FROM HAPTIC INTERACTION TO DESIGN INSIGHT: AN EMPIRICAL COMPARISON OF COMMERCIAL HAND-TRACKING TECHNOLOGY

Cox, Christopher Michael Jason;
Hicks, Ben;
Gopsill, James;
Snider, Chris

University of Bristol

ABSTRACT

Advancements in prototyping technologies – haptics and extended reality – are creating exciting new environments to enhance stakeholder and user interaction with design concepts. These interactions can now occur earlier in the design process, transforming feedback mechanisms resulting in greater and faster iterations. This is essential for bringing right-first-time products to market as quickly as possible.

While existing feedback tools, such as speak-aloud, surveys and/or questionnaires, are a useful means for capturing user feedback and reflections on interactions, there is a desire to explicitly map user feedback to their physical prototype interaction. Over the past decade, several hand-tracking tools have been developed that can, in principle, capture product user interaction.

In this paper, we explore the capability of the LeapMotion Controller, MediaPipe and Manus Prime X Haptic gloves to capture user interaction with prototypes. A broad perspective of capability is adopted, including accuracy as well as the practical aspects of knowledge, skills, and ease of use. In this study, challenges in accuracy, occlusion and data processing were elicited in the capture and translation of user interaction into design insights.

Keywords: hand tracking, haptic technology, Technology, New product development, Design process

Contact:
Cox, Christopher Michael Jason
University of Bristol
United Kingdom
christopher.cox@bristol.ac.uk

Cite this article: Cox, C. M. J., Hicks, B., Gopsill, J., Snider, C. (2023) 'From Haptic Interaction to Design Insight: An Empirical Comparison of Commercial Hand-Tracking Technology', in *Proceedings of the International Conference on Engineering Design (ICED23),* Bordeaux, France, 24-28 July 2023. DOI:10.1017/pds.2023.197

1 INTRODUCTION

The advancement of haptic technologies has given rise to new modes of interaction that designers can utilise in a product's design and design process. Examples of products using haptics include Apple's iPhone with its "Haptic Touch" system that emulates the sensation of physical buttons on the touchscreen interface, and Sony's PlayStation 5 DualSense controller that uses adaptive force feedback in the triggers to emulate the sensation of in-game actions (such as pulling back a bow-string). Examples of haptics used in the design process include the emulation of product interaction (Bordegoni and Ferrise, 2013) and the capture of haptic interactions to improve ergonomic design (Tekscan, 2020).

The capability of haptic technology continues to increase, and the fidelity and breadth of sensory modes that can be emulated and recorded (Cox, Hicks and Gopsill, 2022). Examples include the HaptX haptic gloves, and Ultraleap's Mid-Air haptics device (Figure 1). Coupled with Mixed Reality (MR), haptic technology offers richer environments in which to interact with virtual prototypes, affording more tangible feedback and improved product evaluation. Additionally, updates to a design can be pushed in near real-time to the environment with the stakeholder being able to interact and provide an immediate response to the design team. However, there are still significant roadblocks, such as prohibitive cost and a lack of sensory realism, which need to be overcome before we can fully and immersively interact with our virtual prototypes. Another method that can provide haptic feedback for a virtual model seen through Mixed or Virtual Reality (VR) headset, is the use of passive haptics (Insko, 2001). This uses physical "props" that are tracked to the virtual model, so that objects seen in VR can be physically felt.

Human's haptic interaction is a closed loop process with the brain continually processing and reacting to incoming sensory data (Lederman and Klatzky, 2009). When we interact with an object, using the sensors in our skin and muscle, can determine several pieces of information about it, including mass, shape, and surface properties. This process is reliant on both our sensory mechanisms and the manner in which we interact with the object in question. This is based not only on the particular interaction but mental models and dominant logics regarding products, the tasks they perform and way they are used. As such, to understand how we interact with an object we need to be able to capture both the way that we manipulate and hold objects, and map it back to user feedback of their experience.

A primary mode of human-product interaction is through the hands, therefore designers need a simple and reliable way to capture a user's hands. Historically, it has been difficult to reliably capture accurate data without impairing hand function; but the past decade has seen a surge in affordable and "easy-to-use" tools, capable of tracking hand movements (Buckingham, 2021; Caeiro-Rodríguez et al., 2021). Thus, there is significant opportunity to enhance a design team's ability to study user behaviour and interaction when designing new products. A reliable method to capture user interactions, coupled with user's opinions and responses (e.g., interviews, surveys), could enable correlations to be drawn between successful product characteristics and modes of interaction. It could also be used to compare the interaction between a prototype and real product to assess whether the prototype interaction has been representative, and the evaluation given is therefore valid or misleading.

