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A Scoping Review of the Use of Lab Streaming Layer Framework in Virtual and Augmented Reality Research

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Abstract

The use of multimodal data allows excellent opportunities for human-computer interaction research and novel techniques regarding virtual and augmented reality (VR/AR) experiences. Collecting, coordinating, and synchronizing a large amount of data from multiple VR/AR hardware while maintaining a high frame rate can be a daunting task, despite the compelling nature of multimodal data. The Lab Streaming Layer (LSL) is an open-source framework that enables the synchronous collection of various types of multimodal data, unlike existing expensive alternatives. However, despite its potential benefits, this framework has not been fully adopted by the VR/AR research community. In this paper, we present a guideline of the LSL framework's use in VR/AR research as well as report current trends by performing a comprehensive literature review on the subject. We extract 549 publications using LSL from January 2015 to March 2022. We analyze types of data, displays, and targeted application areas. We describe in-depth reviews of 38 selected papers and provide use of LSL in the VR/AR research community while highlighting benefits, challenges, and future opportunities.

Keywords: Virtual Reality, Augmented Reality, Multimodal Data Collection, Lab Streaming Layer, Open Source Data Collection, Literature Review

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1 Introduction

With recent advancements and public interests in immersive technologies, such as virtual/augmented reality (VR/AR), designing and developing novel interaction techniques and metaphors, and evaluating the effectiveness of VR/AR have become more and more important from the perspective of human-computer interaction (HCI) research. With more sensing and control devices proposed and invented in VR/AR, numerous types of multimodal data from heterogeneous devices have been investigated. Most commonly, these types of data involve information about users' emotions, behavior, and physiological signal (Wang, Beardsley, Zhang, Kim, & Barmaki, 2021). Furthermore, reliable data collecting and sharing procedures are necessary for accurate and robust evaluations in VR/AR applications and research. It can help us gain a deeper knowledge of users' perception and cognition processes during their VR/AR experiences.

Previously, there have been several seminal works in the development of such data collection and sharing frameworks. For example, Reitmayr and Schmalstieg (2005) proposed an open software architecture, OpenTracker, which used a modular design to track input devices and process the data for VR application development. Taylor et al. (2001) presented the Virtual Reality Peripheral Network (VRPN), which has been actively used for decades while covering different VR/AR devices (Cuevas-Rodríguez, Poyade, Reyes-Lecuona, & Molina-Tanco, 2012; Thomas, Bashyal, Goldstein, & Suma, 2014). Pavlik and Vance (2010) developed an extension of the VRPN to collect and synchronize data from the Nintendo Wii Remote game controllers and sensors for use in a VR application.

While VRPN and OpenTracker were useful for collecting data with different sensors, such middleware platforms could not adaptively update the system structure to change the sensors dynamically. To overcome this, UbiTrack was developed based on middleware that allows users to dynamically introduce their devices into the data collection framework at run-time, particularly for AR tracking (Newman et al., 2004).

As a solution for the unified gathering of measurement time series data in research experiments, the open-source *Lab Streaming Layer (LSL)* has recently attracted a lot of interest from data scientists and researchers (Kothe, 2014). Networking, time synchronization, (near-) real-time access, and optionally centralized data gathering, display, and disk recording can all be handled by LSL. Collecting electroencephalogram (EEG) data is one of the most common uses for LSL (Si-Mohammed et al., 2020; Wunderlich & Gramann, 2020).

Given the potential of LSL for effective and reliable data collection in VR/AR research and practices, our overarching goal in this paper is to explore and understand how or for what purposes the LSL framework has been used in VR/AR research. We conduct a scoping review using a systematic literature survey approach to explore different uses of LSL in VR/AR research for multimodal sensor data acquisition and streaming. We present the recent trends in the use of LSL, particularly focusing on what types of data and displays have been involved and what application areas were considered in the papers, while maintaining our scope narrow within the research that used VR/AR technologies. We also performed in-depth reviews of selected papers by summarizing in what context the LSL was used in their work. This review helps us

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understand the growing use of LSL in VR/AR research and identify the potential gap(s). The contributions of our work include the following:

- We introduce and describe the LSL as an effective data collection tool for VR/AR researchers who are currently working or are interested in multimodal data collection and human (perception/behavior) analysis.
- We provide comprehensive knowledge that captures the recent trends and use cases of LSL in VR/AR research domains by a systematic literature review.
- We identify the limited use of LSL in VR/AR research and share some insights and potential research directions.

The rest of this paper is organized as follows. In Section 2, we introduce the LSL framework and describe the features that could directly benefit VR/AR or HCI research. We describe the methodology of our literature review about the use of LSL in VR/AR research in Section 3, and report the results of high-level trends analysis in Section 4. Section 5 presents our in-depth reviews of selected papers, and the findings are discussed with future research directions and possible limitations in Section 6. We conclude our paper in Section 7 by summarizing our work and contributions.

2 Lab Streaming Layer (LSL) Framework

The core library of the LSL framework was first introduced by Kothe (2014). The first application was used to record and synchronize multimodal data with Brain Computer Interfaces (BCIs), Mobile Brain, and Body Imaging (MoBI) paradigms. In recent years, LSL has become a standard for synchronizing and collecting multiple data streams. Furthermore, LSL's preferred data storage format, XDF, exists as an ANSI standard under the name "Attuned Container Format".[1]

2.1 LSL Functionality

LSL is a low-level technology to communicate time series and events between programs and computers. LSL establishes stream discovery, data transmission, and time-synchronization protocols. The data transmission protocol includes extensible descriptive metadata and a simple encoding format. The time-synchronization protocol calculates clock offsets using a subset of the Precision Time Protocol (PTP) algorithm, and consumers of LSL streams can correct for clock offsets in real time or store the clock offsets for offline correction.

On top of the protocol is the LSL library, which includes the core transport library, liblsl, and its language interfaces (C, C++, Python, Java, C#, Rust, Julia, MATLAB). The library is general-purpose and cross-platform (OS Support: Win/Linux/macOS/Android/iOS; Architecture Support: x86/amd64/arm). The LSL distribution consists of the core library, examples for each interface, and a suite of tools built on top of the library.

LSL is mostly used to acquire brain data into a common format and optionally synchronize with other data modalities. For example, a common method to collect and analyze EEG in an LSL-enabled experiment using OpenBCI hardware requires:

[1] https://webstore.ansi.org/Standards/ANSI/ansicta20602017

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- An OpenBCI bundle with embedded software to relay EEG data over LSL
- A stimulus presentation program that sends stimulus events over LSL
- An LSL viewer for visual confirmation of stream contents
- The LSL LabRecorder to store data into XDF format
- An XDF importer to load data into MATLAB
- An analysis tool like EEGLab or MNE-Python to segment, analyze, and visualize the data

2.2 LSL Integrations

The originating use case for LSL was multimodal synchronization and recording during neuropsychological experiments. The suite of official LSL tools includes many applications and plugins to interface with a variety of devices common to neuropsychology experiments, including biophysical sensors, behavioral measurement devices, and stimulus presentation platforms. Many more LSL applications and integrations are provided by the scientific community, industry, and hobbyist communities. As of this writing, there are more than 100 known LSL integrations[2] and many more can be found by searching source code repositories by combining keywords for LSL and the target device or platform. If an integration does not already exist for a particular device, then a software developer may create one following one of the provided example applications and the device's software development kit (SDK) documentation. Some of the major integration modules are described in this section below.

