A Survey on Situational Impairments Research in Mixed Reality

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The integration of Mixed Reality into everyday life has expanded user interaction beyond controlled environments to dynamic scenarios such as shopping and commuting, which introduce situational impairments that challenge standard interaction paradigms. Following PRISMA guidelines, we systematically reviewed 109 papers and mapped situational impairments to four components: Understanding, Modelling, Sensing, and Adapting. We compare how impairments affect tasks and assess user experience using objective and subjective metrics. We also catalogue sensing and adaptation strategies that sustain MR usability across varied conditions. Finally, we provide guidance for ecologically valid evaluation and highlight opportunities for empirically grounded, replicable, and generalisable MR solutions.

CCS Concepts: • **General and reference** → **Surveys and overviews**; • **Human-centered computing** → **Ubiquitous and mobile computing design and evaluation methods**; **Accessibility systems and tools**; **Accessibility technologies**; **Mixed / augmented reality**.

Additional Key Words and Phrases: Situational Impairments, Accessibility, Ubiquitous Computing

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1 INTRODUCTION

Laboratory studies provide a rigorous and repeatable way to examine Mixed Reality (MR) interaction in controlled situations, with simplified contexts and idealised environments. However, it is critically important to also understand how MR can best be applied to real-world scenarios for its full potential

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to be realised [54]. Recent usage trends indicate that people intend to integrate MR into daily activities, such as shopping, commuting, or exercising[1]. This shifts the way we interact with digital devices from "Heads-Down" computing (e.g., smartphones) to "Heads-Up, Hands-Free" computing (e.g., MR devices), thereby maintaining the user's situational awareness [97] and enabling seamless micro-interactions [147]. To realize this vision of ubiquitous MR, we must rethink how the usability of this technology can be enhanced and sustained in diverse situations, dynamic contexts, and complex environments [160]. Given that MR has been in development for decades, it is now timely to examine how it can be effectively deployed in these complex scenarios.

The concept that situations, contexts, and environments can negatively impact human abilities on digital devices has been framed as "Situationally-Induced Impairments and Disabilities" (or "situational impairments" and "SIIDs" for short) [38, 90, 118, 119, 150, 159, 160]. This framework conceptualizes situational impairments as a functional limitation, whereby specific situations may profoundly constrain the expression of our abilities [118, 160]. In recent years, growing research has demonstrated how different situations, contexts, and environments negatively affect interaction with desktop computers [101], smartphones [106, 109, 114], wearable displays [47, 172], and MR devices [64, 66, 72]. Furthermore, researchers in Human-Computer Interaction (HCI) have developed working prototypes to demonstrate the feasibility of sensing and mitigating these situational impairments in MR [67, 70, 75].

Therefore, to pursue the next generation of MR to be used in real-world settings rather than primarily in controlled laboratory conditions, it is crucial to understand *why* these challenges are significant, *how* they affect performance, and *what* improvements can be made. This analysis identifies current research challenges and charts a roadmap for future research in determining appropriate interaction solutions tailored to address specific situational impairments. The detailed research questions are:

- **RQ1.** Why is it necessary to understand the effects of SIIDs on MR interaction?
- **RQ2.** How do distinct SIIDs affect MR user performance?
- **RQ3.** What interaction techniques and design strategies can improve usability and user experience in these scenarios?

To answer these questions, we conducted a systematic literature review of 109 articles following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines [96]. Across the reviewed studies on understanding and modelling situational effects, we synthesised the MR tasks commonly used for evaluation, the objective and subjective measures used to quantify performance and usability, and how situational effects are observed and reported. We also catalogued and compared sensing and adaptation strategies, summarising existing sensing, adaptation, and accommodation approaches aimed at maintaining usability and user experience under varied conditions. Furthermore, we discuss key methodological considerations for rigorous evaluation, including aligning tasks and measures with real-world use, selecting appropriate participants and environments, and reporting situational variables in ways that support replication and comparison. Finally, we highlight opportunities identified in the literature and outline future directions for developing solutions that are empirically grounded, ecologically valid, and generalisable across situational impairments.

2 BACKGROUND

The foundational work of Sears et al. [118] linked situational constraints to the implications of disability. However, the definitions and usage of "impairments", "disabilities", and "handicaps" are frequently conflated in the literature [160]. In this section, we therefore define the scope of our

[1] https://youtu.be/Qqw00uCaGgM?si=-_WahTwGxscBTISQ [Accessed: 2026-01]

survey and clarify the corresponding terminology. With these foundations in place, we introduce the general framework for SIIDs research. We then use this framework to review prior analyses of SIIDs in traditional computing devices, as well as in the context of MR.

2.1 Definitions and Scope

2.1.1 Situationally-Induced Impairments and Disabilities. While early computing research assumed a static environment (i.e., the desktop), the ubiquity of mobile and wearable computing exposes users to dynamic settings where cognitive, perceptual, and motor abilities are frequently taxed [159, 160]. The theoretical foundation of this survey lies on the concept of "Situationally-Induced Impairments and Disabilities", terminology formally introduced by Sears et al. [118]. Their seminal observation was that:

> *"both the environment in which an individual is working and the current context (e.g., the activities in which the person is engaged) can contribute to the existence of impairments, disabilities, and handicaps"*

To disambiguate the terminology used in this domain, we adopt the classifications derived from the "International Classification of Impairments, Disabilities, and Handicaps" from the World Health Organization (WHO) as applied to HCI by Sears et al. [118] and Wobbrock [160]. The detailed definitions are:

- **Impairment:** a loss or abnormality of body structure or function.
- **Disability:** difficulties an individual may have in executing a task or action.
- **Handicap:** problems an individual may experience in involvement in life situations.

