge more effectively (Djavaherpour et al. 2021; Hull and Willett 2017). Additionally, the unique form and appearance of our 3D visualizations are more easily perceived in physical form, facilitating immediate comprehension. The tangible nature of physicalization allows participants to relate to and recall the information more easily, as suggested by Dragicevic (Dragicevic et al. 2020). These factors combined suggest that physical visualizations offer a superior means for users to quickly and effectively comprehend information compared to screen-based displays.
- *Memory Retention.* In the assessment of data retention one week later, the physicalization exhibited superior accuracy compared to digital ones. Nearly, all participants who observed the physicalization could accurately depict the approximate design outline (tree rings), supporting López's conclusion that physical visualizations leave a more profound impression on the audience (López García and Hornecker 2021). This finding also corroborates Stusak's research (Stusak et al. 2015) on memory retention for physical and on-screen bar chart data, which indicated that physicalization tends to mitigate memory loss over time. The tactile and visual engagement with physicalization can reinforce memory encoding, leading to better long-term retention of complex data. Also, this enhanced retention can be attributed to physicalization' clear spatial information and interconnectivity, which help individuals establish stronger spatial relationships and associations in their memory (Hull and Willett 2017).

6.2 Reflections

Here are some key reflections and insights drawn from our work:

- *Comprehensive data collection and analysis.* One notable aspect of our experiment was the extensive data collection, encompassing quantitative and qualitative measures. We evaluated users' comprehension

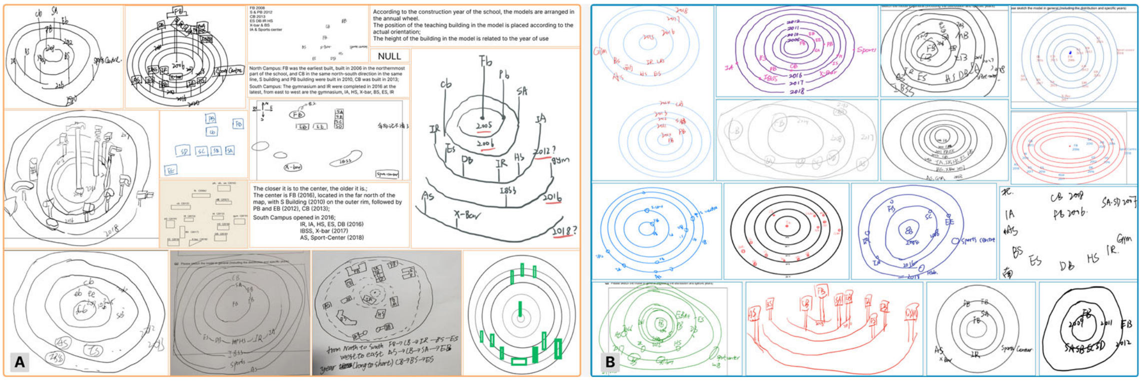

Fig. 7 The sketch drawn by participants: **A** digital visualization (Group A); **B** physical visualization (Group B)

through specific data comparisons, sorting tasks, identification, and the ability to discern patterns and underlying insights. This approach contrasts with many prior comparative studies that often focus solely on basic quantitative metrics. Our study was influenced by research (Elmqvist and Yi 2012) suggesting that the primary purpose of visualization is not merely to recall specific values but to understand and interpret broader data patterns and trends. As noted, effective visualization facilitates insight generation, allowing users to grasp relationships and patterns within the data. Therefore, including pattern recognition tasks in the evaluation was a critical design choice to capture a more holistic understanding of visualization effectiveness. However, it is important to acknowledge that our pattern recognition analysis remains at an early stage, primarily counting the frequency of identified patterns. Additionally, because many participants lacked formal training in visualization, their reflections might have focused more on the visual encoding rules rather than the underlying data patterns (see Table 6 and Table 9 in Appendix). Future studies should develop more sophisticated methods for analyzing and summarizing these insights and explore ways to guide users better or employ alternative methods to elicit meaningful patterns and insights from visualizations.

- *Interaction differences and their impact.* Another significant reflection involves the interaction differences between the two visualization media. Physicalization allows for a more immersive and active exploration, with users physically moving around and viewing the physicalization from various angles. This tactile interaction often results in a more engaging and memorable experience. Inversely, digital visualizations rely on screen-based interactions, such as rotating the visualization on a touch screen. Although we attempted to mitigate interaction complexity by providing an iPad for more manageable navigation, users still preferred the direct, hands-on interaction offered by physicalization. This preference highlights an important consideration for selecting visualization media: the complexity and nature of user interaction. Physicalizations offer more intuitive and satisfying interactions, which can significantly enhance user experience. However, when interaction complexity is minimized, as in our study, the differences in user experience between the two media may be reduced. Despite our efforts to simplify digital interactions, physicalizations still provided a superior user experience.