2.2.1 LSL Integrations for Biophysical Sensors

Brain sensors and products, such as InteraXon Muse[3], EEGO[4], ActiveTwo from BioSemi[5], CGX Quick-20 and CGX Mobile-128 from Cognionics[6], ANT neuro[7], actiCHamp from Brain Products[8], gTec[9], mBrainTrain[10], Emotiv[11], etc. are compatible with LSL or supported through a third party software.

Other bio-physical sensors, such as EEGO Sport from ANT neuro[7] and CGX AIM from Cognionics[6], support collecting electromyography (EMG) using LSL. In addition, for Photoplethysmography (PPG) measurement, sensors such as Bitalino[12] are also supported with LSL.

2.2.2 LSL Integrations for Input Devices

LSL provides integrations for many behavioral measurement and input devices including eye gaze trackers, keyboards, mouse, gamepads, microphones, motion capture, and others.

[2] https://labstreaminglayer.org
[3] https://choosemuse.com/
[4] https://www.ant-neuro.com/products/eego_sports
[5] http://www.biosemi.com/
[6] https://www.cgxsystems.com/
[7] https://www.ant-neuro.com/products/eego_sports
[8] https://www.brainproducts.com/solutions/actichamp/
[9] https://www.gtec.at/
[10] https://mbraintrain.com/smarting-mobi/
[11] https://www.emotiv.com/epoc/
[12] https://www.pluxbiosignals.com/collections/bitalino

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For gaze, interfaces exist for Tobii and Pupil-Labs external devices, as well as for their VR-integrated devices. For example, Tobii has integrated eye trackers in HTC Vive Eye and in the Pico Neo Eye product line, and the gaze data can be streamed over LSL.

Compatible audio input such as the AudioCapture[13] application can use the LSL implementation for cross-platform audio capturing.

Motion-capture systems such as Microsoft Kinect, Nintendo Wiimote, and OpenVR are compatible with LSL. OpenVR supports motion capture from several consumer-oriented VR devices from HTC, Valve, and others.

2.2.3 LSL Integrations for Stimulus Presentation

LSL supports audio-visual stimulus presentation from many platforms. Integration is supported natively or via a simple extension in tools like Psychopy, Psychtoolbox, Presentation, and E-Prime, or with a middleware platform like iMotions. LSL support is available for Unity as a custom package and for Unreal Engine 4 as a plugin available in the marketplace.

Great care must be taken when using LSL to synchronize stimulus presentation events with neural recordings. The instant that the stimulus-generation code is executed, which is usually the hook where the LSL event is generated, typically precedes the instant that the stimulus appears on the display by 15-70 milliseconds. The lag is due to a combination of processing in the stimulus presentation platform and frame buffering. However, if the stimulus presentation platform has low variability in its processing times (i.e., "jitter"), and the display has low variability in its frame buffering times, the lag can be calibrated once and subtracted from all stimulus presentation times. It may even be acceptable to ignore the lag entirely if the jitter is low and the analysis of the stimulus response is independent of the absolute latency. Experimenters should measure the lag for each new hardware configuration. For example, the stimulus presentation software should flash the display and send an LSL event simultaneously, and a photodiode attached to the display should be recorded in an auxiliary input of the biophysical recording device, then the lag between the event and signal change should be evaluated for low jitter.

Most stimulus presentation platforms designed for the neuropsychology community indeed have low jitter. Common game engines, however, may have high jitter, especially when the complexity of the visual scene affects the frame rate. The jitter can be mitigated somewhat by delaying the LSL event generation until the last possible moment before the frame is to be rendered. The LSL4Unity custom package provides an example of reducing jitter by delaying event generation until the WaitForEndOfFrame hook.

2.2.4 Distribution of LSL Integrations

Most LSL integrations exist as a standalone application that reads data from the device and re-streams it using the LSL protocol. The official LSL applications are available in GitHub repositories. Many of these applications have pre-compiled releases attached

[13] https://github.com/labstreaminglayer/App-AudioCapture

to the respective source code repository that the user can simply download and run. In contrast, a few applications require the user to build the application from the source. These standalone applications often require the user to install a driver or run a service from the vendor. For example, the g.NEEDaccess service must be running before the LSL application can retrieve data from any of the g.tec biophysical amplifiers.

In other cases, LSL might be integrated directly into the software the vendor provides for their system (e.g., BioSemi, BrainProducts, ANT Neuro). A small but increasing number of devices integrate LSL directly into the device firmware, so the user does not need to run any device-specific software to receive the data stream. For example, OpenBCI and fNIRS (functional near-infrared spectroscopy) devices NIRx and NIRscout do not require any extra software.

3 Methodology for Scoping Review

To investigate recent trends and identify potential gaps in the use of LSL in VR/AR research, we conducted a scoping review adopting a systematic method. Following the PRISMA method for the systematic review process (Liberati et al., 2009), we first collected 549 papers from five digital libraries: Association for Computing Machinery (ACM) Digital Library, Institute of Electrical and Electronics Engineers (IEEE) Xplore, Google Scholar, ScienceDirect (SD), and Springer. We conducted the full body search without any time constraints using relevant keywords, (*"lab streaming layer" AND "virtual reality," "lab streaming layer" AND "augmented reality," "lab streaming layer" AND "mixed reality"*). The paper search was initially conducted on June 29–30 2021, and was updated again on March 24, 2022 with newly published papers.

Figure 1 shows the overall review flow with paper counts selected in each level. After removing redundant papers, we further screened certain types of publications, such as books, book chapters, dissertations/theses, technical reports, and non-English manuscripts, to focus our review to research articles and published extended abstracts and posters, which reduced the number of papers to 209. Four coders—the first three and the fifth co-authors of this paper—further screened the papers, filtering those that are not related to VR or AR research by reviewing the abstracts and skimming through the papers, and the final pool for our analysis included 92 papers. Using this pool of 92 papers, the coders conducted a high-level analysis that classifies the papers in the following categories using a majority voting mechanism:

- **VR/AR Research**: Whether the research in the paper is targeted to VR, AR, or Both.
- **Data Types**: What types of data were collected/processed through the LSL for the research in the paper, e.g., brain signals like EEG, brain imaging like fNIRS, eye gaze, body movement, etc.
- **Display Types**: What kinds of displays were used in the paper, e.g., head-mounted displays (HMDs), monitors, and projection.
- **Application Areas**: What application areas the research in the paper were targeted, e.g., human perception/cognition studies, training, education, and systems evaluation.