SIIDs is the combination of two notions: "Situational Impairment" and "Situational Disability". Wobbrock [160] defined the two terms as:

- **Situational Impairment:** a functional limitation experienced by a user in a specific circumstance.
- **Situational Disability:** the task or activity limitation experienced by a user in a specific circumstance.

While "Situational Impairment" describes the root cause—a physiological or sensory constraint such as cold fingers or glare—"situational disability" captures the resulting failure in interaction, such as the inability to type or read a screen. This perspective is critical because the source of a situational impairment is often external and immutable. As mentioned by Wobbrock [160], directly addressing a physiological impairment (e.g., stiff fingers caused by cold temperatures) is rare within the scope of a technological solution (e.g., a device cannot change the ambient temperature). However, the resulting *disability* (e.g., the inability to effectively type on a small touchscreen) is a specific interaction failure that can be improved through design. By framing the problem at the level of task-based activity, designers can focus on adapting the system's demands to accommodate the user's limited ability. Consequently, the goal is to ensure the user can access the system's functionality in the moment by accommodating situationally reduced capabilities.

To precisely scope the external factors affecting user interaction, Dey et al. [30] decomposed the notion of "situational" into three components: Situation, Context, and Environment. Together, these three components define the situational factors that can temporarily constrain users' capabilities, and thus constitute the core aspects of situational impairments. Wobbrock [160] later synthesised and defined them as follows:

- **Situation:** the specific circumstance in which the user finds him- or herself. The situation encompasses the "immediate now" of the user.

- **Context:** the current activities in which the user is generally engaged, including the user's purpose, goals, and motivations for those activities, and the user's physical, mental, and emotional state while doing those activities.
- **Environment:** the larger setting the user is in, including both the physical and social setting.

Based on the aforementioned definitions, the scope of this review is the intersection of device interaction and the external constraints imposed by real-world usage. We examined constraints across the broader physical and social *environment*, the user's specific activity and internal *context*, and the immediate, transient *situation*. While we analyse situational impairments as functional root causes, our primary focus lies on *situational disabilities*—limitations at the task or activity level—as this is where design interventions are most effective.

2.1.2 Mixed Reality. The foundational definition of *Mixed Reality* was established by Milgram and Kishino [83]. They introduced the concept as:

> *"...the merging of real and virtual worlds somewhere along the virtuality continuum which connects completely real environments to completely virtual ones."*

In this framework, Augmented Reality (AR) is defined as a subset of Mixed Reality where the real world is the primary environment, augmented by computer-generated content [83]. While the theoretical roots of AR and MR are grounded in the virtuality continuum, recent HCI research often distinguishes them by hardware and immersion levels. As noted by Speicher et al. [132], the term *"Augmented Reality"* is frequently associated with handheld, mobile-based overlays such as "Pokémon GO", whereas *"Mixed Reality"* typically denotes immersive, head-mounted displays (HMDs) that enable deeper spatial interaction (e.g., Microsoft HoloLens).

In this review, we adopt the term *Mixed Reality* to emphasize the critical interdependence of both the physical world and the virtual environment, and to distinguish between experiences generated by immersive HMDs and handheld mobile-based overlays. Although the user is physically grounded in the real world where situational impairments originate, their primary interaction is directed toward the virtual world. Because the user must navigate physical constraints while manipulating virtual elements, both environments are equally significant to the interaction. Consequently, while some studies in our corpus self-identify as Augmented Reality, we include them in our analysis as they fundamentally address the blending of real and virtual contexts to the broader Mixed Reality field.

2.2 SIIDs Research Framework

Research into SIIDs generally adheres to a four-component framework as proposed by Tigwell et al. [144]: *Understanding, Modelling, Sensing, and Adapting*. This framework provides a structured approach to analysing how environmental factors impact interaction and how systems can be designed to mitigate these effects [144].

2.2.1 Understanding and Modelling Contextual Challenges. The foundation of SIIDs research lies in *understanding* how specific contexts affect user performance [144]. In HCI, context is derived from the combination of the user, the application, and the location [30]. Previous studies have investigated these factors, such as the impact of walking on MR interaction [66], the effects of encumbrance on mobile interaction [93], and how ambient noise degrades performance [64, 114]. Furthermore, understanding SIIDs is closely linked to accessibility research [50]. Investigating how people with situationally induced limitations interact with devices often overlaps with, and informs, the understanding of needs for users with motor or visual impairments [50].

Next, after understanding the effects of different SIIDs, comes *modelling*, which involves creating representations of the user or environment to predict situational impairments and inform design [144]. Robust models allow researchers to simulate constrained environments or user capabilities. Prior work has successfully modelled colour perception to assist those with impaired colour vision and used situation-specific models to improve recolouring tools [143]. Similarly, biomechanical models such as Weight-Induced Consumed Endurance have been developed to estimate shoulder fatigue and then inform a novel adaptive interface [67]. Modelling is essential for creating simulations that allow designers to test interfaces against potential situational impairments without needing to physically recreate the environment.

