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Visualization in Motion: A Research Agenda and Two Evaluations

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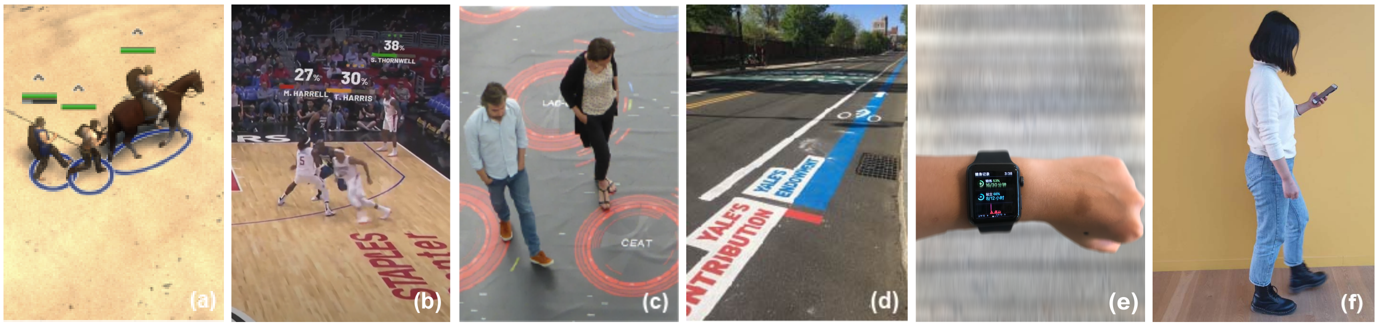

Moving visualization & stationary viewer. Stationary visualization & moving viewer. Moving visualization & moving viewer.

Fig. 1: Visualization scenarios that involve different types of relative movement between viewers and visualization: (a): 0 A.D. game characters with attached health meters, (b): an augmented basketball match from the tool Clipper CourtVision. (c): a walkable visualization of the general organization of scholars at ENAC in France [75], [76]. (d): an on-street bar chart that can be driven or walked by created by the *Respect New Haven* activist group. (e): a runner looking at her fitness data. (f): a person checking financial charts on her phone while walking to a meeting. *Image permissions are listed in the acknowledgments.*

Abstract—We contribute a research agenda for *visualization in motion* and two experiments to understand how well viewers can read data from moving visualizations. We define visualizations in motion as visual data representations that are used in contexts that exhibit relative motion between a viewer and an entire visualization. Sports analytics, video games, wearable devices, or data physicalizations are example contexts that involve different types of relative motion between a viewer and a visualization. To analyze the opportunities and challenges for designing *visualization in motion*, we show example scenarios and outline a first research agenda. Motivated primarily by the prevalence of and opportunities for visualizations in sports and video games we started to investigate a small aspect of our research agenda: the impact of two important characteristics of motion—speed and trajectory on a stationary viewer's ability to read data from moving donut and bar charts. We found that increasing speed and trajectory complexity did negatively affect the accuracy of reading values from the charts and that bar charts were more negatively impacted. In practice, however, this impact was small: both charts were still read fairly accurately.

Index Terms—Visualization, visualization in motion, perception, research agenda, movement, motion.

1 Introduction

With the development of computing technology, data visualizations have moved off paper and onto interactive media, offering opportunities for animation and motion. Animation as part of or between visualization states is frequently used to express highlights, smooth transitions of data points in time [6], [18], [82], [99], or to morph between different representations [10], [28], [37], [74], [78]. In contrast, we are interested in studying the effect of relative motion of *entire* visualizations in respect to a viewer. Examples of this type of visualization movement exist in real life scenarios already: player tracking in sports allows companies to embed match-related charts that move with players or game equipment such as balls (see Fig. 1b and Fig. 2); automated traffic tracking allows to embed data next to vehicles moving in a video stream [53], [97]; and embedded dynamic representations have been common for years in video games (Fig. 1a) to show character health [103], [104]. We call visualizations such as these *visualizations in motion* and define them as follows:

> *Visualizations in motion are visual data representations used in contexts that exhibit relative motion between a viewer and an entire visualization.*

The impact of relative motion will depend on the type and magnitude of the relative motion itself. Some types of relative motion like saccadic eye movements or simple head movements

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will likely not lead to interesting impact on reading visualizations; while higher magnitudes of relative motion will lead to a more measurable impact, depending on the scenario. In our work, we outline scenarios where we expect that such relative movement may affect how a viewer experiences and reads a visualization.

Our definition points to a research space that is much larger than the previously outlined scenarios. The examples from video games and sports analytics above include entire visualizations moving on-screen in front of a seated viewer. Relative motion can, however, also occur when viewers themselves are in motion. For example, many data physicalizations are static and involve viewers moving along, over, or around them, as can be seen in Fig. 1c and 1d. Moreover, in Fig. 1e, the scenario involves both a moving viewer and a visualization moving at the same time but independently, as both head and arm exhibit slightly different motion trajectories. While examples of visualizations in motion already exist, there currently are no systematic investigations of the research space itself. In this article, we aim to address this challenge and make two contributions towards a broader understanding of how to design for *visualizations in motion*. In particular, we detail example scenarios and present a broad research agenda for *visualization in motion*. In addition, to these two broader contributions, we conducted two experiments on a particularly promising visualization in motion scenario: moving visualizations and a stationary viewer. As such, we tackle a first small portion of the research agenda. We assess how speed and trajectory complexity affect the reading accuracy of two simple chart types and find that increasing speed and complexity of trajectories impacted participants' performance negatively, but in different degrees. Our results are promising first steps for future work towards an ultimate design space for *visualization in motion*.

2 VISUALIZATION IN MOTION SCENARIOS

We introduce scenarios and challenges for different types of visualizations in motion —as well as their related work. While *visualization in motion* as a research direction has not been systematically explored, past work exists in situations that involved relative motion between viewer and visualization. We focus on three types of relative motion between viewer and visualization and associated challenges that point to possible research directions:[1]

	Viewer stationary	Viewer moving
Vis stationary		×
Vis moving	×	×

2.1 Moving Visualization, Stationary Viewer

In this scenario, a stationary viewer sees an entire visualization move and is required to move their eyes and/or head to possibly track the visualization in order to read it accurately (depending on the complexity of the data and the motion characteristics). It is important to recall that our definition focuses on *entire* visualizations moving, rather than data point animations or morphing, for example, where individual parts of visualization have different motion characteristics such as directions, trajectories, or speeds.

Moving visualizations for stationary viewers exist in sports analytics, where charts are attached to moving players or game equipment. Several companies (like Footovision [31] or SportsDynamics [89]) now commercialize tools that embed visualizations in videos (e. g., Fig. 1b, Fig. 2). Such tools may be used by team coaches and players but also non-expert audiences during replays or debrief sessions on TV. In contrast to these moving visualizations, several static sports visualizations have been developed in research as well. These tools add statistical analysis visualizations for sports such as table tennis [17], [101], [109], soccer [4], [90], [110], basketball [8], [96], cycling [48], badminton [68], [112], or tennis [69]. Consistently, here, the visualizations stay still; for example, in VisCommentator [17] visualizations are embedded on static video screenshots. Motion is visible in cases where users can interact through zoom, pan, or rotation [69], [108], [110], [112], or when animated traces are replayed in the tools [4], [68], [90], [101]. However, in contrast to our work, this literature does not discuss how to design moving visualizations and most visualizations are not embedded with a data referent.

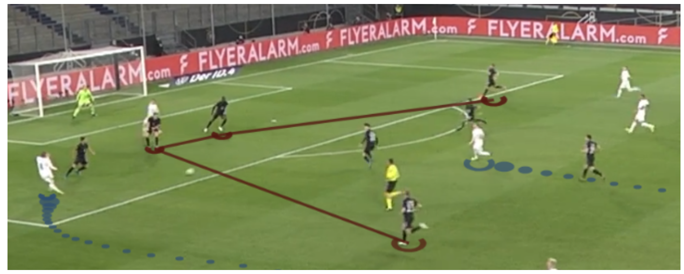

Fig. 2: Examples of player video tracking for performance analysis. In this figure, the circle under each player's feet and its motion tail are individual representations of the player's current and past positions as well as his/her team membership. *Image ©, courtesy of Footovision [31].*

Video games are another domain that frequently involves moving visualizations attached to game entities. Past work on game visualizations has mainly focused on the retrospective analysis of player cooperation and performance (e. g., [1], [32], [54]). Real-time situated visualizations that move with characters often have the goal of providing situational information that helps players make quick decisions and perform and cooperate effectively. Bowman et al. defined a design space and proposed design patterns for visualization in games [12] but did not specifically discuss the design of visualizations in motion.