(a) HaptX Haptic gloves (HaptX, 2021)

(b) UltraLeap Mid-Air Haptics (Carter et al., 2013)

Figure 1. Advancements in haptic technologies.

https://doi.org/10.1017/pds.2023.197 Published online by Cambridge University Press

While the capability to capture some of these haptic components exists, there is little to no guidance, best practice, or strategies to support designers in determining how an experience should be reliably captured and translated into design insights. In order to more accurately and easily evaluate a haptic experience, be it of a real product, prototype or as part of a process, a set of guidelines or recommended practices of how to capture this experience is required. To meet this need goal, this paper *explores and characterises the relative strengths and weaknesses of affordable hand tracking technologies for capturing stakeholder interaction with a prototype product or process.*
For the purpose of this study, three of the most widely used commercial technologies are considered: LeapMotion Controllers, MediaPipe hand tracking and MANUS Prime X Haptic gloves. The methods were both quantitively and qualitatively compared to each other, and the relative advantages and disadvantages discussed. Additionally, some potential improvements that could mitigate the disadvantages are offered, and reflection is made on how close the design process is to having this type of feedback as a readily available source of information.
The paper continues with a summary of the related work on haptics (Section 2). This is followed by presentation of the methodology (Section 3). The results are presented in Section 4 and a discussion in Section 5 includes recommended future work. Section 6 concludes the paper with the key findings.

2 RELATED WORK

The study of ergonomics and human-product interaction is a crucial part of successful product design (Openshaw and Taylor, 2006). Haptic technology allows us to better understand this interaction and can in turn help us to design better products (Tekscan, 2020). This section provides a summary of the commercial technology that can be used to track the pose and position of a person's hands. This technology can allow us to better understand the way that we dynamically interact with products and processes with the insights being fed back to support the design process.

Haptic technology can largely be classified as "optical methods" and "worn sensors". Optical methods rely on a video-feed of the hands, which may be augmented with a set of markers, that is processed to determine the most probable hand position and pose for the hands (Guna et al., 2014).
Optical methods (Figure 2) work by capturing a continuous video stream, and often use a combination of AI and feature detection to identify where a hand is located and what pose it is taking (Lugaresi et al., 2019). There are, however, some variations on how this concept is realised. Motion Capture companies such as Vicon (Vicon, 2021) use markers attached to the hand to track the location and pose of the hand to a bank of IR cameras surrounding the user. MediaPipe by Google takes an alternative approach and uses any existing camera or webcam coupled with Machine Learning (ML) to identify the pose and position of hands in the frame. However, the single view perspective affords little capability in capturing the depth of the hands (Zhang et al., 2020).
Another approach has been taken by UltraLeap with their LeapMotion controller. The controller features a bespoke camera unit that includes infrared LEDs to help illuminate the hands in the scene. The unit contains two cameras that use binocular vision to ascertain the depth of the hand from the camera.

(a) LeapMotion (b) MediaPipe (c) Vicon Motion Capture

Figure 2. Optical tracking methods

The Oculus Quest 2 also uses this approach albeit with a greater number of cameras to increase the accuracy of the depth perception and minimise the effects of occlusion (Buckingham, 2021).