2.2.2 Sensing Context and Adapting Interfaces. Once the nature of an impairment is understood and modelled, the focus shifts to *sensing* the impairment. Detecting SIIDs is a fundamental prerequisite for successful adaptive interface [112]. Ideally, this detection leverages the built-in sensors of digital devices to avoid burdening users with extra instrumentation [115]. Researchers have utilized various sensor data to detect specific environmental constraints; for example, smartphone battery temperature has been used to detect drops in ambient temperature [115], and accelerometer data has been utilized to detect when a user is walking [39].

The final stage of the framework is *adapting* the interface to best accommodate detected situational impairments. Adaptation techniques aim to compensate for the negative effects of SIIDs by modifying the interaction paradigm. Common examples include increasing target sizes to accommodate reduced accuracy [117] and providing audio guidance when visual attention is fragmented [148].

2.2.3 Factors that Can Cause SIIDs. Additionally, Wobbrock [160] summarised a categorical list of factors that can cause SIIDs, highlighting the vast range of potential impairments that users of interactive technologies may encounter. Consequently, research in this domain can be categorised according to both the above four procedural steps and the specific SIIDs categories. Wobbrock [160] further combined the four stages into two parts, as these are often studied in conjunction, with *understanding* and *modelling* frequently evaluated together, and *sensing* and *adapting* commonly integrated as a combined approach to mitigation.

In this survey, we adopt the *Understanding, Modelling, Sensing, and Adapting* framework, alongside the established SIIDs categories, to systematically evaluate the current state of MR research regarding situational impairments.

2.3 Why is it necessary to understand the effects of SIIDs? (RQ1)

2.3.1 SIIDs in Mobile, Desktop, and Wearable Computing. In the domain of mobile computing, devices such as smartphones and tablets allow users to work in diverse contexts, yet this mobility exposes interactions to environmental interference. Studies have extensively evaluated several challenges on smartphones, where walking imposes significant constraints on mobile interaction [91, 94], encumbrance also shows similar trends [92, 93], and both dim and bright light can increase movement time [111]. While cold environments primarily hinder visual search speeds [107] and noise significantly slows down complex input tasks, e.g., text entry [114], stress creates a unique behavioural pattern whereby users rush through tasks faster but with significant compromise in accuracy [109].

The challenges identified in mobile computing often draw parallels to desktop accessibility research. For instance, input errors and challenges faced by users of small mobile devices have been found to be similar to those experienced by users with vision impairments using desktop computers [22]. This relationship suggests that understanding SIIDs can enhance the broader understanding of accessibility needs and adaptive user interfaces.

As technology evolves, the scope of SIIDs research is expanding to wearable computing. Devices such as smartwatches, fitness trackers, and smart glasses are becoming increasingly vital but remain susceptible to interaction challenges caused by changing contexts. The constant evolution of the internet of things and wearable devices suggests that addressing SIIDs will become even more critical, requiring new methods to sense and model unforeseen situations [47]. Consequently, researchers argue that solutions must leverage built-in sensors—such as accelerometers [39] or battery temperature sensors [115]—to detect these constraints without adding burden to the user.

2.3.2 Extending SIIDs to Mixed Reality. Understanding SIIDs is important for MR because it blends digital content with the physical world, turning the user's immediate environment into part of the interface. Unlike mobile or desktop computing, where the user can often opt out of a distracting environment by looking away, MR users are constantly exposed to dynamic spatial factors. Furthermore, MR interactions (e.g., mid-air gestures and gaze tracking) are physically demanding and highly sensitive to physical fatigue and environmental instability [68]. Without a deep understanding of SIIDs, MR systems risk becoming unusable in the real-world scenarios they are designed to augment [65]. By understanding and modelling these situational impairments, researchers can develop MR interfaces that can dynamically adapt to different real-world scenarios [73].

3 METHOD

To investigate how situational impairments are evaluated, operationalised, and addressed in MR, we conducted a systematic review following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines [96].

3.1 Research Questions

Building on the research questions introduced earlier, we decompose them into specific, comparable dimensions (e.g., measurement choices, evaluation approaches, and mitigation strategies) to guide the systematic review and structure our analysis. This decomposition enables consistent analysis of individual studies and supports the synthesis of patterns and gaps across the literature. Now that we have addressed RQ1 (Section 2.3), we move on to RQ2 and RQ3.

> **RQ2.** How do distinct SIIDs affect MR user performance?

This question aims to examine the effects of overall trends and specific factors on user performance. We focus on this question because MR is increasingly used beyond controlled laboratory settings, where users face dynamic, real-world conditions that can systematically disrupt interaction. In addressing RQ2, we aim to characterise the MR tasks and evaluation methods used to study performance effects, identify which SIIDs are most consistently linked to performance degradation, and understand the mechanisms underlying these effects. Understanding these mechanisms can inform the design and evaluation of MR systems that target the underlying sources of impairment rather than only its surface problem.

> **RQ3.** What interaction techniques and design strategies can improve usability and user experience in these scenarios?

This question examines practical applications and solutions to mitigate the effects of SIIDs on MR interaction, and the evidence supporting their effectiveness. We focus on this question to chart the current research landscape and identify areas for improvement. Addressing RQ3 allows us to map solution approaches to the specific challenges they target. In our analysis, we therefore organise the literature by factors and further break each factor into distinct, recurring problems. For each problem, we extract the corresponding mitigation strategies and summarise how they are evaluated and under what conditions they appear to be effective. This synthesis highlights which design patterns are repeatedly successful, where trade-offs emerge, and which problem solution pairings remain underexplored.