With the development of artificial intelligence, recognizing objects and labeling them in video frames has been the focus of object tracking [59]. In this domain, visualizations are mostly simple rectangles, sometimes with labels and/or a categorical color code, that visualizes the tracked objects' position, size, and potential type. While these are simple visualizations, the technology can be used in the future to embed more complex representations on tracked objects.

Finally, interaction more broadly can result in visualizations in motion when a user applies an interaction like panning, zooming, rotating, or changing viewing position to an *entire* visualization. In HCI, the impact of these operations has been studied for interactive user interfaces [41], [45], more specifically, in navigating maps [77]. However, reading visualizations during motion created by certain interactions may not always be a primary goal; for example, when a viewer scrolls a web page, embedded visualizations would typically be read before or after the scroll interaction. Nevertheless,

1. While stationary viewers may also experience illusory motion with stationary visualizations (e. g., stroboscopic motion or the phi phenomenon), we exclude this scenario as no relative motion between viewer and visualization is present.

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a set of glyphs embedded on a map may be read during panning to identify locations with certain data characteristics.

2.2 Stationary Visualization, Moving Viewer

In this scenario, a moving viewer focuses on a stationary visualization and experiences additional optical flow during self-motion in the world. A main consequence of viewer movement is changing the viewing angle and orientation towards the visualization. The effect of this type of motion has been researched sparsely in visualization, for example, in wall-sized display, data physicalization, and AR/VR research. Past research has looked at moving viewers in front of wall displays, for example as part of basic perception experiments [9], as input to change a visualization or its presentation—e. g., through proxemic interaction [7], [43], [72] or hybrid images [42]—, or to visualize viewer movement [15]. The experiment by Bezerianos and Isenberg [9] is most closely related. It showed no difference in the accuracy of moving participants and static ones standing far from the display wall when performing magnitude production trials on simple visual stimuli. However, participants who walked had better accuracy than those who stood close to the wall. In a previous study on how people approach and explore data physicalizations, Taher et al. [92] provided evidence that body movement is an important part of both data exploration and presentation. The authors pose further research questions regarding which extent movement leads to better insights or more accurate reading due to changes in viewpoints. Thanks to head-mounted devices, previous research such as [95], [96], which combined sports visualization and AR/VR, provided the possibility for users to move around and observe their previous basketball shooting trajectories in a 3D space.

2.3 Moving Visualization, Moving Viewer

Both visualization and viewer might also move independently at the same time with relative motion between both. This motion can range from visualizations on smartwatches worn on the arm during a run (Fig. 1e) to larger changes in motion when visualizations are projected onto approaching traffic and seen from a moving vehicle.

A relevant research area for this scenario is wearable and mobile visualization (see also Section 4) as well as immersive analytics. Several previous studies on mobile phones have shown that walking increased workload and reduced performance in reading tasks [64], [81], [98] and the psychology literature has shown that walking in VR may negatively impact multi-object tracking [94]. As cognitive resources need to be similarly shared between navigation and reading data, it seems reasonable to expect similar negative effects for visualizations in motion. Several research efforts in VR have focused on the viewer's motion, such as examples illustrated in Locomotion Vault [23]. For example, research has shown that in a virtual environment, common motion effects such as walking can benefit the viewer's spatial memory [79]. However, impact on reading visualizations in motion still required more dedicated work in VR.

So far, research on wearable visualization has largely concentrated on smartwatches [11], [65], [66]. Much of the past work did not specifically design for or study moving observers. Exceptions are, for example, Schiewe et al.'s [80] work on visualizations for real-time feedback during running activities. Amini et al. [3] interviewed quantified-selfers about their in-situ data analysis activities and showed the variety of reasons people checked their fitness trackers during sports activities.

3 Additional Related Work

To complement the related work in the previous section, we present relevant past work on design considerations for animation in visualization and work related to our two experiments.

3.1 Animation in Visualization

While *visualizations in motion* have not received much research attention, animated visualizations have been studied more extensively. Work on animation has often focused on how to animate between different arrangements of data points [18], [99], changes in data (e. g., graph) topologies or dimensions over time [6], [28], for zooming into data [10], [82], morphing from one representation to another [37], or for changing perspective in 3D scenes [74], [78]. In general, work on animation in visualization is related to ours through the joint interest in motion. Yet, our focus is on *entire* visualizations exhibiting relative motion with the viewer. Real-world visualizations in motion have to often deal with additional complexities due to changing context conditions and unpredictable motion characteristics. In the next section, we discuss some of their application contexts and related work in these contexts.

3.2 Studying Visualization in Motion

Although motion relationships between viewers and visualizations have not been systematically explored in the visualization community, they have been discussed in psychological studies. The work most closely related to ours concerns dynamic visual acuity. Dynamic visual acuity (DVA) [56], [57] describes the ability of an observer to discriminate an object when there is relative motion between the observer and the object. In contrast to our work, the visual targets in DVA experiments are often Landolt C, optotypes on Snellen chart, or strings of numbers. In DVA experiments, participants are generally asked to identify the orientation of optotypes or to read the numbers rather than reading magnitude proportions, as in our case.

Previous research on DVA [14], [58], [63], [102], in which stationary participants were asked to identify the orientation of Landolt Cs moving at different angular velocities, found that with increasing velocity visual acuity decreased. Similar decreases in acuity were also found for moving participants judging stationary targets [35], [40], [67]. It remains unclear if these results also hold for more complex targets such as certain visualizations and more complex types of movements such as irregular trajectories.

In our experiments, we tested how effective stationary viewers were at reading quantitative values from moving proportion visualizations (bar and donut charts) inspired by those seen in Fig. 1a and 1b. Our methodology involved a magnitude estimation experiment [19] performed on a crowdsourcing platform. Our study methodology differs slightly from previous work on crowdsourced perception experiments [22], [36], [49], [84], [85], [100], [113] in that we paid particular attention to control the physical size (and speed) of the stimuli shown on participants' screens through a dedicated screen calibration step.

Previous work has compared the two general chart types we tested in static scenarios and under different variations. Blascheck et al.'s work [11] found that people were slightly faster at comparing two values in smartwatch-sized donut charts than in regular bar charts. The related work on pie charts vs. stacked bar charts found that often pie charts outperformed or were en par with stacked bars according to accuracy [20], [27], [46] but that stacked bar tasks were often completed more quickly [27], [46], [83]. Redmond [71]

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compared proportion visualizations similar to ours and used pies vs. a two-segment horizontal bar. Similar to past work, he found that pie segments were more accurately estimated than bar segments. Simkin & Hastie [83] also tested a proportion judgment task like ours and found that pie chart proportions judgments were more accurate than those on bar charts but took longer. In summary, the past body of work comparing pies to bar charts might predict a slightly better accuracy for donut charts.

4 A Research Agenda for Visualizations in Motion

As previously mentioned, there is still little work dedicated to the impact of motion on reading visualizations. Our goal is to point to new possibilities for research and to show important factors that need more exploration. In this section, we summarize important future research in this space related to the scenarios introduced in Section 2. As Fig. 1 shows, visualizations in motion may be overlaid in 2D, maybe physicalized, or shown in 3D virtual worlds, which are drastically different viewing contexts with varying types of motion. We, therefore, focus our research agenda on four broad properties: a) work that studies the influence of different characteristics of motion, b) work related to the spatial relationship between the viewer(s) and the visualization(s), c) future work on the situatedness of the visualization, and d) technologies for visualization in motion. Some aspects of these properties may be interrelated, as our goal is not to provide distinct boundaries between properties. Rather, we focus on pointing out the base properties that may affect visualization reading and their research prospects. Of course, their combinations need to be further researched as well.

4.1 Characteristics of Motion

In physics, motion is described as the phenomenon in which an object changes its position over time [106] according to a frame of reference. To research *visualizations in motion*, we, thus, first have to consider appropriate reference points. Taking the human viewer as the reference, a visualization can exhibit relative motion or relative immobility. If we consider a human viewer to be a fixed point of reference (even if the viewer is actually moving), relative motion exists if a visualization moves relative to this fixed viewer due to a different speed or motion trajectory. If both the human and the visualization do not move or move at the same speed along the same trajectory (e. g., a human reading a stationary visualization on a moving airplane), there is no relative motion.