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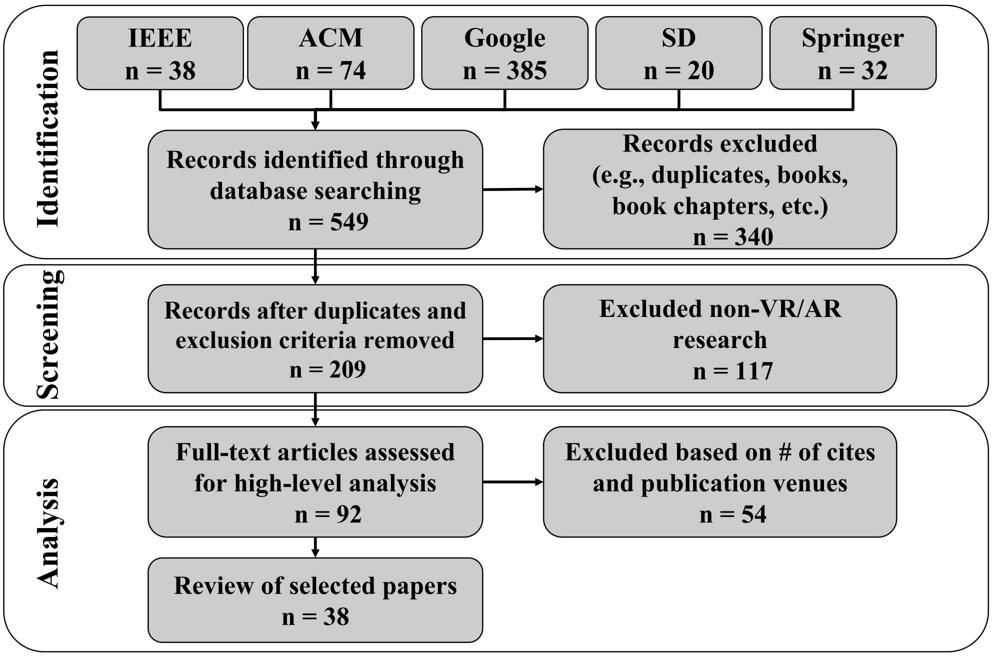

Fig. 1 Scoping review process based on the PRISMA flow chart (Liberati et al., 2009)

The results of the high-level analysis is described in Section 4. To understand how the LSL framework was used in the papers in detail, we further reviewed some selected papers by the citation count—average annual cites greater than or equal to five evaluated on April 12, 2022 via Google Scholar. We also included some recent works from peer-reviewed journal articles and full-length conference papers in 2021 and 2022, which did not have enough time to get cited. The detailed reviews of the selected 38 papers are included in Section 5.

4 High-Level Trends Analysis

We analyzed general trends in the use of LSL based on the classification categories listed in Section 3: (1) VR/AR Research, (2) Data Types, (3) Display Types, and (4) Application Areas. Here we report some of the high-level results.

First, we found that the number of papers that used LSL in their research has been gradually increasing over the past years from 2015 to 2021 (see Figure 2). Given that our paper collection was finalized in March 2022, the paper count for the year 2022 (currently seven) is expected to increase compared to the previous year. This increasing number of research papers indicates that there is a growing interest and potential benefits in the use of LSL for the unified collection of measurement time series data in research experiments.

After screening these papers to identify *VR/AR Research* papers, we found that a majority of the papers (76 out of 92) were focused on VR settings while there were only 12 papers that targeted AR settings—four papers covered both AR and VR

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settings. Most research in the papers had human participants seated or at a static location to examine their neurological or physiological signals accurately, which could be more suitable in VR settings than in AR which often involved locomotion and navigation scenarios. The dominance of VR settings in the papers could also be due to the accessibility of VR HMDs in the field. LSL is commonly utilized with bio-sensors in wearable technology. Our analysis indicates that HMDs are the dominant form of VR devices. This prevalence of VR HMDs may be a contributing factor to the greater popularity of VR compared to AR.

Regarding the *Data Types*, many papers used different types and modalities of data in their work, e.g., collecting EEG signals together with participant's eye gaze. Considering the multiple data types in a single paper, we established four categories of data types: (1) brain signals, e.g., EEG and fNIRS; (2) other physiological data, e.g., EMG, galvanic skin response (GSR), and electrocardiogram (ECG); (3) gaze data based on computer vision methods or EOG; (4) body motion data collected from optical cameras or magnetic tracking sensors. We finally ended up with 139 classifications among the 92 papers (see Figure 3 for the detailed distribution of the Data Types classifications). We identified that the LSL was mostly used to collect neurological brain and other physiological data, as we expected because it was the original purpose of LSL inception. The body motion data was not dominantly used despite the potential of LSL for effective human motion/behavioral data in VR/AR (Wang et al., 2021).

In terms of the *Display Types*, we found that the LSL has been mostly used for immersive HMD settings (79 out of 92 papers), followed by the traditional desktop monitor (16 papers), and projection setting (6 papers – see Figure 4 to learn more). This reflects the recent increasing trend of research with wearable devices in VR/AR. Portable smartphones or tablets are possible to use as an AR/VR display together with LSL; however, LSL is primarily utilized with wearable technology. This may explain the absence of smartphone and tablet devices in our data. Interestingly, there was one paper that involved audio-based AR (Nagele et al., 2021). We included this paper considering a broad concept of AR, which could cover not only the visual modality but also different sensory modality extensions, e.g., audio AR.

While classifying the papers, we were able to categorize eight *Application Areas* that these selected 92 papers were focused on: (1) Human Study for understanding perception/cognition process and brain activities, (2) New Interface, e.g., BCIs, (3) Healthcare for therapy and rehabilitation, (4) Education, e.g., for measuring learning performance, (5) Military for tactical training and evaluation, (6) System Evaluation, e.g., system latency benchmark, (7) Visualization for better visual layout and representations, and (8) Social Connection among the users. The two most popular areas were "Human Study" and "New Interface." Someone might say that "Human Study" is not necessarily an application per se, which we understand, but we included this as one of our area categories because a lot of papers focused on human-subjects studies to understand their neurological or behavioral responses. The findings in those papers could be beneficial to various applications, but they did not specifically mention the target applications and instead generally focused on the understanding of humans. With the continuous increase of public and research interests in BCI in VR/AR, LSL

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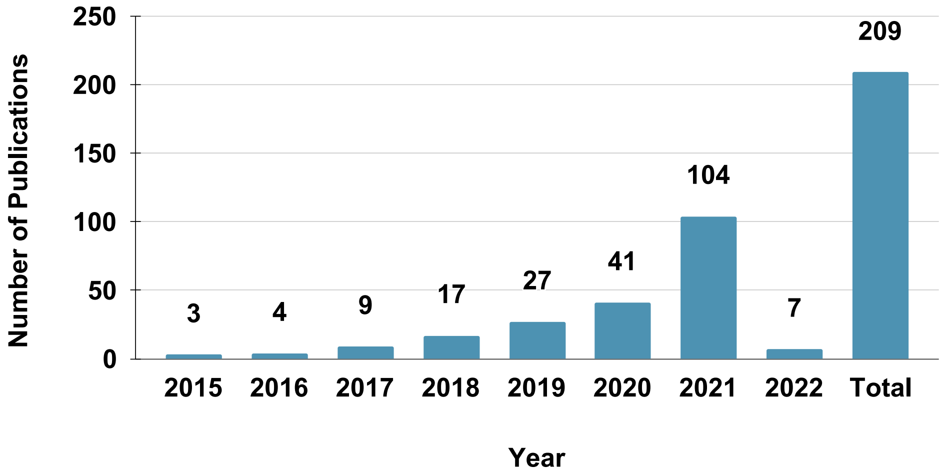

Fig. 2 The numbers of papers collected by our keyword search after the screening are based on redundancy and exclusion criteria. The covered period is from January 2015 to March 2022, and the total column is the sum of all the papers. As we collected papers only up to March 2022, there are only a limited number of papers collected for the year 2022.

was actively used to develop novel interfaces beyond the traditional input mechanisms (Lecuyer et al., 2008). Given the trend that the brain (neurological) and physiological signals were dominant in the used Data Types, the "Healthcare" Application Area was also quite popular for collecting and monitoring those signals in patient-care scenarios. The details of the application area classifications are shown in Figure 5.