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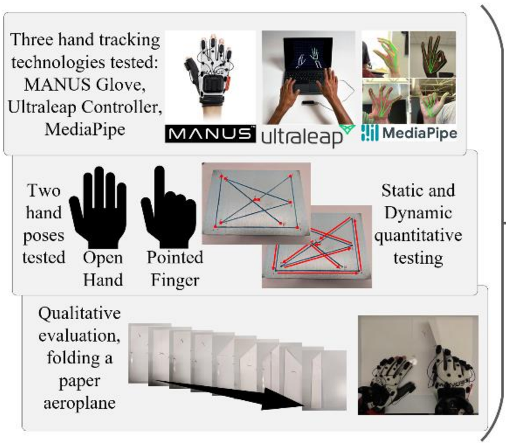
UltraLeap also provide a “mid-air haptics” device that uses ultrasound to create a physical sensation in mid-air (Figure 1b) (Carter et al., 2013).
While more established “Mo-Cap” optical systems cost $5k - $25k, the systems discussed previously cost as little as £100 or are even open-source (Guna et al., 2014; Zhang et al., 2020), making them viable for a greater number of design teams. This reduction has been achieved through the use of low-cost or existing physical sensors coupled with modern computational aids such as Artificial Intelligence (AI).
“Worn sensors” are often in the form of a glove, and include sensors that can monitor the angle of individual digits and the pose of the hand (Caeiro-Rodríguez et al., 2021). Globally tracking a hand's position is often achieved through 6 Degree Of Freedom (DOF) tracker such as a HTC Vive. The operational concepts behind worn sensors (Figure 3) are more varied, but the overall architecture is often similar. It usually involves a worn “glove” or sensors attached to the hand to determine the pose of the hand, and a 3D tracker (e.g., HTC Vive tracker) to localise the hands position. To determine the hand’s pose, some manufacturers have opted for a purely IMU (Inertial Measurement Unit) based system, such as the Senso Glove (Senso, 2022). This relies on the acceleration of the fingers to calculate their position in space. Another option is to use resistive sensors along the fingers, that have a variable resistance depending on how much they are deformed, as demonstrated by the MANUS Prime X gloves (MANUS, 2022a). A newer option is to use magnetic tracking, sensing the position of the different sensors in the glove by detecting fluctuations in the magnetic field around the glove. This novel technique is employed by the HaptX glove and Manus Quantum MetaGlove (MANUS, 2022b), neither yet commercially available at the time of writing. The variation in implementation of these different sensors may affect the design insights that can be generated, the most appropriate use case and the practical knowledge and skills required to use them.

3 EXPERIMENTAL SETUP

For the purpose of the study the three hand tracking tools selected were the LeapMotion Controller (£100), MediaPipe (£0) and the MANUS Prime X gloves (~€4000). These three options were chosen as they are some of the most popular, affordable hand tracking tools, meaning that they are accessible to design teams. Additionally, they utilise three different approaches – the MANUS Prime X is a worn glove, the LeapMotion device uses dual camera IR optical tracking and MediaPipe uses a single camera with visible light. By covering different approaches, more insight can be gained about the applicability of different tools for different use cases, and a direct comparison can be made between them.
The experiment featured three phases evaluating three aspects of hand tracking performance. The first assessed static point accuracy, the second assessed path accuracy and the third assessed repeatability across an extended period of human interaction. These aspects give a complete picture of how accurately hand position can be tracked, both dynamically and statically, and during complex interaction.



Key Assessment Metrics		
1. Data Completeness		How complete is the data? How often is the output data unreliable due to occlusion or tracking errors?
2. Data Accuracy / Precision		How accurate is the tracking system? How precise and consistent are the readings?
3. System Reliability		How regularly does the system fail or break?
4. System Cost		How much does the system cost to buy and implement?
5. Required Skills / Competencies		What skills or competencies are required to use and operate the system?
6. Ease of Use (EoU)	a. Experiment Creation	How easy is the system to use to create an experiment to track a user’s hands?
	b. Calibration	How easy is the system to calibrate and how effective is the calibration?
	c. Experiment Set-Up	How easy is the system to set up for each experiment participant?
	d. Experiment Conduction	How easy is it to carry out an experiment / dexterous tasks while using the system?
	e. Output Data Analysis	How easy is it to extract meaningful information from the output data?

Figure 4. Experimental method.

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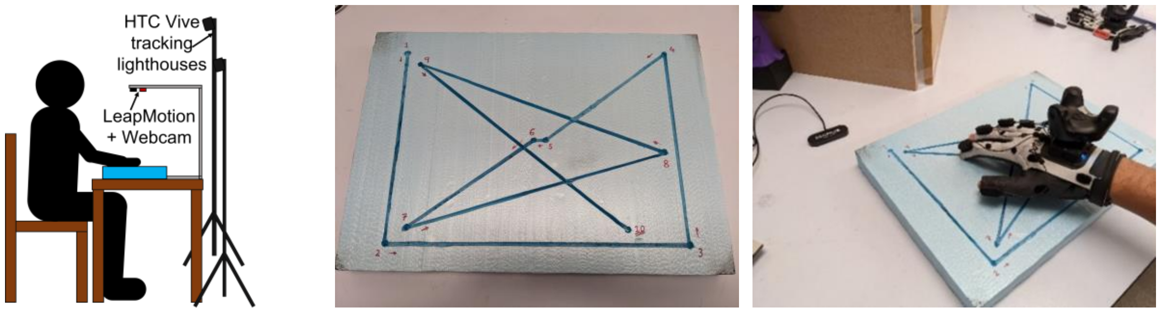


(a) Side-view (b) Foam template (c) Example of phase 2 experiment

Figure 5. Experiment set-up.