6.3 Limitation and future work

This study has provided insightful contributions to understanding the effects of data physicalization. However, several limitations must be recognized, opening opportunities for further exploration.

- *Demographic Specificity.* Our study predominantly involved participants with a relatively young average age. This demographic focus limits the generalizability of our findings to young individuals who may have particular aptitudes or preferences for engaging with physicalized data. To develop a more comprehensive understanding of how different age groups and demographic backgrounds respond to data physicalization, future studies should encompass a broader range of participants. This expansion would help ascertain whether the observed benefits of physicalization hold across diverse populations and how different demographic characteristics influence the effectiveness of visualization techniques.
- *Scale of Physical Visualization.* Although our study tested larger-sized physical entities and digital forms, we also observed larger-scale data physicalizations in practice, akin to the size of an entire wall or

half a floor. The comparison between these grand-scale physicalizations and similar-sized digital displays remains unexplored. Investigating how the size and scale of physicalization affect user interaction and memory could provide crucial information for designing data visualizations in large public or educational spaces.

- *3D Visualization.* We recognize that when data is transformed into a physicalized form, it inevitably takes on a 3D representation, which can introduce certain challenges. Specifically, users may have difficulties accurately perceiving relative positions or distances between data points. However, in our study, we controlled for this factor by ensuring that both media used identical 3D visualizations, thus effectively controlling the experimental variables and minimizing their impact on our findings. Moreover, the results indicated that participants' accuracy in understanding the data was consistently high across both media, suggesting that any potential perceptual biases brought about by the 3D representation were offset by the interactive features provided. The physical representation allowed for different forms of interaction compared to the traditional screen-based medium, with participants having the freedom to walk around and explore the data. This experiment highlighted that users may indeed benefit from more natural, movement-based interactions, which could further enhance their understanding and engagement with the data.
- *Data Type and Representation.* This research predominantly focused on static data types, specifically those related to years and geographic locations, utilizing tangible geometric visualization or solid materials for representation. According to visualization theory (Huron et al. 2014), the choice of medium for displaying data is often dictated by the target audience and the specific tasks at hand. In public settings, where the general audience interacts with visualizations, the complexity of these visualizations is typically kept to a minimum. Building on previous research that primarily explored simple visual forms like bar charts and conventional maps, this study ventured into less familiar territory by experimenting with innovative spatiotemporal data visualizations. This study initiates an important dialog about the adaptability of data visualization strategies to accommodate more complex or varied data types. Future research could leverage this foundation to comprehensively explore the potential complexities in data visualization, aiming to enhance understanding and interaction across a broader spectrum of public and specialized audiences. Such investigations would not only enrich the field of data visualization but also refine the practical applications of these technologies in diverse real-world scenarios.
- *Diverse Physicalization Techniques.* Our experiment focused on most traditional methods of physicalization, yet innovative approaches, such as dynamic wheeled microrobots (Le Goc et al. 2019), are emerging. Future studies could examine the effectiveness of these novel physicalization techniques compared to counterparts on the digital screen. Such research would expand the toolkit for data visualization, potentially leading to more engaging and effective ways to represent and interact with data.
- *Longitudinal Impact.* This study did not address the long-term effects (more than seven days) of data physicalization on memory retention. Understanding how physical and digital data representations influence memory over extended periods could provide deeper insights into their efficacy as educational and communicative tools.

Addressing these limitations and incorporating these suggestions into future work will refine the understanding of data physicalization's benefits and broaden the scope of its applicability in real-world scenarios.

6.4 Key highlights

Our work presents several key highlights in the field of data visualization. First, we address a significant gap in the literature by focusing on table-sized physicalizations, moving beyond the small-scale physical representations examined in many prior studies (Jansen et al. 2013; Stusak et al. 2015; Teng et al. 2024; Herman et al. 2024). The focus on table-sized physicalizations is significant because the larger physical scale allows for more immersive experiences compared to small-scale physical representations (López García and Hornecker 2021). This scale is particularly beneficial when dealing with complex, multidimensional data, like temporal and spatial information, as it provides enough physical space to represent different variables in a tangible, meaningful way. Users can engage with these physicalizations in a more intuitive manner—walking around, touching, and viewing from different perspectives—which enhances understanding, memory retention, and overall user experience. This is especially important for settings like exhibitions and museums, where an engaging and comprehensible representation of data is key to effectively communicating complex information to a broad audience (Dragicevic et al. 2020).