3.2 Paper Identification and Selection

Initially, a search strategy was implemented to retrieve study records from publication databases, supplemented by key literature identified through prior research experience (Section 3.2.1). Subsequently, titles and abstracts were screened to exclude irrelevant studies, and full-text articles were evaluated against the eligibility criteria (Section 3.2.2), ultimately yielding the final set of included articles. Figure 1 provides a visual overview of this filtering workflow.

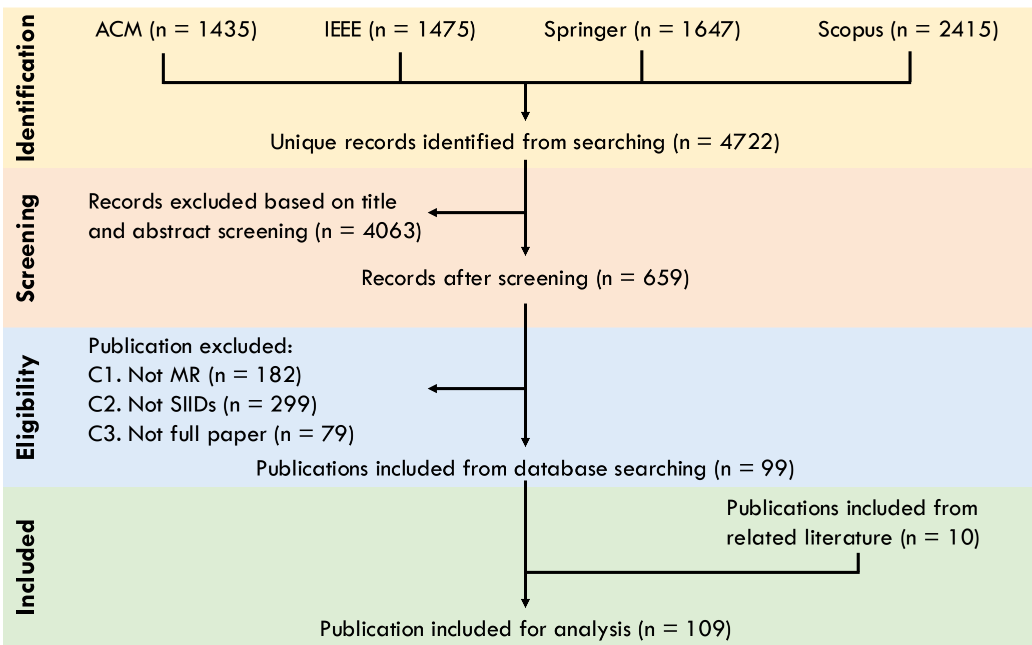

Fig. 1. PRISMA flow chart of our systematic review.