Six metrics (referred to herein as MX) were used to compare the different technologies: M1-Data Completeness, M2-Data Accuracy / Precision, M3-System Reliability, M4-Cost, M5-Required Skills / Competencies and M6-Ease of Use; these are further elaborated on in Figure 4. These metrics were selected as they cover the “usage value” (M1,2,3,6) and the “adoption barriers” (M4,5,6) that should be considered when adopting a new technology (PRYSM Group, 2022).

3.1 Phase 1 – static point accuracy

Phase 1 assessed how consistent the three methods were at recording the pose and position of a stationary hand. Each joint and bone of the hand was tracked, though for this experiment only the position of the fingertip of the right index finger was recorded and analysed. Participants were asked to move their finger to 10 different points indicated on a foam template (Figure 5b), and to keep their finger stationary for ten seconds at each point. An indentation in the foam template ensured the finger was constrained to the same position for each repeat. 5 repeats for each position were performed.

The variance of the finger position was calculated to provide an insight into the variation or noise produced when the hand is stationary, and the positional variance between repeats demonstrated the accuracy and repeatability of each system (Table 1). While these values do not give us the absolute accuracy of each system, it allows us to assess the relative accuracy and self-consistency, informing M2. Additionally, the creation and running of the experiment informs M1, M3, M5 and M6.

3.2 Phase 2 - dynamic point accuracy (path accuracy)

In Phase 2, participants were asked to move their finger between the 10 points (Figure 5c). Figure 5b shows the path taken by the participants. A groove in the modelling foam was used to reduce the degree of random error in the signal. The process was repeated 5 times.

The output from each method was a time-series dataset of x, y, z positions for the index fingertip. The error was calculated by comparing each coordinate to the nearest position along the path. The distribution of this error was calculated to assess how well the system captures dynamic movement. To compare the reliability of the tracking between repeats of the same path, the gradient (or angle) of the line of best fit from each path was calculated and the variance compared between repeats (Table 1). This further informed M2 on the accuracy and precision of the system, and once again the creating and conduction of the experiment also informed M1, M3, M5 and M6.

3.3 Phase 3 – qualitative assessment (human interaction episode)

In Phase 3, participants were asked to fold 5 paper aeroplanes following a set of instructions. A top-down video of the operation was recorded alongside the hand tracking. The video was then reviewed to identify what percentage of the output data was reliable, by comparing the tracked hand pose and position to the real hand pose.

This phase of the experiment was conducted so that the tracking of a more complicated process could be evaluated, allowing a more representative understanding of how each system handled fine dexterous movement and minor occlusion due to the paper and hands covering each other. This directly informed M1 and M2, but the usage of the systems during a dexterous task allowed the evaluation of M6d (Ease of Use), an important factor when considering what the system might be used for.

Table 1. The accuracy / precision results from phases one and two of the experiment.

	Static, intra-repeat position variance (mm^2)		Static, inter-repeat position variance (mm^2)		Dynamic, inter-repeat ang. of best-fit variance (deg^2)	
	Maximum	Average	Maximum	Average	Maximum	Average
Leap.M-Open hand	6.60	1.66	13.97	7.95	7.08	1.99
*Leap.M-Point finger**	N / A	N / A	N / A	N / A	N / A	N / A
M.Pipe-Open hand	0.00	0.00	3.61	2.85	3.40	0.53
M.Pipe-Point finger	0.20	0.02	5.00	3.42	0.16	0.07
Manus-Open hand	7.74	2.68	24.59	16.7	16.16	4.38
Manus-Point finger	9.11	2.70	18.99	11.3	23.53	13.81