Second, our research involves complex data that combines both temporal and spatial dimensions, along with more sophisticated visualization designs, such as an annual-ring-style representation of architectural history. In contrast, previous work (Stusak et al. 2015; Kirshenbaum et al. 2020) typically dealt with simpler data types, like maps and bar charts. Our approach is closer to the complexity of real-world data and visual forms, as real-world applications rarely involve data that is consistently simple in structure or representation. Third, we provide a comprehensive evaluation of physicalization versus screen-based digital visualization, assessing aspects such as immediate comprehension and memory retention on data, usability, and qualitative pattern comprehension and recall. Our findings suggest significant improvements in immediate comprehension and memory retention, indicating the potential effectiveness of physicalization in helping users better remember the data, underlying insights and visualization design.

We believe that table-sized physicalizations hold substantial potential for diverse applications, particularly in public settings where quick comprehension of public data is essential. Previous research (López García et al. 2021) has demonstrated the advantages of large-scale physicalizations over smaller ones, particularly in areas such as user experience. Building upon these findings, our study further highlights that large physicalizations offer significant benefits compared to their screen-based digital counterparts, especially in terms of data comprehension, memory retention, and visual recall. This suggests that in contexts like public education, museums, and galleries, physicalizations can effectively convey information, helping visitors form deeper impressions and gain a more intuitive understanding of the data.

7 Conclusion

In this study, we compared two visualization media forms—screen-based digitization and physicalization on four dimensions: response time, user experience, immediate comprehension and memory retention. The experimental findings revealed a significantly positive impact of data physicalization on immediate comprehension, memory persistence and usability. Furthermore, distinct from prior studies which primarily focused on smaller-scale visualizations, our research emphasized the visualization on larger scales. Unlike the common bar charts or map-based data physicalizations, our study implemented more intricate visualization apparatuses. These findings have important implications for the design and application of data visualization, offering valuable guidance for the selection of table-sized display mediums in settings such as museums, art galleries, or educational tools.

Appendix

This section provides a summary of related literature, detailed questionnaires, and qualitative data from our experiment.

Detailed Experimental Questionnaires

See Tables 4, 5, 6, 7, 8 and 9

Table 4 Detailed Questions and Answers of the Public Data

Q1	Which building was/were the last to be put into use in XJTLU?			
	☐ IBSS	☑ Sport Centre	☐ DB	☐ I don't know
Q2	Which building was/were the last to be put into use in the North campus of XJTLU?			
	☐ SA	☑ CB	☐ EB	☐ I don't know
Q3	Which building was/were the first to be put into use in XJTLU?			
	☐ PB	☑ FB	☐ SD	☐ I don't know
Q4	Which building was/were the first to be put into use in the South campus of XJTLU?			
	☐ X-bar	☑ ES	☐ AS	☐ I don't know
Q5	Which was used earlier, IA or AS?			
	☐ AS	☑ IA	☐ I don't know	
Q6	PB was put into use later than IBSS.			
	☐ Yes	☑ No	☐ I don't know	
Q7	The year difference between SA and FB is smaller than that between CB and PB.			
	☐ Yes	☑ No	☐ I don't know	
Q8	HS and IR were put into use at the same year.			
	☑ Yes	☐No	☐ I don't know	
Q9	Both AS and IA were put into use in 2016.			
	☐ Yes	☑ No	☐ I don't know	
Q10	List the following buildings in descending order of when they were put into use. (The earliest-used building is ranked the first)			
	☐ ES	☐ IBSS	☐ Sport Centre	
	$ES > IBSS > SportCentre$			
Q11	Was PB put into use in 2008?			
	☐ Yes	☑ No	☐ I don't know	
Q12	List the following buildings in descending order of when they were put into use. (The earliest-used building is ranked the first)			
	☐ EE	☐ AS	☐ IA	
	$EE > IA > AS$			
Q13	ES is located in the North Campus.			
	☐ Yes	☑ No	☐ I don't know	
Q14	Which is the easternmost building in the North Campus?			
	☐ PB	☐ SC	☑ EB	☐ I don't know
Q15	DB is located in the South Campus.			
	☑ Yes	☐No	☐ I don't know	
Q16	Which is the easternmost building in the South Campus?			
	☑ Sport Centre	☐ HS	☐ X-bar	☐ I don't know
Q17	SD is west of PB.			
	☑ Yes	☐No	☐ I don't know	
Q18	In the east–west direction, which is closer to CB, FB or SC?			
	☐ SC	☑ FB	☐ I don't know	
Q19	ES is east of DB.			
	☐ Yes	☑ No	☐ I don't know	
Q20	In the east–west direction, which is closer to IBSS, X-bar or Sport Centre?			
	☐ Sport Centre	☑ X-bar	☐ I don't know	
Q21	Arrange the following buildings in order from north to south.			
	☐ PB	☐ IBSS	☐ IR	
	$PB > IR > IBSS$			
Q22	Arrange the following buildings in order from west to east.			
	☐ AS	☐ Sport Centre	☐ SB	
	$AS > SB > SportCentre$			
Q23	Arrange the following buildings in order from north to south.			
	☐ HS	☐ DB	☐ SC	
	$SC > HS > DB$			
Q24	Arrange the following buildings in order from west to east.			
	☐ X-bar	☐ ES	☐ IA	
	$ES > X - bar > IA$			