5 Detailed Reviews

In this section, we describe our in-depth reviews of 38 papers (Table 1) selected from our pool of 92 papers.

We focused on papers with more than five average citations per year in our in-depth reviews. Full papers published at journal/conference venues in 2021 and 2022, which did not have enough time to be cited, were also included to capture the most recent research trends. The reviews are structured based on the *Data Types* that the papers used to reveal the purposes of the use of LSL in VR/AR research, while being also organized by the target Application Areas. Our focus in the reviews is more on the use of LSL in the papers, not necessarily about their research findings.

5.1 Brain Signals

As noted in our high-level trends analysis (Section 4), a majority of the papers used LSL for collecting neurological brain signals, such as EEG and fNIRS. Here we review 15 selected papers in this category, considering the Application Areas.

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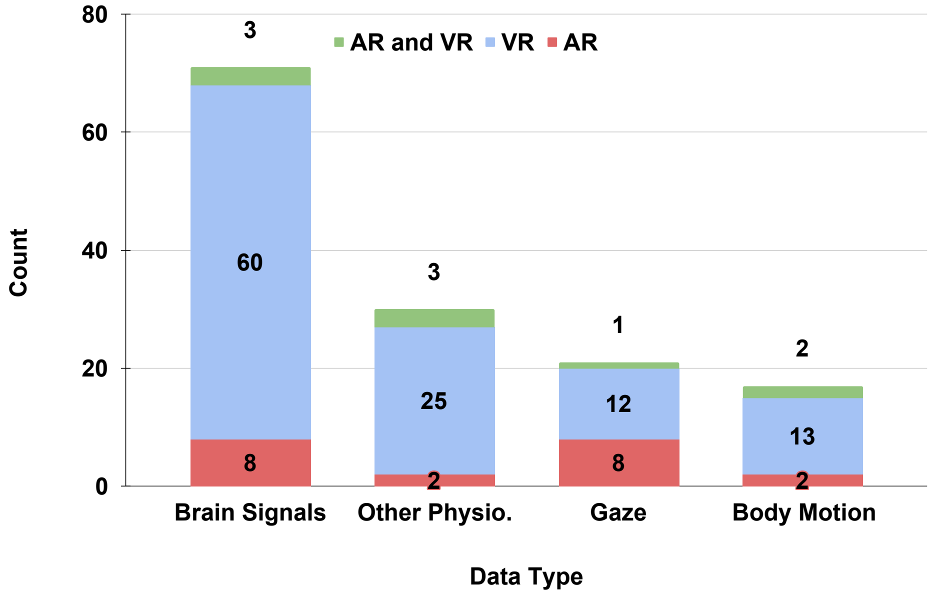

Fig. 3 Different data types were collected through LSL among the collected papers. Different colors represent various targeted devices.

5.1.1 Human Studies

Many publications investigated the user's perception/cognition process with brain signals in VR using LSL in human study settings. In order to improve enveloping closed-loop VR for human studies, it's crucial to incorporate feedback on the user's emotive state. Kumar, Delaney, Soroush, Yamani, and Krusienski (2021) demonstrated how EEG readings may be used to assess a viewer's emotional state while they take in immersive VR content. Communication between the EEG and VR environment was performed via LSL (and its recording tool called LabRecorder). Since such VR-EEG neurofeedback requires users to wear VR goggles on top of the electrodes, the user experience with those devices or the technology is an important research aspect. Berger, Wood, Neuper, and Kober (2021) explored the user experience of VR-based neurofeedback paradigms with respect to different genders, and the impact of 3D and 2D VR environments through user research. The outcomes showed that female participants experienced more discomfort than male participants; they concluded that training sessions for the VR experience are more beneficial for females to adapt to the technology that they perceive as less reachable. Also, this research showed that the 3D environment did not necessarily exacerbate cybersickness, compared to the 2D environment. The LSL was used to implement a streaming framework for the incoming EEG data. To achieve the collection of more accurate brain signals as an objective and reliable measure in human studies, Hertweck et al. (2019) experimented EEG

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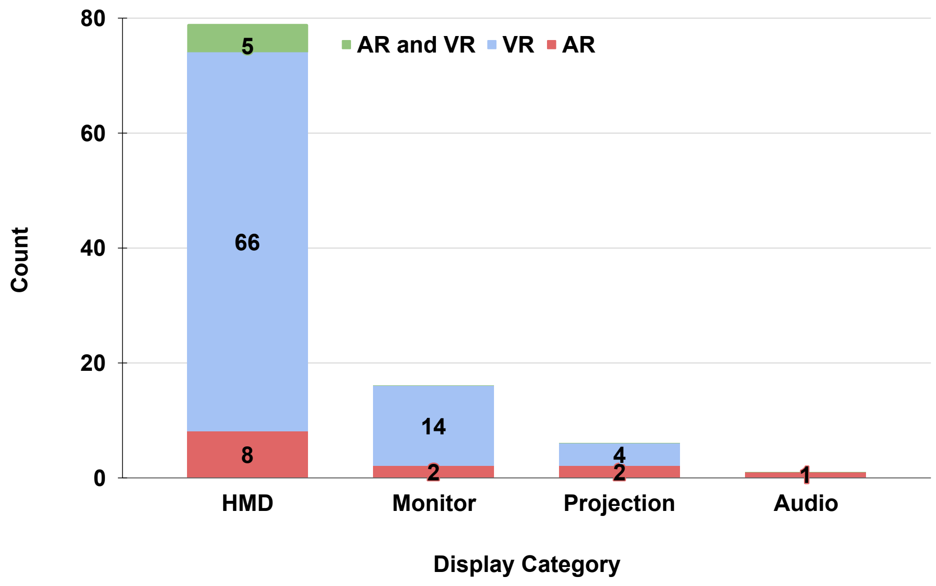

Fig. 4 Distribution of display types used in the collected papers. Each color represents each targeted device.

signal quality while using two VR HMDs, e.g., HTC Vive Pro and Oculus Rift. For the signal quality assessment, LSL was employed to capture and synchronize all of the information and events in VR.

There were many types of research that investigated brain activities in navigation tasks using LSL. Mavros, Austwick, and Smith (2016) analyzed the study of urban navigation behavior by using EEG, and recorded the signal by electrodes and Emotiv EPOC hardware[11]. Open-source software tools using the LSL framework, which permits the simultaneous mixing of data streams from several sources, were created to manage accurate time synchronization. Park, Dudchenko, and Donaldson (2018) studied brain activity in spatial navigation by using mobile brain imaging, involving both EEG and fNIRS systems. The analysis and processing of mobile EEG and fNIRS signals were made possible by the use of the LSL framework, which made it easier to integrate various neurological and physiological methodologies. Nenna, Do, Protzak, and Gramann (2020) studied the brain dynamics being adjusted in single-/dual-task scenarios using a visual discernment task in a simulated VR setting. Participants in the user research stood (single-task) or walked (dual-task) while completing the visual discrimination task in VR. P3[14] amplitude reduction was observed, which is typically related to anxiety and depression. The walking use of LSL in the VR implementations was particularly useful for them to control the study systematically. Beyond

[14]P300 (P3): the largest positive peak of an event-related potential (ERP) waveform within the time window of 300–500 ms, which is elicited in the process of decision making.