* Tracking failed for over 90% of repeats so no reliable data could be produced

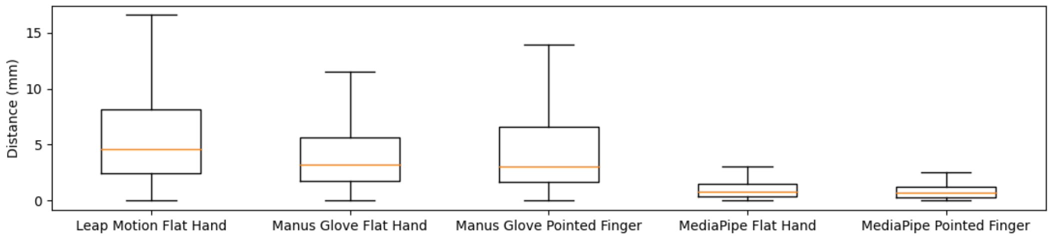
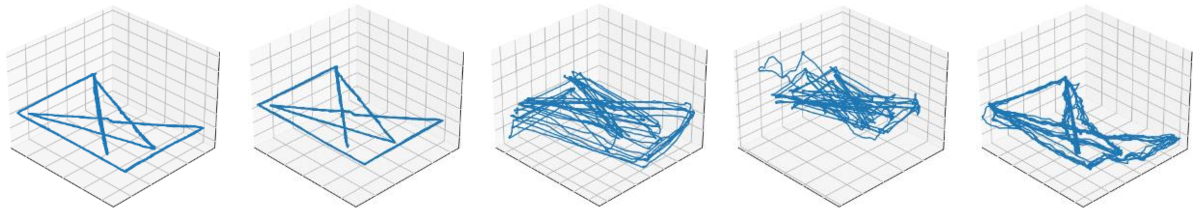


Figure 6. Distribution of error between tracked data and the path's line of best fit (phase 2)

4 RESULTS

This section outlines the results from all three phases of the experiment explained in Section 3. Table 1 contains the accuracy / precision results from Phases 1 and 2 of the experiment, with the maximum and average variance of each participant's finger position across each repeat. Figure 6 shows the error distribution of the dynamic finger position from the line of best fit for each transition from point to point in phase two of the experiment. Figure 7 shows the 3D visualisations of finger-tip position in Phase 2, allowing a clear visual demonstration of the tracking accuracy and reliability of each system. Figure 8 shows examples of the MANUS Glove's poor hand tracking in phase three of the experiment.



(a) MediaPipe w. flat hand (b) MediaPipe w. pointed finger (c) Manus w. flat hand (d) Manus w. pointed finger (c) LeapMotion w. flat hand

Figure 7. 3D visualisations of the tracked finger position in phase 2 of the experiment

Figure 8. Examples of the Manus glove tracked position while folding the paper aeroplane in phase 3, highlighting the poor tracking and sensor drift.

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Phase 3 qualitatively assessed the metrics outlined in Section 3, and these results have been combined with the results from phases 1 and 2, as well as the authors findings while creating and conducting the experiment. These results are summarised in Table 2, with rankings of each tool. Table 3 reports the time taken to complete the phase 3 task, and the fraction of usable data output for each tool.

Table 2. Rankings of different tracking systems, based on the metrics outlined in Figure 4

Metric \ Tracking System	*LeapMotion*	*MediaPipe*	*Manus Glove*	Comments
Data Completeness	2	1	3	MediaPipe did not lose tracking once, LeapMotion dropped tracking several times (13% of phase 3), Manus glove gave constant, but unreliable data.
Data Accuracy / Precision	2	1	3	See Tables above, MediaPipe showed greatest accuracy / precision followed by LeapMotion and then the Manus Glove.
System Reliability	2	1	3	MediaPipe did not fail, LeapMotion required restarting several times due to tracking failures. Manus Gloves required many recalibrations.
System Cost	2	1	3	MediaPipe: Opensource (£0). LeapMotion: ~£100. Manus gloves: ~ €4k
Required Skills / Competencies	1	1	1	LeapMotion and Manus gloves require familiarity with Unity or Unreal engine. MediaPipe requires familiarity with Python. All could be used satisfactorily with intermediate coding skill.
EoU: Experiment Creation	2	1	1	Given familiarity with the required coding language, all systems were reasonably simple to integrate. Leapmotion has sparce documentation, so required more development time to extract the fingertip position.
EoU: Calibration	1	2	3	Calibration for the Manus glove was simple, but completely ineffective. The optical tools required no official calibration, but the MediaPipe system has no inherent units, so a video transform was required.
EoU: Individual Experiment Setup	1	1	3	Optical methods only required software to be run and cameras plugged in. Sizing the glove to an individual was fiddly and unprecise (sliding Velcro tab).
EoU: Experiment Conduction	2	1	3	Optical tools caused no physical encumberment but Leapmotion tracking losses required hand waving to regain tracking. Manus gloves reduced dexterity and haptic sensation due to the bulky glove over the hand.
EoU: Output Data Analysis	1	1	1	All systems were similarly easy to process and analyse the output data.