Table 5 User experience about the memorability of data physicalization

For the assessment of the product, please fill out the following questionnaire. The questionnaire consists of pairs of contrasting attributes that may apply to the product. The circles between the attributes represent gradations between the opposites. You can express your agreement with the attributes by ticking the circle that most closely reflects your impression.

Example:

attractive	☐	☐	☐	☐	☐	☐	☐	unattractive

This response would mean that you rate the application as more attractive than unattractive.
Please decide spontaneously. Don't think too long about your decision to make sure that you convey your original impression.
Sometimes you may not be completely sure about your agreement with a particular attribute or you may find that the attribute does not apply completely to the particular product. Nevertheless, please tick a circle in every line.
It is your personal opinion that counts. Please remember: there is no wrong or right answer!
Please assess the model now by ticking one circle per line

	1	2	3	4	5	6	7	
Obstructive	☐	☐	☐	☐	☐	☐	☐	Supportive
Complicated	☐	☐	☐	☐	☐	☐	☐	Easy
Inefficient	☐	☐	☐	☐	☐	☐	☐	Efficient
Confusing	☐	☐	☐	☐	☐	☐	☐	Clear
Boring	☐	☐	☐	☐	☐	☐	☐	Exciting
Not interesting	☐	☐	☐	☐	☐	☐	☐	Interesting
Conventional	☐	☐	☐	☐	☐	☐	☐	Inventive
Usual	☐	☐	☐	☐	☐	☐	☐	Leading edge

Table 6 Patterns described by participants using digital visualization

ID	Immediate comprehension	Memory retention
1	1. Arrange the buildings from inside to outside according to the time they are put into use 2. Buildings put into use in the same year are placed in the same circle	From the inside out in chronological order
2	With FB as the center, the North campus is distributed in the north of FB, and the south campus is distributed in the south of FB	With FB as the center, the North campus is on the north side and the south campus is on the south side
3	The buildings are arranged chronologically from the inside out	The models are arranged in layers of annual wheels according to the construction year of the school
4	The circle represents the year equipotential line (from inside out indicates the service time from long to short)	The closer the building is to the center, the longer it has been in use
5	From the center to the sides, the year is getting newer and newer	The time gap between buildings being put into use can be judged by the distance between corresponding circles. The location of the building in the timeline is the same as in real life
6	The buildings on the same circle are placed according to the actual geographical location	Each model conforms to the east–west direction in reality
7	The innermost part of the disk represents the earliest year when it is put into use, and the years are evenly distributed	It is logical and clear to memorize
8	The denser the disk is, the closer the time it is put into use. Buildings put into use in the same year are on the same circle	Each building of the school is in a time circle with the earliest time in the inner circle and the latest time in the outer circle The location of the building in the timeline is the same as in real life