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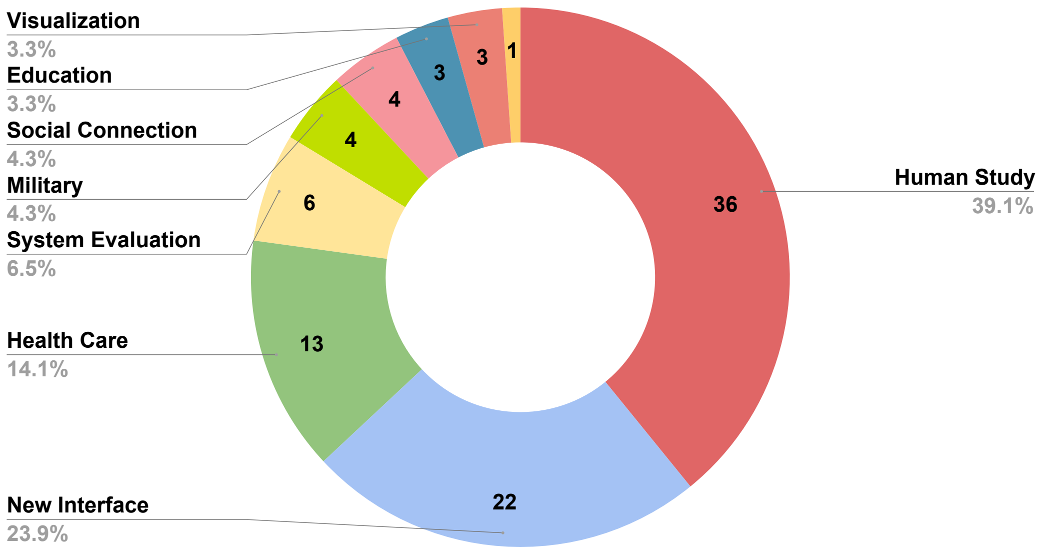

Fig. 5 Application areas targeted in the collected papers.

the ground navigation, Faller, Cummings, Saproo, and Sajda (2019) studied the relationship between arousal and task performance using a boundary-avoidance task in VR-based aerial navigation. The participants in their study could control their navigation directions via a BCI equipped on an HMD, which was achieved by using the LSL to collect and analyze the brain signals.

To study neural signals and the effects in the process of memory encoding and attention cueing, Gregory, Wang, and Kessler (2022) developed a data set that consists of EEG and behavioral data collected from 47 candidates during a visual working memory assignment in VR. During the memory task, participants had to recall information about virtual objects on a table in VR, including their state and specifics, and either a non-social pointing object (stick cue) or embodied virtual avatar was used as attentional cues. Further research is encouraged using this dataset in the context of convergence research between VR and neural signal processing.

5.1.2 New Interfaces

Given the growing interest in novel human-computer interfaces, such as BCI, there were also some papers that used LSL for developing new human interfaces and investigating the effects (Bablani, Edla, Tripathi, & Cheruku, 2020). Mladenović, Frey, Pramij, Mattout, and Lotte (2022) studied the feedback of BCI regarding motor imagery in a video game, Tux Racer[15]. They used LSL to control a virtual joystick in real-time while streaming the classifier output from OpenViBE (Renard et al., 2010). Gorman and Wang (2021) developed a convenient, closed-loop AR-based BCI,

[15]https://tuxracer.sourceforge.net/

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which can provide users with accurate object/environment control ability. The system assessed the practicability of controlling a physical device by steady-state visually evoked potentials (SSVEP) applying LSL. The conducted study with three participants showed that the proposed system could be an effective interface to control a navigation robot, indicating the potential use for individuals with special physical needs. Brain signals tend to be noisy, especially when different electronic devices are used simultaneously. Weber et al. (2021) suggested a methodical approach to check HMDs for electromagnetic (EM) noise that might interfere with EEG measurements. They synchronized the EEG and task cues via LSL to analyze the signal quality and status of EEG data in frequency and time domain quality.

Similarly, Klug and Gramann (2021) provided policies for various experimental settings and conditions, which could influence the robustness of EEG signals. They compared settings for stationary and mobile (non-stationary) to investigate the effects of preprocessing, e.g., data filtering, on independent component analysis (ICA) decomposition, which is a frequently used method to eliminate noise artifacts from the data. Through the experiment with 20 healthy adult participants, they found clear differences between the mobile and stationary data. While the ICA results were acceptable in the stationary setting, high-pass filters should be applied to make the ICA results reliable in the mobile setting. Using LSL, data measurement and event marker streams in divergent sources were recorded and time-stamped.

5.1.3 Other Application Areas

There were different application areas considered in the papers using brain signal data. For example, in the context of healthcare, in particular post-stroke rehabilitation, Rezaee et al. (2021) studied VR-based balance training with fNIRS and EEG systems combined with a wireless simulator and Wii Balance Board. The neuroimaging and triaxial accelerometry data were handled simultaneously using LSL. Sánchez-Cuesta et al. (2021) studied the efficacy of immersive multimodal BCI-VR training for clinical stroke rehabilitation protocols. The results showed that immersive motor imagery in VR could be combined with non-invasive brain stimulation, e.g., neuromodulation approach to increase the rehabilitation effects. The EEG data acquisition, processing, and the control of the VR environment were achieved through OpenViBE and LSL.

For education, Cruz-Garza, Darfler, Rounds, Gao, and Kalantari (2021) investigated the neural dynamics associated with different VR classroom settings, such as different window locations and room sizes. In their study, participants were involved in various cognitive tasks, such as the Stroop test, and they measured EEG data together with the test performance through LSL. The outcomes illustrated that the classroom design could influence brain activity features during cognitive tasks, implying the potential of neurophysiological analysis for effective classroom design.

5.2 Other Physiological Data

A variety of physiological signals, e.g., electrodermal activity (EDA), EMG, ECG, heart-rate variability (HRV), and GSR have been used in many of the reviewed papers in different contexts. Those signals could be collected and analyzed through LSL,

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together with or separately from brain signals. We selected 9 papers for in-depth reviews, which involved different physiological data beyond EEG or fNIRS.

5.2.1 Human Studies

To measure (or recognize) the users' (affective/emotional) states during VR/AR experiences, physiological signals have been actively used, e.g., changes in heart rate, skin conductance, and temperature could be a good indicator of perceived stress in VR (Insko, 2003; Meehan, Insko, Whitton, & Brooks, 2002). The use of LSL could provide an ability to measure accurate response times while collecting such physiological signals, e.g., ECG, HRV, and heart rate, together with behavioral data and game event timing. For example, Li et al. (2021) presented a multimodal sensing system to detect cybersickness that VR users experience by collecting and analyzing neural and physiological signals. They conducted a human-subjects study where participants experienced different levels of cybersickness-inducing tasks in an immersive VR environment. Photoplethysmogram (PPG)-based HRV, and temperatures on fingertip and forehead collected with LSL were used to estimate and correlate the level of cybersickness together with EEG and EOG signals. The results showed that cognitive control capability—specifically the extent of attentional engagement—is negatively influenced by cybersickness. They also revealed that different vestibular network domains—cognitive, sensorimotor, and autonomic domains—measured by both physiological and neural signals have different implications in cybersickness.