3.2.1 *Systematic Query Search Strategy.* To identify relevant, high-impact literature on SIIDs in MR, we first conducted systematic queries across four major online databases: ACM Digital Library, IEEE Xplore, SpringerLink, and Scopus. Scopus was used to source additional unique papers. Our search strategy was based on the "Categorized List of Factors That Can Cause SIIDs" proposed by Wobbrock [160], which guided our identification of publications primarily focused on SIIDs and allowed for a comprehensive analysis of the field. For each category within the framework, we constructed search strings by combining category-specific keywords using "OR" operator and linking them to a unified set of general terms using "AND". As illustrated in the simplified example below (formatted for the ACM Digital Library), we restricted our search to publication titles following prior studies [166], as preliminary searches including abstracts yielded a large volume of irrelevant records:

```
Title:(([Category-Specific Keywords]) AND (mixed reality OR MR OR
augmented reality OR AR))
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A comprehensive list of the search categories, corresponding keyword sets, and the initial number of publications identified from each database is provided in Table 6 in the Appendix. Our initial database search yielded 6,972 records across ACM (n=1435), IEEE (n=1475), Springer (n=1647), and Scopus (n=2415). After excluding duplicates by DOI, 4,722 studies were initially included for screening and eligibility assessment.

3.2.2 Publication Selection Strategy. Following the initial retrieval, we screened titles and abstracts to remove irrelevant entries (e.g., non-HCI studies), resulting in a subset of 659 records. We then conducted a full-text eligibility assessment based on three exclusion criteria: (1) the study does not involve MR; (2) the study is not related to SIIDs; and (3) the publication is not a full paper. The first two criteria ensured adherence to the research scope, while the third excluded posters and extended abstracts as they lack the depth of full evaluation. Two researchers independently performed the whole data cleaning process using the criteria and procedures described above, achieving an inter-rater reliability score of Cohen's $\kappa = 0.906$, which indicates strong agreement [26, 60]. Any discrepancies were resolved through discussion to produce the final dataset. After applying these filters, the final corpus selected via the query consisted of 99 publications.

To ensure comprehensive coverage, we also manually screened for papers identified in the relevant literature, from the references of the selected publications, and from prior research experience that were absent from the database search results. We targeted relevant papers from high-impact venues, including CHI, UIST, VRST, SUI, CSCW, Ubicomp, DIS, IUI, TOG, IMWUT, PACM HCI, TOCHI, IEEE VR, ISMAR, TVCG, Computer Graphics Forum, IJHCS, Computers & Graphics, IJHCI, and Springer VR. We selected these venues based on their prominence in the HCI and XR fields, as well as their high impact rankings in Google Scholar Metrics. This process resulted in 10 additional papers. In total, 109 studies were included in this review.

4 RESULTS

We categorised the 109 identified papers based on the framework (Section 2.2), which outlines four key components: Understanding, Modelling, Sensing, and Adapting. We synthesised these into two primary clusters [160]. We combined studies that mainly focus on characterising the nature and theoretical behaviour of SIIDs prior to system intervention under Understanding and Modelling, and grouped studies that mainly focus on the technical solutions used to detect and adapt to these impairments under Sensing and Adapting. Table 7 in Appendix B provides an overview of all identified papers corresponding to their respective categories.

4.1 Statistics

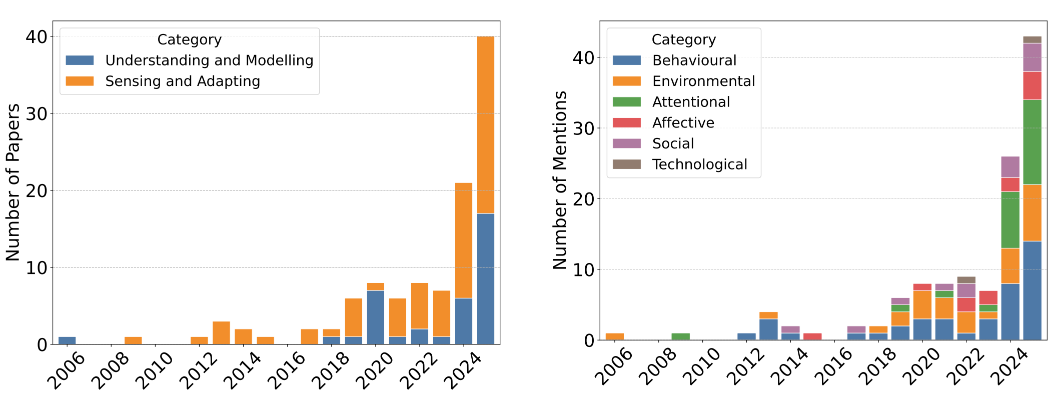

Fig. 2. Distribution of papers by publication year. Left: The stacked bars categorise the literature into two primary clusters. Right: The stacked bars categorise the literature into six SIIDs groups.

The selected publications span the period from 2006 to 2025. The analysis of publication trends reveals a significant growth in relevant research activity, particularly in the later years. A large portion of the studies (72 of 109, 66.1%) are classified as Sensing and Adapting strategies, while 37 studies (33.9%) are Understanding and Modelling studies. While the field was historically dominated by sensing and adapting strategies, research activity has accelerated across both categories, culminating in record highs in both by 2025. This rise is likely due to the broader growth in the overall volume of published research in HCI [65, 110]. These findings regarding the study types are presented in Figure 2 left.

We subsequently examined the specific thematic categories addressed in the selected studies, as illustrated in Figure 2 right. Given that individual studies often addressed multiple categories simultaneously, the aggregate number of categorised instances (n = 121) exceeds the total count of unique publications (n = 109). The analysis indicates that Environmental factors and Behavioural factors constitute the largest proportions of the literature, appearing in 41 instances (33.9%) and 29 instances (24%) respectively. These are followed by Attentional factors (n = 24, 19.8%) and Social factors (n = 13, 10.7%). The remaining classifications comprise Affective (n = 12, 9.9%) and Technological factors (n = 2, 1.7%). Our results show that while Environmental factors were historically dominant, the number of studies investigating Behavioural factors in the most recent year is greater than the number of studies examining Environmental or Attentional factors.

4.2 Understanding and Modelling Studies (RQ2)

We analysed 37 papers that categorised as Understanding and Modelling from our dataset to identify common tasks and their corresponding metrics, and the effects of distinct factors on user performance.