Table 7 Patterns described by participants using physical visualization

ID	Immediate comprehension	Memory retention
9	The North campus to be put into use first and the South campus to be put into use later.	The building is built from the inside out, and the year when the building is put into use increases
	Put into use the building with higher columns first, and then put into the shorter building	Fewer buildings are put into use in the early stage and more intensive in the later stage.
		The buildings on the North campus are put into use first, followed by those on the South campus.
10	The closer to the center, the earlier the building is put into use	The oldest building located at the center and the highest. The newest building located away from the center
	Buildings put into the same year are located on the same circle	Buildings put into use in the same year are on the same annual rings
	The distance of gaps between circles are correlated to the years	
11	The building is from the inner circle to the outer circle, from high to low, representing the year of the building being put into use from early to late	The year when the building was put into use is very clear, and the buildings on the same horizontal line can be remembered by association
		The height of the buildings in different years is different, so it is easy to remember the order of the years
12	The year marked on the bottom disk tells you the year each building is put into use	This model presents the various buildings in the north and south campuses on a concentric circle with time as the axis, based on their geographical location and relative distance
13	The buildings of the South Campus are distributed symmetrically	This is a circular model that integrates the location of the building and the construction time
	The use time of the South Campus is shorter when the overall building is put into use, while the North Campus is longer when the overall building is put into use.	The farther away from the center point of the circular disc, the larger the radius, and the shorter the construction time
14	The closer the buildings are, the more similar the years they are used.	The closer the building is, the closer the year it was put into use.
		The layout of the building corresponds to the actual situation
15	All the buildings are allocated according to both time lines and their actual locations	1The model adopts the form of time-space distribution and displays the building model from the inside out according to the time of building construction in the horizontal direction
	Additionally, the general trend shows that all the buildings in the north campus appear earlier than those in south.	Since the buildings in different time loops are arranged according to the actual orientation, I can intuitively and quickly understand what the model wants to describe

Table 8 Patterns described by participants using physical visualization

ID	Immediate comprehension	Memory retention
16	The closer it is to the center of the circle, the earlier the building will be put into use	The farther from the center of the circle, the newer the year the building was put into use
17	The buildings are distributed according to time, and the inner circle buildings are put into use earliest	The color of the building model is consistent with the reality The building gradually transforms from inside to outside
18	The buildings of the South Campus are put into use from 2016 to 2018.	The model distributed every building in XJTLU in a circle, with the latest outside and the oldest inside
19	The buildings of the North Campus are all put into use before 2013. The North campus buildings are put into use in a relatively scattered time, while the South campus buildings are more concentrated. The buildings placed in the outer ring are newer Buildings are prioritized according to time, and buildings of the same year refer to the actual geographical location	The buildings located from west to the east is allocated from the left to the right in the model Use established years and locations to distinguish different buildings, and the established years are shown in concentric circles
20	Building height gradually decreases from inside to outside	Building height gradually decreases from inside to outside
21	Buildings in the same circle are distributed according to their actual geographical location	The buildings near the center of the circle were put into use the earliest
22	The buildings of the North Campus are generally put into use earlier than those of the South Campus.	The distribution is roughly based on the actual geographical location The buildings of the North Campus were put into use earlier than those of the South Campus.
23	The building of the South Campus has been put into use for a shorter time than that of the North Campus. The buildings of the North Campus are generally put into use earlier.	Buildings near the center of the circle are invested the earliest
24	The construction of the South Campus is generally late and time intensive. The different heights of the model buildings indicate the time of being put into use	The position of the model is designed in concentric circles, which makes it easy to remember which buildings are in the same year
25	All the buildings outside are put into use relatively recently	Different models have different color heights and appearance, giving people a deeper impression The closer the building is placed to the outer ring, the newer the year it is put into use

Table 9 Patterns described by participants using physical visualization

ID	Immediate comprehension	Memory retention
26	The number of buildings put into use in the early stage is small, and the number of buildings put into use in the later stage is more.	This 3D model contains the content of the year and geography information and so on
27	The buildings of North campus are put into use earlier, while those of South Campus are put into use later.	It is a 3D model
28	The closer the buildings are to the time when they are put into use, the closer the models are.	1. Building investment time gradually increases from inside to outside
		2. The closer the time the building is put into use, the more compact it is.
29	1. More buildings have been put into use in the South Campus.	The South Campus building was put into use relatively late.
	2. The buildings of the North Campus are put into use relatively early.	
30	1. The buildings of South Campus are put into use in 2016-2018.	1. The pattern is combined in time and space
	2. The buildings on the south campus are relatively concentrated, while the buildings on the North campus are relatively evacuated.	2. But it is only easier for me to remember the relative location instead of the specific location
31	1. The location of the South campus buildings are near the periphery of the ring (the year they are put into use is relatively new)	1. It is a circular model
	2. The North campus buildings are near the circle center	2. The closer to the center, the older the building
		3. The farther away from the center, the closer to the present time it was built
32	1. The year in which the building is put into use gradually decreases from the inside out	1. Circular distribution
	2. The building is centered on FB, which is the first put into use	2. The closer to the center of the circle, the older the building is

Qualitative result

Overall, we can see that users' understanding of patterns and insights may not align with those trained in data visualization, who typically explore from a data perspective. General users may instead derive patterns based on the visualization encoding rules. Therefore, we will provide further guidance on pattern and insight identification in future experiments to obtain more reasonable and accurate insight discoveries.

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