5.2.2 New Interfaces

Physiological signals could also be used to design novel user interfaces, e.g., EMG-based gestural interaction (Nymoen, Haugen, & Jensenius, 2015), or breath-based gaming interfaces (Sra, Xu, & Maes, 2018). In our review, Quintero, Munoz, De Mooij, and Gaebler (2021) developed an open-source software framework called Excite-O-Meter, which collects and processes physiological data using LSL. The framework integrated cardiac activity signals, such as ECG, PPG, and resulting HRV, in interactive VR applications while providing real-time analysis. During the virtual game interaction, they recorded ECG data to measure heart rate and HRV, which are typically considered valid stress markers. Their results showed that the developed tool based on the framework could be easily used and provide scientifically valid data for researchers and practitioners.

5.2.3 Other Application Areas

A variety of application areas were considered in the reviewed papers using physiological signals. Since physiological changes are closely associated with emotion, e.g., arousal and valence, physiological data was often used in the context of social interactions. Gupta et al. (2020) measured the confidence level in a virtual helper by using different physiological signals in VR. In particular, they used LSL to collect GSR and HRV using Shimmer sensors and EEG signals[16]. Kroczek, Pfaller, Lange, Müller, and Mühlberger (2020) studied interpersonal distance during real-time social interaction

[16] https://shimmersensing.com/

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using physiological measurements like ECG, EDA, and EMG. The LSL framework with a recording feature was used to record and synchronize data from various sources regarding the distance and physiology measures. In AR, Valente, Lopes, Nunes, and Esteves (2022) developed a neural network model for emotion recognition using ECG data and created a novel AR communication cue. They evaluated the effects of the AR system in various situations by gathering the data from the ECG sensors and delivering it using LSL.

These physiological data were also utilized in consideration of medical/clinical applications. For example, Peterson and Ferris (2018) used the LSL framework to collect and synchronize electrocortical responses and EMG activity to analyze physical and visual balance perturbations. Vourvopoulos et al. (2019) used a VR system for post-stroke rehabilitation. In their pilot study with stroke survivors, EEG and EMG signals collected through LSL were compared to move their virtual avatars' arms. The findings showed that patients with serious motor impairments were more advantaged through EEG-based neuro-feedback, while patients with gentle impairments benefited more through EMG-based reports. Bustamante, Peters, Schölkopf, Grosse-Wentrup, and Jayaram (2021) introduced a robot arm system that allows researchers to conduct various studies on how humans may control a robotic arm in a range of scenarios from an upper limb prosthetic to a wheelchair-mounted robot controller in VR. The use of LSL allowed linking any additional control modalities, such as EMG or gaze, to fulfill the need for prosthetic or robotic assistance research. To study learning performance and experience in educational settings, researchers also investigated the use of physiological signals in different learning environments. Kalantari, Rounds, Kan, Tripathi, and Cruz-Garza (2021) conducted an experiment that examined physiological signals in real and virtual classroom environments. Participants in the study were engaged in different cognitive tests, which involve various physiological responses, such as EEG, ECG, EOG, and GSR. However, the consequences did not illustrate any major variances between the real and virtual settings. All the data including brain signals, were collected and synchronized through LSL.

5.3 Gaze

Regarding the use of gaze data, we found that most papers were focused on AR research or applications. Here we introduce 8 papers that utilized gaze data in their research using LSL.

5.3.1 Human Studies

Gaze is one of the most important social cues, which lets us share our attention and intention with other people, by looking at the target of interest (Langton, Watt, & Bruce, 2000). Unsurprisingly, gaze has been used in many human-subjects studies to understand human behavior and mental states. Vortmann, Kroll, and Putze (2019) tackled an interesting question about visual interference of virtual contents in an AR user's view, which could influence the user's focus of attention and internal thought process. To investigate the effects of visual AR contents, they designed a user study with a special alignment task in AR. They collected participants' gaze and behavioral

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data, together with EEG signals through the LSL. Lapborisuth, Koorathota, Wang, and Sajda (2022) aim to get a deeper understanding of the link between attention reorientation and gaze by utilizing a realistic VR-based target detection paradigm. They were able to capture and combine the reorienting signals across several modalities by using LSL to synchronize the EEG and gaze data streams together via a local network. As for many aspects of the VR user experience, Eckert, Habets, and Rummukainen (2021) assessed the objective evaluation of the cognitive load. In a six-degrees-of-freedom (6-DoF) VR scenario with uncontrolled scene illumination, they provided a technique to measure the cognitive load using pupil dilation. To investigate an individual sigmoidal mapping function between brightness levels and pupil size, the LSL was employed to record and synchronize the data from the eye trackers. Callahan-Flintoft, Barentine, Touryan, and Ries (2021) studied eye and head movements during navigating VR experiences while emphasizing the potential of VR systems as a tool for vision researchers. Eye and head tracking in controlled VR environments allows researchers to capture naturalistic human behaviors without sacrificing strict experimental control. The study used LSL to assess behavioral eye and head movements that were timed to environmental factors/events in VR, proving the viability of the created system in behavioral data gathering.

5.3.2 New Interfaces

In terms of the use of gaze to develop novel user interfaces in VR/AR, a series of research was conducted incorporating the AR user's gaze data with the EEG signals. Putze, Weiβ, Vortmann, and Schultz (2019) proposed a multimodal interface consisting of Microsoft HoloLens, Pupil Labs binocular eye-tracker, and BCI to control smart home devices (e.g., a window blind). The device component and the control system were connected and communicated with each other via LSL. The paper also noted some challenges in the use of LSL, e.g., the difficulty of compiling on the Microsoft Universal Windows Platform. Vortmann and Putze (2020) further used their AR system in a multimodal smart-home environment context and suggested the benefits of attention-aware systems that track the user's attentional state. Vortmann, Schwenke, and Putze (2021) also studied whether an AR system can identify whether the user's attended object in AR is real or virtual by classifying data from EEG and eye-tracking data via LSL. Recently they conducted research about a person-independent and training-free BCI in AR settings, using Microsoft HoloLens equipped with Pupil Labs eye-tracker and an EEG cap (Vortmann & Putze, 2021). Those data were captured and processed through LSL and MNE-Python toolbox[17].

5.4 Body Motion

Motion data, such as body movement or location, gestures, and postures, could be one of the most common and important data types used in VR/AR research and applications. Interestingly, however, there were not many papers that used LSL to deal with such data in our trend analysis in Section 4 (see Figure 3). Here we review

[17] https://mne.tools/stable/index.html

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6 papers that incorporate the body motion data in their research—mostly together with brain signal data.