Central to our definition of *visualization in motion* is the existence of such relative motion of sufficient magnitude—beyond eye saccades or simple head movements that all human viewers would exhibit. In Section 2 we already discussed several research areas in which visualizations often need to be read under relative motion. The effects of relative motion for the viewer may involve changes in viewing angles, orientations, motion blur, or changing visualization sizes, among others – all of which will be more or less pronounced depending on the characteristics of motion. Next, we list specific properties of motion we expect to impact the effectiveness of moving visualizations but for which the gravity of the impact still needs to be empirically established. A main research challenge related to motion characteristics includes finding out how well people can track visualizations that are moving very fast and in unpredictable directions while at the same time trying to read and understand the presented data.

Speed: Simply said, speed determines how quickly the spatial relationship between viewer and visualization changes. While we are not aware of studies in visualization that assessed speed for visualizations in motion, previous studies [33], [47] on dynamic text reading indicate that text moving speed influenced reading comprehension. We expect effects on reading data visualizations as well, but their extent needs to still be evaluated.

Trajectory: For visualizations in motion, the trajectory is the path along which the spatial relationship between viewer and visualization changes. Trajectories can be more or less regular and predictable and be embedded in a plane or 3D space. We expect trajectory complexity to impact the accuracy of reading moving visualizations and future studies should find ways to test simple trajectories (e. g., during panning) and more complex ones (e. g., during tracking of certain sports).

Acceleration: Acceleration describes the rate of change in speed. Although acceleration has not been extensively studied in the visualization community, previous research on animation still touched on changes in acceleration. Dragicevic et al. [26], for example, studied different types of pacing for animated transitions and recommended slow-in/slow-out transitions where objects begin to move slowly and then increase speed before decelerating close to the endpoint of the animation. The effect of acceleration, and in particular, unpredictable changes in speed, remains to be explored for visualizations in motion.

Direction of Motion: Direction of motion refers to where in a reference space a visualization seems to be moving. Direction of motion has been little explored, even for animated visualizations. Indications for a possible effect might come from studies on reading direction. A past eye-tracking study [38], for example, indicated that reading direction has an influence on attention and memory. Other studies from psychology [2], [29], [62], [86] also confirmed that reading direction affects perception. How these effects transfer to reading visualizations should be further explored.

4.2 Spatial Relationship Between Viewer and Vis

Our next area for future research involves the spatial relationship properties to consider when designing visualizations in motion.

Viewing Distance: Let us consider the viewing distance as the linear distance between the viewer and the visualization. A change in viewing distance varies how the visualization appears on the viewer's retina. Either a change in distance comes with a change in position on the retina and/or a change in visualization size. For example, look at Fig. 3–Left, a visualization attached to a flying soccer ball would appear to change in size as the ball moves close to the viewer and might (unless the ball flies directly at the viewer) also appear to move through changes in position. How combined changes in visualization size and position would affect reading the data is still an open question.

Viewer vs. Visualization Space: A visualization has an inherent local coordinate system. Similarly, a viewer of this visualization can be modeled using a local coordinate system that changes with head and/or eye movement. The relationship of these two coordinate systems in a world impacts how a person sees a visualization in their field of view. For example, in Fig. 3–Center, a cyclist riding past a visualization on a static sign will see the visualization at different viewing angles as the visualization-to-viewer coordinate system transformation changes. When, instead, a viewer looks straight at a visualization that moves along their line of sight, the two coordinate

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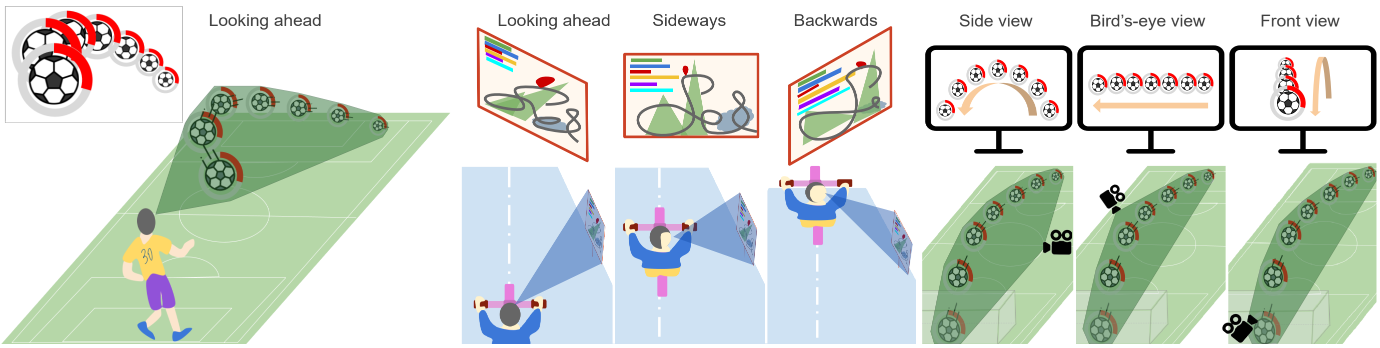

Fig. 3: Left: Changes to the perception of a soccer ball's size and position based on the distance between viewer and visualization. Center: Changes of a moving cyclist's perception of a static map and bar chart based on changes between the viewer and the visualization space. Right: The same physical motion of a soccer ball will lead to different trajectories on the viewer's retina based on the relationship of viewer to world space.

systems stay aligned, and viewing angles will not change. In this case, motion effects will be seen through characteristics associated with changes in viewing distance. In most cases, however, the relationship between the two local coordinate systems will change over time when the viewer tracks a visualization in motion.

Viewer vs. World Space: The world a visualization resides in can similarly be defined with a world-coordinate system. The relationship between the viewer's coordinate system and the world-coordinate system describes how the viewer looks at a specific scene. For a single visualization in motion, the viewer-to-world space relationship will affect the perception of motion on the viewer's retina. Let's look at three kinds of views that are important: the front view, side view, and bird's-eye view. When a soccer game is broadcast, highlighted moments are often given a multi-angle, all-around camera replay. Fig. 3–Right shows how the same movement would be seen from the three different views. From the side view, the soccer ball with a situated donut moves from right to left in a beautiful arc. However, from the bird's-eye view, the movement seems to be linear. In the front view, not only is the trajectory changed from curved to linear movement, and the soccer moved up and down, but it is accompanied by a change in view distance as well – the soccer ball becomes bigger and bigger.

Especially in scenarios with moving viewers and stationary visualizations, a main research challenge includes finding out how people experience and how effectively they read visualizations under changing viewing angles and potential inherent changes of visualization orientation.

4.3 Situation, Context, and Design

In our exploration of visualizations in motion, we saw a wide variety of ways in which visualizations are displayed and related to the environment. In contrast to more standard data representations used for analysis in desktop environments, these visualizations were displayed with a large number of varying contextual factors and ways to connect to potential physical or virtual data referents [107]. The influence of factors such as the ones listed next require further research attention:

Autonomy of Motion: Depending on the situation and context of the visualization, the movement of a visualization may be outside human control (autonomous). This type of movement is widespread in natural environments, in flowing streams, falling leaves, swimming fish, etc. For example, an aquarium might add visualizations around swimming fish to represent their age, sex, or size. When the motion is non-autonomous, the movement is under the control of or influenceable by a human. For example, a player controls a moving character with an attached health bar in a video game. To what extent the autonomy of motion plays a role in how well visualizations can be tracked and read is still an open problem.

Predictability of Motion: To a viewer, the relative motion of a visualization may be predictable or not. Predictable motion can come in the form of: a) motion with naturally predictable properties, for example, the movement trajectory of a swimmer in a swimming competition – each swimmer completes the race in their lane, and audiences understand that the swimmer's trajectory will be approximately linear; b) movement under the control of the viewer, for example, when a viewer zooms, pans, rotates or scrolls a visualization, they can more easily predict where the visualization will move. Unpredictable motion occurs when the movement does not have predictable properties because it does not follow natural motion paths. The same motion can be predictable for one viewer but unpredictable for another. For example, a soccer player can predict the ball's movement before kicking it, but for the audience, the ball's movement is unpredictable because it depends on the player's footwork. Previous research from neuroscience pointed out that viewers can better predict motion by tracking a moving target object [87]. However, their visual target was a Gaussian dot. We did not find any research explicitly stating that the predictability of motion positively or negatively influences visualization readability. Thus, it is still hard to tell if the predictability of motion would impact a visualization's readability.