4.2.1 Common Tasks and Evaluation Methods. Table 1 provides a comprehensive taxonomy of these tasks and their specific evaluation criteria. The distribution of research focus highlights a primary interest in fundamental interaction, with Fitts' Law tasks (target acquisition via gaze, pinch, direct selection, or ray-casting) being the most prevalent, appearing in 27% of the analysed literature within the behavioural and environmental category. These tasks are predominantly used to evaluate the efficiency and precision of different input methods by modelling the speed-accuracy trade-off. Specifically, they measure the time required to move to and select a target based on its distance and size, using metrics such as Movement Time and Throughput, and measure the accuracy using Error Rate, and Pointing Offset. Within the behavioural and environmental categories, Fitts' Law is frequently paired with Text Entry and Voice Dictation tasks (13.5%). These assess input efficiency by requiring users to input specific sentences or strings, with performance analysed through Words Per Minute, Word Error Rate, and Task Completion Rate.

Table 1. Taxonomy of Mixed Reality Tasks and Performance Metrics

Tasks	Types	Performance Metrics	Ref.
Behavioural and Environmental Category			
Fitt's Law Task	Direct selection, ray-casting, gaze, pinch, head gaze	Movement/completion time, throughput, accuracy/error rate, pointing/euclidean/horizontal angular/vertical angular/reach offset, contact time, cursor stability	[3, 64, 66, 69, 72, 116, 124, 137, 164, 171]
Text Entry / Voice Dictation	Keypad, voice	Words per minute, word error rate (substitution, insertion, omission), task completion rate, corrected error rate, uncorrected error rate	[29, 64, 66, 72, 127]
Obstacle Navigation	Avoiding/bypassing real or virtual static pedestrians	Average velocity, walking trajectory, max lateral displacement, minimum distance	[20]

Continued on next page

Table 1 – Continued from previous page

Tasks	Types	Performance Metrics	Ref.
3D Cube Task	Gaze, pinch, drag gestures	Joint angle, joint moment, muscle activity, speed	[56, 57]
Environmental and Attentional Category			
Machine Interaction	Power on, alarm check, axis zeroing, drone interaction, learning anatomy	Task completion time, reaction time, hazard prediction score, accuracy, total keypresses, retention test score, gaze metrics (fixation duration/number)	[9, 18, 40, 48]
Sorting / Matching	Image sorting (living, non-living), block-matching, scale perception, colour perception	Reaction time, total completion time, task accuracy, hand use, perceived scale, gaze metrics, motor behaviour speed	[1, 16, 123]
Visual Discrimination	Peripheral targets, navigated viewing, pattern, text identification	Reaction time, accuracy/error rate, completion time, perceived depth, agreement rates	[19, 23, 37, 42, 88, 135]
N-Back Task	Virtual, digital	Accuracy, hand use, total completion time	[1, 100]
Stroop Task	Space	Response time, task accuracy	[154]
Assembly Task	Stacking shapes, Recreating images	Completion time, error rate	[71, 105]

Perceptual and cognitive limits are explored through Visual Discrimination tasks (16.2%), which often test legibility, pattern recognition, and character identification under extreme conditions. These are closely related to Sorting/Matching and Paired-Comparison tasks, where users distinguish between objects based on colour, shape, or depth. The common measures for these activities are Reaction Time, Completion Time, and Accuracy. To further measure cognitive load and executive function, researchers utilize specialized psychological assessments such as the N-Back and Stroop tasks. In the N-Back task, users must identify if a current stimulus matches one presented N steps earlier, testing working memory updating. In the Stroop task, users identify a physical attribute while inhibiting a conflicting stimulus, measuring selective attention and interference. These tasks are often performed while the user is under a certain situation to assess dual-task performance, with analysis focusing on Response Time and Task Accuracy.

4.2.2 Subjective Measures. Beyond objective performance metrics, the analysed studies utilize a range of standardized instruments to capture the multifaceted user experience. We list questionnaires that were employed at least twice across the selected papers, as summarized in Table 2.

Table 2. Summary of Subjective Questionnaires and Measures.

Questionnaire	Constructs Measured	Freq.	Ref
NASA-TLX	Mental work load (mental, physical, and temporal demand, performance, effort, and frustration)	43.2%	[1, 5, 16, 29, 40, 41, 48, 69, 71, 88, 100, 116, 124, 127, 137, 154]
SSQ	Simulator sickness (nausea, oculomotor symptoms, and disorientation)	16.2%	[19, 20, 43, 69, 71, 127]
SUS	Perceived system usability and interface consistency	10.8%	[20, 29, 127, 137]
PQ / IPQ	Spatial presence, involvement, and experienced realism	8.1%	[16, 18, 23]
Borg CR10	Perceived physical exertion and localized muscle fatigue	8.1%	[57, 124, 127]

The NASA Task Load Index (NASA-TLX) [45] emerged as the most prevalent tool, appearing in 43.2% of the literature. It is used for evaluating how situational factors exacerbate mental, physical, and temporal demands. Physical well-being and system accessibility are primarily measured through the Simulator Sickness Questionnaire (SSQ, 16.2%) [51] and the System Usability Scale (SUS, 10.8%) [14], which monitor physiological side effects and overall interface quality, respectively.

To quantify physical strain, the Borg CR10 scale [12] is frequently adopted (8.1%), especially in studies involving mid-air interaction or sustained physical activity. Furthermore, immersion and spatial awareness are assessed via the Presence Questionnaire (PQ) [158] and Igroup Presence Questionnaire (IPQ) [146], totalling 8.1% of the reviewed studies. Beyond these standardized scales, the research landscape includes various specialized measures (used in <5% of studies) such as the Visual Fatigue Questionnaire (VFQ) [46] and Trust in Automation (TiA) [62]. Qualitatively, 18.9% of studies incorporated semi-structured interviews and 16.2% used open-ended feedback to contextualize user behaviours and compensatory strategies.