5.4.1 Human Studies

Body motion data has been actively used to study the cognitive impacts during spatial navigation associated with brain signals. Banaei, Hatami, Yazdanfar, and Gramann (2017) conducted research on how interior shapes in architectural design affect the dynamics of the human brain. Their research's objective was to evaluate the neurophysiological correlation between the physical interior settings and the user's affective state. In the study, participants' motion data, such as walking in diverse interior forms in VR, were recorded and analyzed with EEG signals. Djebbara, Fich, Petrini, and Gramann (2019) tackled one of the ongoing debates in cognitive neuroscience and philosophy—whether the cognitive process is associated with architectural affordances, a way to see the physical structure of the environment based on the perceived uses. They developed a VR HMD-based system to investigate this issue. The LSL framework was used to record human brain dynamics (EEG) and participants' activities while navigating a structured virtual room. Delaux et al. (2021) also used an immersive VR environment to investigate the neurofeedback during active navigation, e.g., cortical correlates of landmark-based navigation. They used the LSL framework to collect participants' behavioral motions, EEG signals, and all other event triggers during the VR experience. Beyond typical visual augmentation in AR, Miyakoshi, Gehrke, Gramann, Makeig, and Iversen (2021) focused on audio augmentation. They studied how the brain works during spatial navigation in a virtual maze while collecting both EEG and motion data synchronously through LSL.

For psychology studies, Kisker et al. (2021) considered VR as an effective tool to induce authentic fear and investigate the reaction from a comprehensive angle. In their study, subjects explored either a negative (fearful) or a neutral VR cave with passive haptic feedback, and their behavioral responses and EEG signals were evaluated. The results did not show significant differences in the EEG signals but revealed that the participants had a more negative effect and fear behavior, such as slower walking or avoidance in the negative setting than in the neutral setting. Since the VR experience could provide real sentimental and behavioral reactions, they came to the conclusion that VR has a significant potential to boost the ecological validity of research findings in these psychological investigations. The LSL was used as a tool for synchronizing and capturing each data stream from the experimental procedure, including body movements, EEG, and events.

5.4.2 Other Application Areas

In the context of healthcare, Muller et al. (2021) presented a study protocol to collect and analyze upper limb kinematics for stroke patient rehabilitation. The goal of the research is to examine the impacts of VR or conventional therapy sessions on the paralyzed upper limb function in chronic stroke. The protocol involved both brain signals and body motion data using an optical motion sensor (Microsoft Kinect v2) and EEG/fNIRS sensors, and LSL would be used as a tool for synchronous measurements of upper limb kinematics and motor cortical area activation (fNIRS and EEG).

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6 Discussion

In this paper, we investigated the use of LSL in VR/AR research using a systematic literature review approach. Based on the rising number of papers in recent years, we discovered that LSL has been receiving an increasing amount of attention from researchers that use VR/AR for their studies (see Figure 2). We also identified that the use of LSL is largely focused on neurological brain data collection as the development of LSL originally targeted such use cases. Based on our analysis results presented in the previous sections, here, we discuss the findings and potential research directions, while addressing missing and potential opportunities in the use of LSL for human-centered VR/AR research.

6.1 Benefits of LSL to Human Studies in VR/AR

In a large number of papers that we reviewed, LSL was used for collecting and analyzing brain signals in the context of human perception/cognition and behavioral studies. This trend is particularly interesting in VR/AR research given the recent increase of user studies in VR/AR publications (Dey, Billinghurst, Lindeman, & Swan, 2018). As the field of VR/AR research and industry is growing both qualitatively and quantitatively, researchers are more aware of the importance of human-subjects studies to evaluate their developed systems, and understand human perception and behaviors during interactions with virtual entities. Subjective measures, e.g., participant-reported questionnaires and data collected from interviews, have been qualitatively analyzed or converted into quantitative values, such as Likert scales (Likert, 1932). For decades, however, researchers addressed the potential issues with such subjective questionnaires because of the ambiguity in interpreting the questions and concepts to measure (Slater, 2004). Associated with subjective qualitative measures, objective quantitative measures have become more important and emphasized as concrete evidence to support the research claims or effects. Brain signals, other physiological signals, and user's behaviors, including gaze and body motions, can be used as objective measures in VR/AR studies. For example, several papers studied simulator sickness (or cybersickness) in VR/AR by analyzing the user's EEG, EOG, and HRV in our review (Berger et al., 2021; Li et al., 2021). Understanding the causing factors and effects of simulator sickness is crucial to extending the use of VR/AR technologies in our daily lives.

Despite the potential of multimodality in improving user experience, immersion, or even performance in certain tasks, Martin, Malpica, Gutierrez, Masia, and Serrano (2022) pointed out that such modalities should be carefully designed considering the purpose. As human studies in VR/AR would involve more and more multimodal data captured through a variety of heterogeneous sensing devices, e.g., visual, auditory, haptic, and proprioceptive modalities (Martin et al., 2022), LSL is a promising tool to manage such large and dynamic data reliably.

6.2 Novel VR/AR Interface Research with LSL

For decades, VR/AR and HCI researchers have pursued novel user interfaces for more effective, efficient, and natural interactions with virtual entities, more broadly with

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computing devices. Developing such effective interfaces or interaction methods is crucial, particularly in VR/AR due to the complexity or ambiguity of the data visualized in 3D spatial environments (LaViola Jr., Kruijff, McMahan, Bowman, & Poupyrev, 2017).

Our review in this paper shows that LSL has been actively used in the context of novel interface development and evaluation, e.g., BCI. The early research on BCI traces back to the 70s (Vidal, 1973), and it has recently gained a lot of attention from both researchers and the public because of the advances in the technology and the potential to replace traditional input mechanisms, e.g., keyboards and mice (Bablani et al., 2020; Torres, Torres, Hernández-Álvarez, & Yoo, 2020). BCI has been around for decades even in the field of VR/AR, specifically in the context of rehabilitation and training (Lecuyer et al., 2008). Considering the accessibility and potential use of this technology for people with disabilities, more rigorous research is required and will be conducted in the future (Mane, Chouhan, & Guan, 2020). The use of LSL would be highly beneficial to perform such research, not only for collecting and analyzing the data, but also for generating and sharing valid data sets for large-scale and repeatable studies (Gregory et al., 2022).

Beyond the neurological signals, there was quite a bit of research that collected and used eye gaze data in our review. Eye gaze is one of the most important social cues that people use for sharing their attention and intention (Langton et al., 2000).

The usage of gaze cues in VR/AR has received significantly more attention than previously. Many commercial VR/AR headsets come with eye trackers due to the growing popularity of social VR/AR setups with multiple users' avatars. VR/AR researchers have used gaze data to develop novel forms of spatial user interaction in various interaction settings and applications (Plopski et al., 2022). LSL is useful and attractive to such researchers as it supports different types of eye-tracking hardware.

Although LSL also supports some motion tracking hardware, such as Microsoft Kinect, NaturalPoint OptiTrack, or Vicon, we did not find many papers that used body motion data with LSL in the review. This may be because of the wide use of the existing individual tools and APIs provided by the manufacturers, which does not require the VR/AR developers and researchers to use LSL. However, the use of LSL still has a lot of benefits with synchronized multimodal data as VR/AR applications and research involve more complex and multimodal signals. The range of LSL-supported devices should be continuously increased and updated to include newer devices, e.g., Microsoft Azure Kinect, Windows Mixed Reality VR headset and controllers (Wang et al., 2021), while also reflecting the recent trends with various types of smart devices in different VR/AR interaction scenarios, such as AR interfaces to control Internet-of-Things (IoT) devices. In this sense, Huo et al. (2018) and Jo and Kim (2019) emphasize the potential of LSL in VR/AR due to its scalability and adaptability.