Table 3 – Summary of data completeness from phase 3, and average time taken to carry out the task.

Tracking System	Average time taken to fold paper plane (seconds)	Percentage of usable data (categorised as present, and visually accurate)
MediaPipe	46	100%
LeapMotion	46	87% (Unusable data caused by lost hand tracking)
Manus Glove	73	0% (Hand pose was incorrect for all repeats)

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5 DISCUSSION

The results ranked MediaPipe highly in both accuracy and reliability. Throughout all the experiments the system never lost tracking (100% data completeness), had the least noise when a finger is stationary (average variance of 0.01 mm^2) and had the least variance between repeats (3.4 mm^2). During dynamic tests it also had the least variation from the idealised / planned path (median 1.3 mm). The LeapMotion controller was also successful but did not have the same accuracy or consistency as MediaPipe (87% data completeness, 1.66 mm^2 stationary variance, 8.95 mm^2 positional variance between repeats and median 4.59 mm dynamic error). However, it was capable of tracking in the z-axis, which MediaPipe cannot. The Manus glove's hand tracking was poor in comparison (0% data completeness due to unreliable data, 2.69 mm^2 stationary variance, 14.0 mm^2 positional variance between repeats and median 3.15 mm dynamic error). Some visual examples of the tracking quality are shown in Figure 8. The error in the Manus glove tracking could not be solved by following the advised calibration process and as such, the recorded data output embodies a number of major anomalies in the poses. The tracking of the HTC Vive tracker was significantly better than the glove's pose tracking, which led to the result shown in Figure 6 where the glove appears to have more consistent results than the LeapMotion. This figure was created by comparing each data point to the line of best fit created for each path, so while the Manus glove was more precise, the accuracy was low, as shown in Table 1.

As noted previously, the MediaPipe system did not lose tracking throughout the experiments. However, the LeapMotion tracker regularly lost tracking, losing 13% of data in Phase 3 and being unable to maintain tracking for more than a couple of seconds when the hand was in a finger pointing pose; despite being set up following the instructions given by the manufacturer. Of note is that the LeapMotion controller was set-up in "screentop" mode, which has only recently been added as a new option and it is possible that these errors were caused by teething problems in this new mode. It also struggled greatly with occlusion when the hand was in certain poses. However, if further development supports multi-cameras, or further intelligence is added to the software to predict where the hand is based on certain poses or trajectories, this problem could be mitigated.

The Manus gloves also did not drop tracking, but as illustrated in Figures 7 and 8 and by the results shown in Section 4, the output data proved unusable, with sufficient anomalies that any meaningful analysis is all but prevented. As such, the completeness of viable data is unfortunately 0%, as shown in Table 2. However, as Manus are now releasing their new "Quantum MetaGlove" with a new magnetic pose detection system, it is likely that these problems will be solved or at least reduced as the technology develops further. Though it is probable that it will take longer for the cost of these devices to reduce enough to be viable for most design teams.

While MediaPipe was ranked 1st across all bar one of the metrics, it was not without limitations. These included a lack of 3D tracking and requirement for unit conversion. It is expected that by using a binocular or multi camera system with this technology, a level of 3D tracking could be achieved. With this development, it is expected that MediaPipe will be one of, if not the best value optical hand-tracking method commercially available; and with sufficient cameras and further development of the predictive AI, the problems with occlusion could be mitigated. The LeapMotion system is also very affordable, at less than £100 for a controller at the time of purchase. As this includes the required hardware, it is monetarily comparable to the MediaPipe system, for which a sufficiently high-quality webcam is required. If there is further update and optimisation of the "screentop" recording mode used for this experiment, it is expected that LeapMotion will remain a strong, good value candidate for 3D hand tracking. Especially if a 3D development engine such as Unity or Unreal is being used in the tracking pipeline due to its simple integration with this software.

The Manus Gloves were by far the most expensive option (~€4,000), and consistently ranked below the MediaPipe and LeapMotion implementations, with poor tracking accuracy and unhelpful calibration that does not assist in tracking accuracy. The gloves are cumbersome and restrictive enough to significantly impair dexterous motion by restricting touch sensation and blocking the fingertips from normal interaction. This may be evidence that optical tracking methods are the most appropriate for hand tracking and that gloves may not be the ideal solution. Or, it may just be that the capability of haptic tracking gloves has not yet reached maturity and in time will catch up with optical methods; the success of the Quantum MetaGlove will be an indication of the trajectory of this tracking paradigm.