Contextual Factors: The scenarios outlined in Section 1 and 2 show a variety of contextual factors that can have an impact on how visualizations in motion are perceived. The examples involve visualizations of various backgrounds, in scenarios that potentially involve noise or viewers with primary tasks such as riding a bike or fighting another game character. Especially when reading a visualization is not a primary task, visualization often cannot be focused on for longer periods of time. While researchers have studied the glanceability of smartwatch visualizations [11], the in-situ reading of data from visualizations will likely be impacted by relative motion and require design attention. Data physicalization scenarios also often include social challenges related to movement and contextual factors such as lighting or distractors like noise that might affect how people experience visualizations while moving.

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As such, studying the impact of contextual factors on visualizations in motion will be important.

Connection to Data Referents: Willet et al. introduced data referents as (physical) entities and spaces to which data corresponds. We saw many examples of situated visualizations (according to the definition used by Willett et al. [13]) with varying degrees of connection between visualization and what the represented data referred to. The examples involving visualization over or around game characters Fig. 1a, players in live sports tracking Fig. 1b, or fitness data shown on wearables Fig. 1e, include very close connections; while the data physicalizations in Fig. 1c and Fig. 1d show abstract data more broadly related to the place they are displayed in. Thanks to advances in technology, it is becoming easier to embed visualization in certain scenarios such as live videos or on wearables that collect data in real-time related to specific locations or the wearer [5], and as such, there is a large design space to explore for embedded visualizations in motion.

Visualization Design: There is ample evidence that visualization choice and design will impact the effectiveness and efficiency with which data can be read and understood without motion. These design choices also need to be studied specifically for visualizations in motion. For example, the representation type [115], [116], the visualization complexity [19], [93], the decoration of the representation [24], [84], [85], the size of the visualization [16], or its color selection [91], [114], may affect how people perceive a visualization in motion. Nevertheless, there is some limited past research in visualization that involved looking at effects of motion. Researchers, for example, studied labeling and annotation in immersive analytics under motion and specifically factors such as viewing angle changes [55], [60] and spatial location changes [55], [61] of objects in the environment. As such, there are limited dedicated design guidelines for people who already create visualizations in motion in practice. In our recent IEEE VIS poster [111], we made first steps and collected design considerations from a set of 87 example images collected online as well as 110 designs elicited during a design workshop. From these, we propose several visualization design characteristics to focus on for future research: the design of labels, the salience of the design, the distance to objects of interest, and the complexity of the design or shown data. In addition, several visualization in motion scenarios (object tracking, fitness tracking, sports analytics, . . .) involve dynamically updating data. It is still unclear how updates would be noticed and evaluated by viewers under relative motion.

4.4 Technology

Many of the visualization in motion scenarios outlined above depend on available technology such as wearables, AR/VR, or fabrication technology. Research on visualizations in motion can draw from and inspire available technology and can perhaps even shape future technologies. Here, we list a few technologies where research on visualizations in motion is particularly important.

Stationary Screens: Seated viewers may experience visualizations in motion on any type of screen, such as in Fig. 1a and 1b. Despite the existing examples in games and sports analytics, we know relatively little about how visualizations moving across a screen are perceived by seated viewers. Exploring visualizations in motion for general screens can already have a large impact on growing and well-established industries and help improve how viewers experience data visualization.

Mobile and Wearable Devices: Mobile and wearable devices already carry visualizations in motion experienced by moving viewers, such as in Fig. 1e and 1f. Smartwatches, in particular, are a growing market involving many wearers who aim to improve their health and well-being by tracking their data. Again, conducting research on how best to design visualizations under contextual factors such as the types of movement (running vs. walking) as well as lighting or primary tasks under which these devices are checked is important.

Physicalizations: Data physicalizations can be constructed from a variety of materials and for a variety of purposes [44]. We mostly saw static physicalizations and moving viewers, such as Fig. 1c and 1d, and for these scenarios, it would be interesting to explore physicalization properties and how they affect how moving viewers are able to experience the data. In these cases, in particular, the viewing distance and the spatial relationship between the viewer, physicalization, and the world would be changed with the viewer's movement. It might also be an interesting challenge for designers to come up with future moving physicalizations for static observers.

AR/VR: Visualizations in motion are particularly common in AR/VR scenarios as soon as viewers are free to move their viewpoints and positions in a 3D scene. One interesting opportunity for AR/VR is real-time visual feedback. Both Wu et al.'s work on VR table tennis skill training [108] and Lin et al's work on AR visualization for basketball free-throw training [96] showed that the real-time visual feedback can improve the player's performance. In some sense visualizations in motion in AR/VR share challenges with other scenarios, for example, when data representations can be moved around in a 3D scene (data physicalizations or flat screens) or when data is embedded with objects or devices (mobile and wearable devices). Many future projects on visualizations in motion in immersive analytics are open to be explored in particular in relation to immersive experiences with data visualizations.

Advanced Techniques: Apart from the existing and known technologies that involve visualizations in motion, there are a number of future technologies for which visualizations in motion can help to produce promising applications scenarios, suggesting types of visualizations to display on holographic projections, visualizations on or by drones, or visualizations embedded on robots [52]. Future advanced technologies can help to build visualizations that are hybrids of data physicalization and digital representations in 3D spaces that could move autonomously (like robots) or can be flown (like drones). Understanding how the choice of technology may affect the perception of visualizations in motion remains an open research direction.

4.5 Summary

In summary, visualizations in motion are still a wide-open research space. They include opportunities for design as well as for in-depth empirical research as outlined above. Some inspiration and hypotheses for empirical studies can be derived from related work, but almost no work exists that has looked specifically at moving data representations.

5 Studies on Visualization in Motion

Motivated by the wide-open research space and, in particular, the potential of visualization in sports analytics and video games, we chose to explore the stationary viewer+moving visualization scenario in more detail. To address the lack of empirical work in this

TABLE 1: Example stimuli used in our experiments that, if printed without scaling, are shown at the size displayed on participants' screens. All stimuli images (0%, 18%, 32%, 43%, 58%, 72%, and 83%) are available in the supplementary material.

Proportions	Donuts	Bars
72%		

scenario, we began to study three aspects of our research agenda: two related to **characteristics of motion** together with a factor of **visualization design**. In particular, we wanted to understand how accurately people can perceive *quantitative* information from two different visual representations under motion. We chose to start with studying the effects of **speed** and **trajectory complexity** on **representation type** as we hypothesized that the readability of different representations could be highly influenced by these basic characteristics of motion. In both experiments, we used a magnitude estimation task that required people to read a quantitative value from a proportion visualization, similar to tasks that would be required in our target domains.

Our choice for speeds, trajectories, and visualizations was motivated by common examples in sports or video games (Fig. 1a & 1b) where stationary viewers see visualizations of player or game performance move across the screen. As we are just beginning empirical investigations on visualizations in motion, we tested these simple motion characteristics in controlled settings to be able to isolate the effects of the tested motion characteristics more clearly.

Next, we discuss the study design criteria shared by the experiments we conducted. We describe the design choices that differed in the individual experiment sections. Documents, original experiment data, code for the statistical analysis, detailed results, and the link to the studies are available in the sup. material. All experiments were pre-registered. Experiment-Speed-Donut: https://osf.io/km3s2/, Experiment-Speed-Bar: https://osf.io/t748d/, Experiment-Trajectory-Donut/Bar: https://osf.io/9c4bz/.

5.1 Study Parameters and Variables

We assessed the readability of moving bars and donuts showing proportions under two motion characteristics: speed and trajectory. To determine ecologically valid speed values and chart sizes, we analyzed a LaLiga soccer match [30] in full screen on a 27-inch 4K screen. We selected 100 random start positions from a player kick and recorded both the physical and temporal start and end positions of the ball relative to the screen. From this data, we calculated the average physical speed of the soccer ball on the screen as an approximation using a linear trajectory between start and end points; and measured the average diameter of the soccer ball.

Choice of Visualization Representations: From our online example exploration and design workshop collection [111], we collected 197 designs in total. We classified these 197 designs into 15 genres according to their representations, such as donut charts, bar charts, pie charts, labels/text, icons, and heatmaps. Among which, by count the most common were donut charts (34/197) and bar charts (23/197). Considering in practice the prevalence of the donut chart and the bar chart (see also Fig. 1 & Fig. 2), we chose donut and bar charts for our experiments. The charts were drawn at the same physical size in cm for each participant. For `Donut`, we set the inner diameter to 0.75 cm and the outer diameter to 1 cm. This sizing would encircle soccer balls with a diameter of 0.5 cm on the screen, which was the most frequent soccer ball size according to our video analysis. We set the length of `Bar` equal to the average of the inner and outer perimeters of the `Donut` to ensure that the data resolution is the same, with a width of 0.25 cm (equaling to the thickness of `Donut` slice) and a length of 2.36 cm, see Table 1. In each chart, the target slice was colored in #E90738 and the other slice in #C3C1C1 to make the target warmer and higher chroma and reach an appropriate contrast ratio (4.61) with the white background.