6.3 Potential of LSL for Designing VR/AR Applications

As fundamental techniques to realize VR/AR have experienced significant advances, more diverse VR/AR applications are considered and proposed for the past decades (Aukstakalnis, 2016). Here in our review, we also observed that LSL has been used in several specific VR/AR application areas, e.g., healthcare, social interaction, and

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education, but the diversity is still quite limited. For example, most use cases in the papers involved neurological and other physiological signals in social interactions and healthcare contexts, but the use of motion data for behavioral analysis and applications was still limited (Wang et al., 2021). As we pointed out above in Section 6.2, the LSL middleware or plugins for motion devices, which are commonly used in VR/AR research, should be more introduced considering the potential in comprehensive data collection and management in VR/AR applications.

In a broader field of HCI, the use of multimodal data becomes more and more popular, and necessary in many cases to improve the accuracy of human behavior analysis and the contextual understanding. For example, in a mobile healthcare scenario, Blum, Hölle, Bleichner, and Debener (2021) used LSL to collect patients' data from smartphone sensors. The wearable technologies for VR/AR displays will continue to be improved to the level of lightweight portable form factors and are anticipated to be widely used by consumers in daily life (Welch, Bruder, Squire, & Schubert, 2019). Such VR/AR displays will be equipped with various types of sensors, and a range of daily applications should be designed and developed incorporating such sensors. In that context, a comprehensive data collection and processing framework, such as LSL, is essential.

Not surprisingly, considering the daily use of VR/AR nowadays and in the near future, social applications will be one of the important application areas as we are also currently witnessing the increase of social VR/AR platforms, e.g., Meta's Horizon Worlds [18] or Microsoft AltspaceVR[19]. In such social settings, affective analysis of user emotional states and detecting or recognizing user behaviors would be needed for effective communication. Also, the use of multimodal embodied interactions through visually sophisticated virtual avatars would require collecting and processing of larger embodied social data. Given the strong potential of LSL in social VR/AR with complex and diverse data, other VR/AR application areas, which often involve multi-user settings, will benefit from the use of LSL, such as training and education, entertainment, collaboration, product design, building maintenance, etc.

7 Conclusions and Future Work

Human measurement in VR/AR using physiological and behavioral motion data is growing because of new hardware and software technology advancements. In this paper, we introduced the LSL framework as a renowned data collection tool in certain fields, and suggested the potential benefits of its utilization in VR/AR research based on its capability and potential to collect, record, and synchronize multimodal data from various sensing devices. To understand the current use of LSL in VR/AR research, and identify possible gaps in the use, we conducted a literature review that covered high-level trend analyses about what types of data and displays were involved and what application areas were targeted while using the LSL. We also reviewed impactful selected papers in depth to further understand the use cases of the LSL with

[18] https://www.meta.com/horizon-worlds/
[19] https://altvr.com/

different types of data. In conclusion, we provided comprehensive knowledge of the current trends in the use of LSL in VR/AR research and discussed the opportunities.

It is important to acknowledge that our literature research has some limitations, which can guide our plans for future work. The search keywords that we used might have missed some research papers, e.g., if the papers used terms like "extended reality," or "immersive technology" instead of VR/AR/MR. Future work could include a larger volume of papers by using more comprehensive keywords. Also, the present research, particularly the in-depth reviews, mostly focused on the latest publications. This is somewhat inevitable because of the relatively short history of LSL, but it may cause some issues to see the long-term, big-picture of LSL use-cases in VR/AR. However, this is also our intention to cover the recent research trends with LSL. To the best of our knowledge, this is the first literature review research on the use of LSL for multimodal data collection in/from VR/AR, which can help VR/AR researchers and practitioners understand the benefits and potentials. We aim to follow up on the continuous developments and use of the LSL and multimodal data collection, fusion and analysis in the VR/AR/HCI research fields.

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Data availability. All data generated or analysed during this study are included in this published article and its supplementary information files.

Declarations

Conflict of Interest. The authors have no competing interests to declare that are relevant to the content of this article. The authors declare they have no financial interests.

Ethical Approval. Not applicable

Open Access. Not applicable

Table 1 A list of the selected 38 papers for in-depth reviews, and their classifications.

Paper	Year	VR/AR	Display	EEG/fNIRS	Other Physio.	Gaze	Body Motion	Application Area
Mavros et al.	2016	VR	Screen	✓				Human Study
Banaei et al.	2017	VR	HMD	✓			✓	Human Study
Park et al.	2018	VR	HMD	✓				Human Study
Peterson and Ferris	2018	VR	HMD	✓				Human Study
Hertweck et al.	2019	VR	HMD	✓				Human Study
Putze et al.	2019	AR	HMD	✓				New Interface
Djebbara et al.	2019	VR	HMD	✓			✓	Human Study
Faller et al.	2019	VR	HMD	✓	✓	✓		Human Study
Vortmann et al.	2019	AR	HMD	✓		✓	✓	Human Study
Vourvopoulos et al.	2019	VR	HMD	✓	✓			Healthcare
Vortmann and Putze	2020	AR	HMD	✓		✓		New Interface
Gupta et al.	2020	VR	HMD	✓	✓			Human Study
Kroczek et al.	2020	VR	HMD		✓			Healthcare
Nenna et al.	2020	VR	HMD	✓			✓	Human Study
Cruz-Garza et al.	2021	VR	HMD	✓	✓	✓	✓	Education
Delaux et al.	2021	VR	HMD	✓			✓	Human Study
Miyakoshi et al.	2021	AR	-	✓			✓	Human Study
Rezaee et al.	2021	VR	Projection	✓				Healthcare
Kalantari et al.	2021	VR	HMD	✓	✓	✓		Human Study
Vortmann and Putze	2021	AR	HMD	✓		✓		New Interface
Muller et al.	2021	VR	Screen	✓			✓	Healthcare
Mladenović et al.	2021	VR	Screen	✓				New Interface
Vortmann et al.	2021	AR	HMD	✓		✓		New Interface
Kumar et al.	2021	VR	HMD	✓				Human Study
Eckert et al.	2021	VR	HMD		✓	✓		Human Study
Weber et al.	2021	VR	HMD	✓				System Evaluation
Quintero et al.	2021	VR	HMD		✓			New Interface
Bustamante et al.	2021	VR	HMD		✓	✓		System Evaluation
Klug and Gramann	2021	VR	HMD, Screen	✓				System Evaluation
Berger et al.	2021	VR	HMD	✓				Human Study
Sánchez-Cuesta et al.	2021	VR	HMD	✓				Healthcare
Li et al.	2021	VR	HMD	✓				Human Study
Gorman and Wang	2021	AR	HMD	✓				New Interface
Callahan-Flintoft et al.	2021	VR	HMD		✓			Human Study
Kisker et al.	2021	VR & AR	HMD	✓	✓		✓	Human Study
Gregory et al.	2022	VR	HMD	✓				Human Study
Lapborisuth et al.	2022	VR	HMD	✓	✓	✓		Human Study
Valente et al.	2022	AR	HMD, Screen		✓			Social Connection

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