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Overall, it is clear that each of these technologies are suited to different situations, as the optical methods are more susceptible to occlusion, but the glove-based method reduces dexterity, and currently has poor tracking without extensive calibration and fine tuning beyond the manufacturer's recommendations. Some of the situations that would be most suited to the different tracking methods have been summarised in Table 4, based on the findings of this experiment.

With the imminent commercial release of the Quantum MetaGlove, and continuous functionality improvements added to the optical tracking methods, it is entirely plausible that the balance in usefulness between optical and worn sensors with vary in the future. But, as it currently stands none of these techniques are quite ready for easy, reliable 3D tracking of product interaction. However, this technology is on the brink of being useful for this scenario, as only a few developments are required for the optical systems to work as required, with the MediaPipe system already being an effective tool for use in 2D interactions.

Table 4. Summary of which tracking tools are best suited to different scenarios.

Tracking System	2D tracking	3D tracking	Occlusion	Precise hand pose	Fast movement	Tactile activities	Low Cost	Fast setup
LeapMotion	Good	Good	Poor	Moderate	Moderate	V. Good	Good	Good
MediaPipe	V. Good	Poor	Moderate	Good	Good	V. Good	V. Good	V. Good
Manus glove	Poor	Poor	Good	Poor	Moderate	Poor	Poor	Moderate

5.1 Implications for supporting new product design and development

Having evaluated and compared these different technologies in terms of usability and accuracy, the next step towards utilising them as part of the design process is to further test and understand their value in more design tasks. It is clear that MediaPipe is the most accurate and robust tool, but how should the output data be processed to generate valuable design insight, and what different types of insight can be gained from this data? Is 2D tracking sufficient or is the third dimension required, and how would 3D tracking be implemented using the MediaPipe system? We have established an overview of what processes are best suited to the different technologies. But further refinement, clarification and testing is required to develop an understanding of the best practices to apply to these applications, and how to best utilise the output data to generate new and valuable design insights.

Furthermore, these tools need to be tested in tandem with other haptic capture technology, such as contact force, slip and vibration sensors. Will the methods tested in this paper still work with other sensors on the hands, or would they interfere with the image recognition software that detects the hand position?

5.2 Future work

Further to the questions posed in Section 5.1, Further experimentation can be made on the technologies discussed here. In this experiment the hands were almost always visible by the cameras, so occlusion was low. The experimental set-up used in this paper was also quite process specific. While this is appropriate to some interaction types, interactions with different objects and products would be a valuable extension to the work presented here. A close eye should also be kept on the development of the tools assessed here and new tools entering the market as these systems are on the cusp of reliable, accurate tracking and the authors expect that within 5 years the capability will exist. When this happens, these tools will be invaluable for evaluating product, prototype and process interaction and could revolutionise the way we design ergonomics for dynamic interactions. As such, the guidelines for how to best use these tools and the data they generate to evaluate human interactions will be required.

6 CONCLUSION

Our ability to emulate and capture human-product interaction continues to increase. This paper has evaluated the accuracy, knowledge and skills required to use three hand tracking technologies for the purposes of evaluating user-interaction with prototype products and processes.

MediaPipe ranked 1st with highest accuracy (<2 mm) and data completeness (100%) at the lowest cost (open source), but it is limited to 2D tracking without further development. The LeapMotion tracking ranked 2nd with its ability to track in 3D, and the easy integration with Unity or Unreal provides a

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significant bonus over MediaPipe, but inconsistent tracking (87% data completeness) and weakness to tracking certain hand poses mean that the reliability and accuracy have room for improvement. The Manus gloves ranked 3rd with the weakest pose detection and the highest cost of the chosen systems by a factor of ~40, however as new iterations of tracking gloves are released, the opportunity of highly occlusion resistant hand tracking could be valuable. Currently each of these systems is not capable of reliable, accurate 3D hand tracking when interacting with an object or carrying out a process, but the required changes to achieve this goal are expected by the authors to enter the market in the next 5 years.

Based on this rapidly maturing technology sector, the next objective for the research community in this field should be to investigate the data processing and tool pipelines required to take advantage of this data and generate insights to support designers and design process.

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