Choice of Movement Speeds: Among the 100 data pairs in our video analysis, the min speed was 0.4 cm/s, the max speed 32 cm/s, and the average speed 14.08 cm/s. We then converted the highest, lowest, and average speed to the most popular screen sizes. Detailed calculations can be found in the supplementary material.

From these measurements we chose our `Slow` speed to be 15 cm/s which is approximately the average speed for a 27-inch screen and the `Fast` speed as 30 cm/s which is approximately the fastest speed for 27-inch screens and the average speed on 65-inch TVs. In our speed experiments, we also included a `Static` baseline condition in which the stimulus did not move on the screen. Each stimulus was shown on the screen for a fixed time of 1600 ms, to ensure that we measured the impact of speed rather than stimulus exposure duration. Choosing 1600 ms allowed us to display one complete trajectory on our smallest accepted screen size in the experiment, given our `Slow` speed.

Choice of Movement Trajectories: In our speed experiments, we wanted to isolate the impact of speed and chose a simple `Linear` — horizontal trajectory. In our trajectory experiments, we added `Irregular` trajectories. To extract ecologically valid irregular trajectories, we analyzed data from real 2018/2019 Premier League championship games. The data was provided by Footovision [31]—a performance analytic company—using state-of-the-art video tracking of players. We picked a typical game between Leeds United and Swansea and chose 7 trajectories of walking soccer players and 7 trajectories of running soccer players as seen from a birds-eye-view of the field using a custom visual analytics tool [73]. For each trajectory we calculated 2 variations: a 180° clockwise rotation and a mirror on the y axis. We, thus, obtained 21 trajectories per speed (`Slow`, `Fast`). In our trajectory experiments, we therefore tested the following 4 conditions: `Slow` × `Linear` — & `Fast` × `Linear` — (as in our speed experiment but used as baselines in the trajectory experiments), `Slow` × `Irregular` showing a slowly moving stimulus, and `Fast` × `Irregular` showing a fast moving stimulus. Images and data for all trajectories are available in the supplementary material.

Choice of Percentages: We based our choice of percentages to test on prior work. Cleveland & McGill's experiment [19] used 7 distinct proportions: 17.8%, 26.1%, 38.3%, 46.4%, 56.2%, 68.2%, and 82.5%. Using a similar methodology, Kong et al. [50] used four percentages (32%, 48%, 58%, and 72%) that account for participants' tendency to answer as factors of 5. We followed their choices but added additionally one smaller proportion and one larger proportion, leading to our analyzed proportions (Table 1): 18%, 32%, 43%, 58%, 72%, and 83%. We also added 0% as an attention check. For training trials, we used random percentages excluding the above 7 experimental proportions.

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Dependent Variables: The key dependent variable analyzed in our studies was accuracy per trial which included the true error and absolute error of reading a specific proportion. We did not analyze answer time as a dependent variable, as the display time was fixed at 1600 ms to ensure we capture the effect of speed rather than stimulus exposure time. We also collected basic demographic information in a pre-questionnaire, including participants' experience with the type of chart shown (on a 10-point Likert item: 1 (novice) to 10 (expert)) and the frequency of playing video games or watching sports on TV (1 (never) to 10 (every day)). After each condition, participants rated the condition according to how confident they felt about the correctness of their answer on a 5-point Likert item (1 (not at all confident) to 5 (very confident)). At the end of the experiment, participants filled out a post-questionnaire and rated the difficulty of each condition they saw from 1 (not difficult at all) to 10 (very difficult).

5.2 Experimental Software and Apparatus

Our experiments were conducted on Prolific [70]. In crowdsourced experiments, screens and pixel sizes may vary for each participant. While we could not control viewing distance from screens, we implemented a method to ensure at least the same physical display conditions. We controlled a) the movement speed in physical units of cm/s rather than px/s and b) the display size of the chart stimulus in cm instead of in px. Each participant went through a calibration phase where they held a bank-card-sized card (ISO/IEC 7810 ID-1 standard [105]) up to the screen and then adjusted a slider until a rectangle displayed on the screen matched the size of the physical card. From the calibration, we were able to infer a conversion ratio between px and cm for the screen of every single participant. This px/cm ratio was applied for drawing the stimuli, calculating the speed, and checking the participants' eligibility. Our minimum screen size requirement to draw all stimuli was 13.3-inch in diagonal (29.4 cm width). Participants who met this requirement and had completed the calibration phase were no longer allowed to adjust the page or window size. At the beginning of each trial, we drew a focus area/point to show where the stimulus would first appear. After the display of the stimulus, we drew four masking images that flashed during a very brief amount of time (80 ms in total [11] [34]). Then, participants typed their answers and submitted them by clicking a button.

5.3 Procedure

Participants first agreed to an online consent form, followed by the screen calibration phase and the pre-questionnaire. Next, participants read through the experiment and task explanations and instructions and then completed blocks of trials. After completing the trials, participants filled out the post-questionnaire. At the end of each session, participants optionally described their strategies and gave comments.

The experimental trials were grouped in several blocks depending on the number of conditions. In the speed experiments, there were three speed conditions (`Static`, `Slow`, `Fast`), resulting in 3 blocks of trials. While the trajectory experiments had 4 blocks since there were 4 speed × trajectory conditions (`Slow` × `Linear`, `Fast` × `Linear`, `Slow` × `Irregular`, `Fast` × `Irregular`). The condition order was randomized per participant using a Latin square.

Each block was composed of training and experimental trials. In a trial, participants had to estimate in whole numbers the proportion displayed in red. To proceed to the experimental trials, participants had to correctly answer 6 training trials. For each training trial, we accepted as correct any answer in the range of ± 10 percentage points. We displayed feedback about their entered answer, the exact proportion, and their progress in the training. During the experimental trials, we did not provide feedback on correctness.

Each block of experimental trials consisted of 21 trials (7 proportions in a random order per participant × 3 repetitions). We asked participants to make a quick estimate. After each block, participants rated their confidence in the current condition.

We had 3 attention trials per block of experiment trials. These were trials where the proportion was set to 0% and were easy to spot. As the speed experiments had 3 blocks, they included 9 such attention trials, and the trajectory experiments included 12 such trials in its 4 blocks. Our acceptable range for participants' given answers to these attention check trials was 0–10 percentage points. Thus we terminated the experiment for participants that failed 6 attention trials in the speed experiments and 8 in the trajectory experiments. Participants were told clearly in the instructions that the experiment included attention trials and that failure to do them correctly would result in the session to not be completed and paid.

We conducted two speed experiments: one on `Donut` and one `Bar` with 60 participants each × 3 blocks (3 conditions) × 21 trials per block = 3780 trials per experiment. Similarly, there were two trajectory experiments, one per chart type with 60 participants each × 4 blocks (4 conditions) × 21 trials per block = 5040 trials per experiment. The 21 `Irregular` trajectories for `Slow` speed and another 21 `Irregular` trajectories for `Fast` speed were shown in a random order per participant.

5.4 Analysis Approach

We used interval estimation [25] to interpret our results: we report sample means and 95% confidence intervals (CIs).We used BCa bootstrapping to construct confidence intervals (10,000 iterations) to compare chart movement speeds in the speed experiments and speeds × trajectories. The CIs of mean differences were adjusted for multiple comparisons with Bonferroni correction [39]. To compare `Donut` and `Bar` we used bootstrap confidence interval calculations for two independent samples. We drew inferences from the graphically-reported point estimates, and interval estimates [21]: when reading a CI of mean differences, a CI that does not overlap with 0 provides evidence of a difference, which corresponds to statistically significant results in traditional p-value tests. Nonetheless, CIs allow for more subtle interpretations. The farther from 0 and the tighter the CI is, the stronger the evidence. No significance test was performed, but equivalent p-values can be obtained from CI results following Krzywinski and Altman [51]. We also report the mean absolute error per proportion for each condition.

5.5 Participants

Per experiment, we recruited 60 valid participants whose approval rate was above 95%; participants could only take part in one of the experiments as per our experiment settings. All participants had normal or corrected-to-normal vision and reported having no color vision deficiency. We report the composition of participants and their remuneration separately in the section for each experiment.