4.2.3 Participants and Environments. Across the 37 analysed papers, recruitment strategies typically engaged between 10 and 60 participants, with an average sample size of approximately 24 individuals per study. While 59.5% of research relies on university students, 10.8% of the studies targeted specialized populations and 16.2% of the studies target general adults. Gender distribution across these studies varied significantly, ranging from balanced groups to those reflecting the specific demographics of professional sectors like construction or automotive engineering.

The research settings are predominantly conducted in controlled laboratory environments (78.4%). These environments allowed researchers to precisely manipulate real-world factors such as ambient illuminance. Conversely, 16.2% of the research transitioned to real-world or in-the-wild settings to test the resilience of MR systems. These field locations included busy city streets, outdoor university campuses, greenhouses, and the passenger seats of moving vehicles. 5.4% of the studies adopted a hybrid approach, comparing performance in a controlled courtyard against more dynamic outdoor environments.

4.2.4 Effects on User Performance. Physical locomotion and cognitive load appear to have the most severe impact on task performance. Walking imposes the highest effect, reducing text entry throughput by 51% and increasing ray-cast movement time by 63% [66, 124]. This impact is significantly higher than that of encumbrance (e.g., carrying 1 kg), which lowers selection throughput by 22% [66], or driving, which reduces throughput by 19% [116]. High cognitive load is similarly detrimental, increasing operation time by 49% [48]. In comparison, environmental factors tend to produce more moderate variations. Adverse lighting conditions can reduce text entry throughput by 30% [72], whereas the effect of noise is comparatively minor, with meaningless speech lowering throughput by only 5.36% [64]. However, divided attention during multitasking noticeably reduces speed, increasing reaction times by 20% [88].

Accuracy reduces quickly during active movement and high-distraction scenarios. Walking increases error rates, with one study reporting a 500% increase in ray-casting errors [124], while jumping reduces selection accuracy by 67.6% [69]. Multitasking and incongruent distractions can reduce accuracy by approximately 40% to 52% [1, 16], a magnitude comparable to the 50% increase in typing errors observed under physical encumbrance [66]. Environmental noise, specifically at high levels (70 dB) or involving speech, increases word error rates by 49.3% [29].

While physical factors such as walking increase motion intensity [69], environmental stressors such as noise and poor lighting primarily manifest as increased subjective stress, mental demand, and visual fatigue [41, 72]. Interestingly, the source of the load dictates the user's adaptation strategy. Under multitasking conditions, users tend to prioritize real-world tasks over virtual ones [1]. In contrast, when dealing with visual clutter or colouration issues, users may alter their physical approach, such as misjudging scale or depth [71, 123].

Table 3. Summary of the effects of different factors detailed in Understanding and Modelling. – denotes no relevant studies were identified.

Factors	Time/Throughput	Accuracy/Error Rate	User Behaviour
Behavioural			
Walking	• ray-cast movement time ↑ 63% [66] • movement time ↑ [124] • ray-cast throughput ↓ 32% [66] • text entry throughput ↓ 51% [66]	• spatial accuracy ↓ [171] • selection accuracy ↓ 67.6% while jumping [69] • success rate ↓ [124] • performance using torso is better than using head as the reference frame [171] • ray-casting error rate ↑ 500% [124]	• no significant differences in turning kinematics (speed, deviation, distance) when avoiding real vs. virtual obstacles [20] • intensity of user motion ↑ [69]
Driving	• throughput ↓ 19% [116]	• hazard prediction ↓ 19% [40]	• workload ↑ 11% [116]
Encumbrance	• selection movement time ↑ 28% under 1 kg weight [66] • selection throughput ↓ 22% under 1 kg weight [66]	• typing uncorrected error rate ↑ 50% under 1 kg weight [66]	• bend elbows and placed wrists closer to upper body and kept hands lower [66]
Out of reach	• perception time ↑ [135]	• performance ↓ under near and far distance [56]	• shoulder angle and middle deltoid activity ↑ under far target [57] • shoulder flexion and abduction ↑ under far distance [57]
Environmental			
Noise	• text-entry throughput ↓ 5.36% under meaningless speech [64] • throughput ↓ 2.74% under urban outdoor noise [64] • text input speed ↓ under 70 dB [127] • processing time ↑ under 70 dB [127] • typing throughput ↑ 3.33% under urban indoor noise [64] • movement time ↑ 4.44% under fast-tempo music [64]	• pointing offset ↑ 4.07% under slow-tempo music [64] • WER ↑ 49.3% in high noise [29] • accuracy ↓ under 70 dB [29] • accuracy – under all noise [127]	• subjective stress ↑ [41] • task load ↑ [41] • speak volume ↑ [41] • mental demand ↑ under 70 dB [127] • temporal demand ↑ under 70 dB [127] • perceived usability ↓ under 70 dB [127] • self-assessed performance ↓ 54% [41]
Light	• ray-cast throughput ↓ 17% under bright sunlight [72] • ray-cast throughput ↓ 27% under dark ambience [72] • text entry throughput ↓ 30% under dark ambience [72] • text entry throughput ↓ 8% under bright light [72] • response time ↑ under background texture and lighting (2000–25000 lux) [37]	• error rate – [37] • add noticability in the low-quality range under bright light [43] • unusable in outdoor environments with lighting > 10000 lux [32] • sub-optimal contrast in indoor work range (100–1000 lux) [32] • visibility ↓ above 8000 lux [3] • hand rays unstable below 1 lux [3]	• easy to perceive degradation under dark light [43] • visual fatigue ↑ under dark ambience and bright sunlight [72] • immersion presence and usability ↓ under high illuminance [23] • perceived closer under high luminance [42]
Colouration	• response time ↓ with yellow background [154] • task time ↓ under transparency [19] • task time – under colour coding [9] • orange buttons effective under moving backgrounds [164] • blue least effective under moving backgrounds [164]	• accuracy ↑ with yellow background [154] • absolute depth error ↑ under decreasing contrast under black-and-white texture [71] • accuracy of depth judgements ↑ under high colour contrast texture [71] • scale underestimated [123] • virtual colours overestimated [123] • depth perception – under texture density [71]	• cognitive demand ↓ with yellow background [154] • frustration ↓ with yellow background [154] • subjective mental effort ↑ under non-coded material [9] • perceived closer under cool colours [42]