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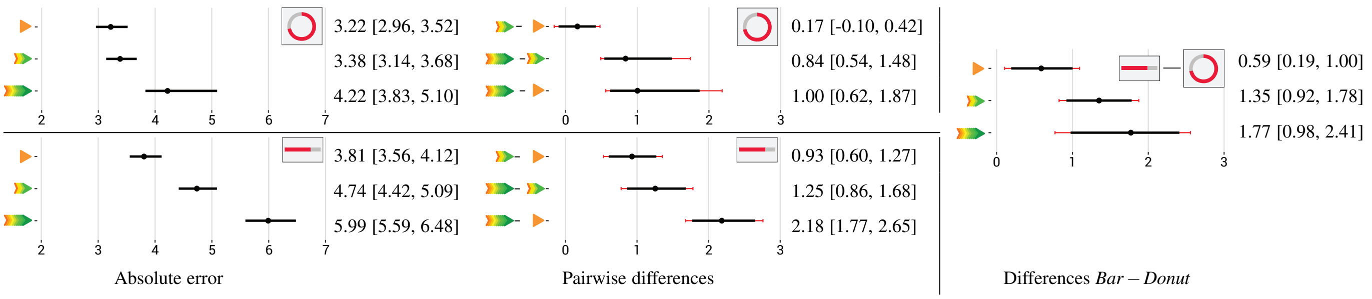
TABLE 2: *Absolute error* analysis for Experiment-Speed. Left: Average mean absolute error in percentage points for each chart type. Middle: Pairwise comparisons for each speed and representation. Right: Differences of mean absolute error across representations. Error bars represent 95% Bootstrap confidence intervals (CIs) in black, adjusted for pairwise comparisons with Bonferroni correction (in red).



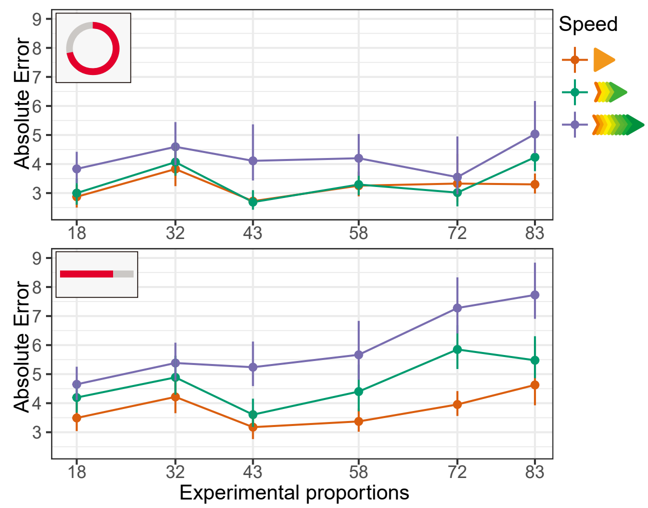


Fig. 4: Experiment-Speed absolute error results for Donut (top) and Bar (bottom) per proportion.

TABLE 3: Experiment-Speed: Confidence in the correctness of responses per speed and chart type with median (MED), average (AVG) and standard deviation (SD). 1: Not at all confident, 5: Very confident.

		1	2	3	4	5	MED	AVG	SD
Static	Donut	0	2	9	34	15	4	4.03	0.74
	Bar	0	1	12	31	16	4	4.03	0.74
Slow	Donut	0	0	13	38	9	4	3.93	0.61
	Bar	0	4	15	32	9	4	3.77	0.79
Fast	Donut	0	4	19	30	7	4	3.67	0.77
	Bar	1	5	19	26	9	4	3.62	0.90

6 Experiment-Speed (Donut / Bar) Results: The Effect of Speed on Reading Accuracy

The 60 participants involved in Donut (24 ♀, 35 ♂, 1 unspecified; 19 students) had an average age of 23.45 years (*SD* = 5.36). Participants' familiarity with donut charts was *M* = 6.10/10, *SD* = 2.50 and their frequency of watching soccer matches on TV or play video games was *M* = 4.66/10, *SD* = 3.07. The 60 participants involved in Bar (23 ♀, 37 ♂; 44 students) had an average age of 24.58 years (*SD* = 5.85). Participants rated their familiarity with bar charts as *M* = 6.45/10, *SD* = 2.45) and their frequency of watching soccer matches on TV or playing video games as *M* = 6.65/10, *SD* = 3.03.

Since our two experiments on speed (Donut, Bar) were conducted separately, the remuneration was a little different. The average completion time for Donut was 17.55 min. Based on an earlier pilot (average completion time was 12 min), we set the remuneration to £1.80. Given the longer actual duration, we improved our remuneration accordingly for the second experiment (Bar). The average time taken to complete the Bar experiment was 17.46 min, and each participant was paid £2.55.

6.1 Speed per Representation

Table 2 shows the participants' mean absolute error per speed, the pairwise differences in absolute error across two speeds per chart type, and the differences across two representations. Fig. 4 includes the absolute errors split by proportion per speed and chart type. For true error charts, see the supplementary material.

Speeds: We can see from Table 2–Left that high speeds did have an influence on human readability. Looking at the pairwise differences (Table 2:Middle), we see evidence that Fast speed caused more errors than Static and Slow speed conditions in both Donut and Bar representations in the respective experiments. But for both chart types in practice the differences were small, around 1–2 percentage points. For Donut, we have no strong evidence for a difference between Slow speed and baseline (Static): participants' average performance on Slow speed was similar to the baseline (Static). However, for Bar, participants' average performance was clearly better on Static conditions than on Slow ones.

Proportions: When looking at absolute errors per proportion for Bar (Fig. 4: Bottom) we see that participants' absolute errors tended to be higher with increased speed for all proportions. There may also be a tendency for error to increase in larger proportions. For Donut, (Fig. 4: Top), similarly, participants on average made more errors under Fast speed for all proportions. But absolute errors were similar under Slow speed and Static condition across proportions with the exception of 83%.

6.2 Speed across Representation

Table 2: Right shows the differences between Bar and Donut across the results from the two experiments. We found some evidence that Donut was more accurate than Bar in all speeds. This evidence is more pronounced on Fast and Slow. It appears that donut charts can be read slightly more accurately than bar charts when in motion.

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TABLE 4: Experiment-Speed: Difficulty rating per speed and per chart type with median (MED), average (AVG) and standard deviation (SD). 1: Not at all difficult, 10: Very difficult.

		1	2	3	4	5	6	7	8	9	10	MED	AVG	SD
Static		21	18	9	2	2	3	3	1	1	0	2	2.63	2.02
		22	21	7	3	1	2	2	1	1	0	2	2.42	1.87
Slow		6	11	15	9	8	7	1	1	2	0	3	3.73	1.93
		6	11	13	16	8	4	1	1	0	0	3.5	3.50	1.57
Fast		1	3	7	8	7	4	7	13	6	4	6.5	6.10	2.44
		3	3	3	8	8	9	10	8	6	2	6	5.87	2.32

6.3 Confidence and Difficulty

Table 3 exhibits how speed and representation impacted confidence rating, while Table 4 illustrates perceived task difficulty.

Confidence: Confidence levels differed only slightly between speed and representation. The mode for all ratings was 4 (confident), but we see a slight trend for higher answers in the Static condition for both Bar and Donut.

Self-rated Difficulty: Participants' perceived the task to be more difficult the higher the speed.

6.4 Strategies

In order to understand potential differences between chart types, we asked participants to voluntarily reveal the strategies they used to read charts under motion. We received 34 descriptions from Donut and 40 from Bar participants. We excluded 1 description for donut and 6 ones for bar chart that did not describe strategies and coded the remaining into 6 groups. Composite strategies were coded into multiple groups. Next, we describe each strategy and how often it was mentioned in the two experiments. All detailed descriptions can be found in the supplementary material.

Following (13 Donut, 18 Bar): This strategy involved simply following the stimuli as it was moving on the screen.

Slicing (13 Donut, 5 Bar): Participants divided the moving chart into slices that they read. Donut participants reported using quarter slices (25%, 50%, 75%, and 100%) or two halves to make estimates, while bar participants divided the bar in halves or in thirds. The strategy was much more common for donuts.

Quick Judgment (3 Donut, 7 Bar): Some participants described estimating the value with a quick glance or saving a snapshot in their mind while ignoring motion.

Fixating (2 Donut, 2 Bar): A few participants stated that they stared at a fixed point (the center of the screen in most cases) and did not follow the movement of stimuli to make their estimation.

Other (2 Donut, 3 Bar): The strategies coded in this group were diverse and rare. Participants mentioned focusing on the smaller slice, reading the chart (better) when it moved left to right, closing one eye, and focusing on the bar end point.

Unclear (1 Donut, 0 Bar): Strategies that we could not classify due to unclear and ambiguous descriptions.

6.5 Summary

In summary, speed had an impact on proportion reading performance, with accuracy decreasing with higher speeds. However, in practice, participants were still able to quite reliably read proportions from moving charts, with an accuracy that was close to 95%. Although in high speeds Donut was more accurate than Bar, in practice, their differences were small (2 percentage points). Overall, participants were confident in their answers, but the self-rated difficulty increased clearly with faster speeds.

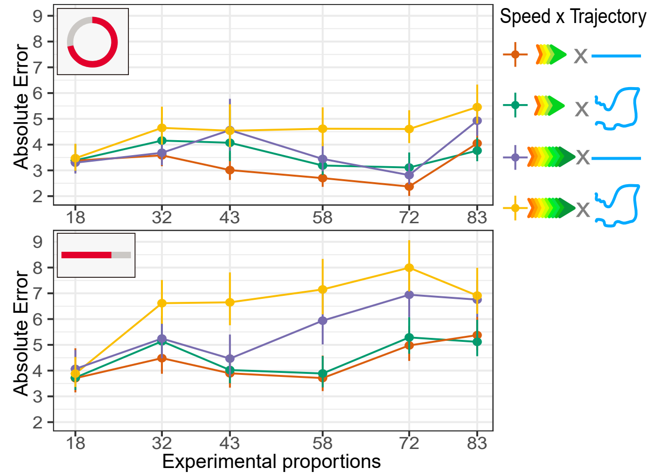

Fig. 5: Experiment-Trajectory absolute error results for Donut (top) and Bar (bottom) per proportion.

7 Experiment-Trajectory (Donut / Bar) Results: The Effect of Trajectory on Reading Accuracy

We recruited 60 new participants per chart type in the trajectory experiments. For Donut, the 60 participants (31 ♀, 29 ♂; 35 students) were on average 27 years old (SD = 7.38). Participants reported just above average familiarity with donut charts (M = 6.20/10, SD = 2.59) and frequency of watching soccer matches on TV or playing video games (M = 6.60/10, SD = 3.09). The average completion time was 27.80 min, with a remuneration of £3.75 per participant. For Bar, the 60 participants (29 ♀, 31 ♂; 36 students) had an average age of 26.38 years (SD = 8.44). Participants also reported just above average familiarity with bar charts (M = 6.78/10, SD = 1.98), and frequency of watching soccer matches on TV or playing video games (M = 6.43/10, SD = 3.14). The average completion time was 28.57 min, with a remuneration of £4.05 per participant.

7.1 Trajectory per Representation

Table 5 shows the participants' mean absolute error per speed × trajectory condition, the pairwise differences in absolute error across two conditions per chart type, and the differences across two representations. Fig. 5 shows the absolute errors split by proportion per condition and chart type. For true error charts, see sup. material.

Trajectories: Looking at the mean absolute errors (Table 5), we see that the trajectory type did have an impact on reading accuracy. Looking at pairwise differences (Table 5: Middle) we have evidence that Irregular trajectories caused more errors than Linear ones for both Donut and Bar, in particular at Fast speed. We even have weak evidence of trajectories having an impact on Donut moving at Slow speed, with Irregular trajectories being less accurate than Linear ones, while for Bar, we do not have such evidence.

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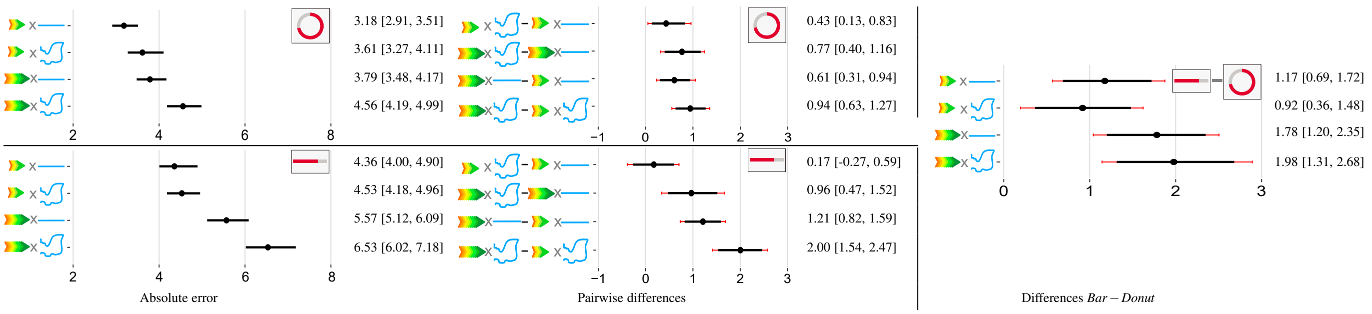
TABLE 5: *Absolute error* analysis for Experiment-Trajectory. Left: Average mean absolute error in percentage points for each chart type. Middle: Pairwise comparisons for each speed × trajectory condition and representation. Right: Differences of mean absolute error across representations. Error bars represent 95% Bootstrap confidence intervals (CIs) in black, adjusted for pairwise comparisons with Bonferroni correction (in red).



Speeds: As expected, and consistent with the previous Experiment-Speed, for both Donut and Bar, Fast speed led to more errors in Linear trajectories and Irregular ones as well. While evidence of a difference between speeds does exist, we noticed that this difference is again practically very small—less than 1 percentage point for Donut and no more than 2 percentage points for Bar.

Proportions: For Bar, looking at absolute error per proportion (Fig. 5: bottom), for Fast speed, the degree of estimation error of Irregular trajectories is bigger than that of its baseline (Linear ones), with the exception of the smallest proportion (18%); for Slow speed, there is no clear difference of estimation error between the Irregular trajectories and the Linear ones across proportions. The tendencies of Donut are less clear, but we can still tell (Fig. 5: top) that participants' estimates of Irregular trajectories were consistently more error prone than its baseline (Linear ones) for all proportions with the exception of 43% for Fast speed and 83% for Slow speed.

7.2 Trajectory across Representations

Table 5-Right illustrates differences between representations used in the two trajectory experiments.

Trajectories and speeds: When comparing the two representations directly, there is evidence that participants' answers were always more accurate with Donut than with Bar by 1–2 percentage points under the same kind of trajectory. This effect is particularly strong at Fast speed.

Proportions: For all speeds and trajectories, participants' answers were consistently more accurate on Donut than on Bar for all proportions. These differences are particularly visible for Irregular trajectories and Fast speed, where differences reached up to 4.13 percentage points in accuracy for some of the larger proportions (58%, 72%). The only exceptions are cases (43% in Slow × Irregular and Fast × Linear condition) where the difference between the two charts is extremely small (less than 0.1 percentage point). So overall, in the majority of cases, Donut was more accurate by 0.33–4.13 percentage points.

7.3 Confidence and Difficulty

Table 6 illustrates how trajectory types, speeds, and representations impacted confidence, while Table 7 shows perceived task difficulty.

Confidence: The mode for all ratings was again 4 (confident). We see a slight trend for higher ratings in the Linear trajectory and

TABLE 6: Experiment-Trajectory: Confidence in the correctness of responses per condition and per representation with median (MED), average (AVG) and standard deviation (SD). 1: Not at all difficult; 10: Very difficult; SL: slow × linear, SI: slow × irregular, FL: fast × linear, FI: fast × irregular.

		1	2	3	4	5	MED	AVG	SD
SL		0	2	12	32	14	4	3.97	0.76
		0	1	13	37	9	4	3.90	0.66
SI		0	3	18	27	12	4	3.80	0.82
		0	3	19	34	4	4	3.65	0.68
FL		0	8	11	31	10	4	3.72	0.90
		0	5	22	28	5	4	3.55	0.77
FI		1	8	19	22	10	4	3.53	0.98
		1	15	22	20	2	3	3.12	0.88

Slow speed as well for both Donut and Bar. Although the average confidences were consistently higher on Donut than on Bar, the confidence differences across representation were extremely small. Therefore, we cannot conclude that participants were clearly more confident in one condition than in another.

Self-rated Difficulty: Under the same speed, participants rated Irregular trajectories as more difficult. Under the same kind of trajectory, participants reported that they felt Fast speed trials were more difficult. Across the two representations, participants rated Bar as more difficult than Donut, in particular in Fast × Irregular condition.

7.4 Strategies

We received 41 descriptions from Donut and 40 from Bar participants. We excluded 4 descriptions for donut and 3 ones for bar chart that did not describe strategies. We found the same groups of strategies as before and only discuss new variations here. The **Slicing** strategy was again common (16 Donut, 15 Bar): In addition to the previous slicing descriptions participants mentioned to use a clock metaphor for dividing the donut and quarters for bar charts. The remaining strategies were used as follows: **Following**: 13 Donut, 13 Bar, **Quick Judgment**: 9 Donut, 8 Bar, **Fixating**: (0 Donut, 1 Bar), and we did not collect any **Unclear** descriptions this time. The **Other** (2 Donut, 2 Bar) strategies used included reading the smaller slice, calculating with fingers, or blinking eyes.

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TABLE 7: Experiment-Trajectory: Difficulty rating per condition and per representation with median (MED), average (AVG) and standard deviation (SD). 1: Not at all difficult; 10: Very difficult; SL: slow × linear, SI: slow × irregular, FL: fast × linear, FI: fast × irregular.

		1	2	3	4	5	6	7	8	9	10	MED	AVG	SD
SL	Donut	17	18	11	4	4	2	4	0	0	0	2	2.70	1.76
	Bar	8	15	21	5	3	0	5	2	1	0	3	3.27	1.96
SI	Donut	9	11	11	9	6	5	4	3	1	1	3	3.85	2.28
	Bar	3	8	18	12	6	5	3	3	1	1	4	4.08	2.01
FL	Donut	6	4	5	12	13	5	8	5	2	0	5	4.77	2.16
	Bar	1	4	11	5	7	11	10	5	4	2	6	5.48	2.24
FI	Donut	4	4	2	7	2	8	6	14	8	5	7	6.33	2.67
	Bar	1	1	2	5	1	5	14	17	11	3	8	7.12	1.99

7.5 Summary

In summary, the regularity of the trajectory had an impact on participants' performance in reading moving proportions, the accuracy decreased with irregular trajectories and higher speeds as well. Participants again performed better on `Donut` than on `Bar`, the difference was more pronounced than in the speed experiments. Nevertheless, the differences still remain small in practice (less than 2 percentage points on average and less than 5 percentage points in all proportions). Overall, participants were confident in their answers for all tasks. The self-reported difficulty was higher for `Irregular` trajectories and for `Fast` speeds.

8 Experiment Discussion and Limitations

Overall, our results showed that speed and the regularity of trajectories impacted participants' performance. Higher speed and irregular trajectories generally led to more errors. The irregular trajectories we tested were not predictable by participants which likely contributed to their poor performance. Some errors our participants' made can be attributed to rounding errors caused by rounding to the nearest 5 (which was always 2 percentage points up or down from the shown magnitude). Yet, in particular for bar charts, errors were consistently above 4 percentage points as soon as motion was involved. Our experimental results do not provide evidence for a linear relationship with the increase in motion speed nor for the rise of irregularity. To establish if an exact mathematical relationship exists, future work needs to look at a larger variation of speeds and irregularities. However, theoretical limits exist beyond which viewing experiences will be severely impacted by increased blur from visually tracking objects on sample-and-hold displays; in addition to limits given by screen refresh rates. It is interesting to note though, that despite the differences we observed, the overall accuracy remained very high (95% or above) across all conditions.

We found overall better performance for the donut chart under motion compared to bar charts, but the practical difference in error between both charts was small—in the range of 1–2 percentage points. Practically, we might be able to ignore such differences and choose a representation that can be more easily embedded in the desired context of use. We had expected for bar charts to be more impacted than they were, especially for linear trajectories, as bar charts become compressed in the direction of motion. While differences between both charts were small, the exacerbated effect of motion blur on linear trajectories might explain why a few participants commented that the irregular trajectories were easier.

A number of participants mentioned that their task strategy did not involve following the whole movement; they briefly glanced or focused on a point and let the visualization pass by before making a quick judgment. This is interesting behavior as it might mimic how people would need to read moving visualizations as a secondary task. It is promising for future work to study how limited attention and shifting focus may affect the performance of a larger number of participants.

Studies with both stationary participants & moving targets and moving participants & stationary targets from DVA suggest that angular velocity affects visual acuity, in particular for fast velocity. While magnitude proportion judgment tasks are more complex, our results consistently show similar evidence for performance differences in our conditions involving motion. For our envisioned scenarios in sports and video games the decrease in performance we measured might be small or irrelevant in many cases. However, a difference of 4 percentage points might still make an important difference in other scenarios or certain contexts, such as when a game character is about to run out of health. In addition, it remains an open question if motion affects performance to a larger degree when viewing more complex visualizations or conducting more complex reading tasks.

One of the limitations of our study is that, due to the pandemic, we did not have the chance to run a lab study. Even though we introduced a calibration phase to make sure the stimuli were displayed at the same size and moved at the same physical speed on different screens, we still could not control the distance between participants and their screen nor the angle at which they looked at the screen. We do not know if their position in front of the screen impacted the results and to what extent it led to noise in our results. Also, our experiments were conducted on a pure white background and without important viewing angle changes. As such, our results are best-case results and performance will likely drop in a real scenario with a much more complex context involving movement in 3D space and noisy backgrounds. We imagine that in immersive scenarios such as AR/VR, the impact of motion factors would be amplified with the superposition of spatial properties.

Combined, our experiments evaluated the most basic visualizations in motion, and the results can be useful to hypothesize about impact in future scenarios. We found that:

- Higher speeds lead to more errors.
- Irregular trajectories decreased the reading accuracy.
- Participants always performed better on donut charts than on bar charts.
- Bar charts under motion had errors consistently above 4 percentage points.
- The overall accuracy remained very high.

Our research agenda proposes a set of promising broad research directions for *visualization in motion*. As this topic will gain more importance in Visualization—especially with mobile, wearable, and immersive technologies evolving—new and updated challenges will emerge. In addition, delving into application scenarios will open up new research spaces with dedicated challenges and concrete research questions related to visualizations in motion. In particular visualizations in AR/VR pose a rich and diverse set of motion-related challenges in the context of moving visualizations and moving viewers (see Section 2.3). Our experiments are most closely related to AR scenarios where 2D visualizations may be embedded in live video streams. However, the motion in 3D space of both viewers and visualizations in AR/VR pose challenges that stem from interaction, head movement, and/or locomotion that are interesting to tackle. However, as with real world movement, we still do not know much about how human perception is affected when both viewer and visualization are moving in immersive scenarios. Regarding our research agenda, our experiments necessarily explored only a small fraction of the larger research space. Our findings cannot be directly transferred to more complex scenarios such as 3D or dynamic environments. However, they can serve both as a foundation for further research and as an initial proof that reading visualizations under motion may be practical and possible.

9 Conclusions

Our research agenda was meant to apply to a broad set of visualization in motion scenarios and as such covers a small and wide-ranging set of aspects to consider. In particular, we included *characteristics of motion*, *spatial relationship between viewer and visualization*, and factors of *situation, context, and design*. As the research space will be explored more, each of the broader scenarios outlined in Section 2 deserves their own individual research agenda and design space. We propose *visualization in motion* as an umbrella under which the impact of relative motion on the experience with and perception of visualizations can be discussed and analyzed, hoping that our common vocabulary can promote such discussions.

Many nascent areas of visualization are impacted and already contain visualizations in motion: data physicalization, wearable visualization, mobile visualization, embedded and situated visualization, for example—are areas that all broadly relate to a vision for making visualizations more ubiquitous in our daily life. Yet, others, such as visualization in virtual worlds, games, or real-time video analytics, similarly require more dedicated guidance about how to deal with a relative motion to make effective visualizations and generate successful experiences that include data displays. Our research agenda attempts to identify a starting point for questions related to such usage scenarios.

In our own future stream of work, we plan to focus on situations with moving visualizations and stationary viewers. Even this scenario is large and can cover a range of example applications from the gaming and video tracking analyses already mentioned, augmented reality visualization for real-time sports, or even flying drone visualizations. Whether findings on the impact of relative motion can be generalized across such ranges of scenarios will need to be found out and will require years of research. We hope that our paper will inspire future work in this vast research space and that our research results show promise for the effectiveness of visualizations even under motion.

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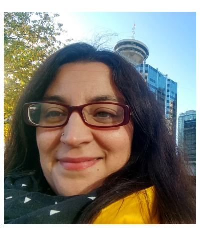

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