Attentional			

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Table 3 – Continued from previous page

Factors	Time/Throughput	Accuracy/Error Rate	User Behaviour
Divided attention	• reaction times ↓ under incongruent distractions [16] • dwell time ↑ 7.68% during collaboration [18]	• accuracy ↓ 40% under incongruent distractions [16] • performance ↓ under top-down distraction [5]	• cognitive load ↑ under incongruent distractions [16] • productivity ↓ 30.4% during collaboration [18] • scattered gaze behaviour under spatial distraction [5]
Multitasking	• reaction time ↑ 20% [88] • virtual answer time ↑ 23% under 2-back task [100] • walking velocity ↓ 13% [88]	• accuracy ↓ 51.96% [1] • walking error ↑ 11% [100]	• prioritize real-world tasks [1]
Cognitive load	• operation time ↑ 49% under high cognitive load [48]	–	–
Social			
Privacy and security	–	• recognition rates ↓ for immersive attacks [105]	–

4.3 Sensing and Adapting Strategies (RQ3)

We analysed 72 papers from our dataset that were categorised as Sensing and Adapting strategies. We identify the specific problems researchers aimed to address, the methods they used, and the resulting improvements in performance.

4.3.1 Problems and Sensing/Adapting Strategies. Table 4 categorises these sensing and adapting strategies into specific problems for each factor. A significant portion of the research focuses on the behavioural category, where the primary goal is maintaining situational awareness while preventing instability. Mitigation techniques often involve "motion-aware" information delivery, such as Velocity Capping to stabilise views during gait oscillations [125] or adaptive UI placement that moves windows to walls to clear the user's path [59]. For Encumbrance, researchers have moved toward hands-free interaction, utilising eye gaze, micro gestures, and even teeth clenching [122] to facilitate input when the hands are occupied or fatigued. In Confined Spaces, techniques like Redirected Walking [134] are used to maximise limited physical tracking areas. Furthermore, to avoid "visual noise" in the real world, systems now adapt virtual object colours based on background contrast or use depth-sensing to highlight hazardous stair edges for the visually impaired [170].

Table 4. Summary of the specific problems and associated sensing and adaptation strategies.

Factors	Specific Problems	Sensing and Adapting Strategies
Behavioural		
Walking	Instability of reference frames and distraction	• Pinch grip with offset [49] • Combined adaptation technique (velocity capping + scoring) [125]
	Detecting and avoiding obstacles	• AR enhancements (3D outlines) [81] • Hybrid deep learning architecture [98] • Multimodal attention model (EEG+IMU+Gaze) [97]
	Adaptation of traffic and meeting types	• High-traffic: smaller, transparent, higher window placement; meetings: larger screens for listening; larger speaker windows for discussion [17] • World-locked cues (3D boxes) [36] • AR collision warning and virtual traffic lights [25]
	General support	• Preferences: auto-centering and manual follow+rotation • Adaptation: moved windows to walls to maintain environmental awareness [59]
	Noisy tracking data and gait oscillations	• Double exponential smoothing • Optimized factors stabilized gait oscillations and enabled turn reactions within 1–2 seconds [89]

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Table 4 – Continued from previous page

Factors	Specific Problems	Sensing and Adapting Strategies
	Improper superimposition of pop-up message	• Motion-aware AR information delivery [74] • High-priority: display-fixed (bottom) improved notification performance; low-priority: body-fixed (right) enhanced walking speed [61]
Driving	Traffic dynamics Distraction	• Assist risk detection [153] • Superimposes a selected number of infotainment data on the windshield only when this is safe [13]
Encumbrance	Arm fatigue and lack of precision/speed	• Eye-gaze and microgestures techniques [15] • Amplifying the visual movement of the object [141] • Sense current arm status to predict fatigue level [67] • Sensing eye blinks on an invisible keyboard [77] • Hands-free alternatives specifically for scrolling and selecting in lists [31] • Increasing object brightness [8]
	Hand occupied	• The system senses input/output channel availability (vision, hearing, hands) using egocentric vision and LLMs [75] • Facial input with personalised classifier [157] • Computer vision-driven model for natural free hand interaction [27] • Hands-free interaction (head-tracking + voice) [104]
	Socially awkward	• Teeth-clenching-based target selection [122]
Out of reach	Impaired depth perception	• Cloning distant objects to near-field [142]
Environmental		
Noise	Speech recognition in noisy environments	• Sensing the target speaker's direction (via eye/hand tracking) and adapting the neural network [120]
Colouration	Uncontrollable real-world background colour	• Adapted virtual object colour [82]
Difficult terrain	Insufficient foot clearance (toe height) or poor foot placement	• Adapting virtual stripe patterns to the user's contrast sensitivity [84]
	Unable to detect stair edges and depth	• Sensing stair geometry to project highlights [170]
Confined space	Lack of physical tracking space Physical space partitioning (virtual boundaries); defining precise 3D virtual borders	• Redirected walking [134] • Larger reference spaces allow gains to be increased further [55] • Private view: faster individual task completion; non-partitioning: faster shared object placement; partitioned + public view: improved object arrangement time [55, 95] • Multi-perspective AR [103]
Force	Lack of force reduce realism Haptic devices preventing natural interaction with real objects	• EMS-based feedback [76] • Increase force sensitivity at the edges of the finger [165]
Attentional		
Divided attention	Inadvertent dangerous behaviour	• Monitoring systems using MR sensors (head, eyes, hands) [21]
	Move eyes/head significantly	• Sensing eye-gaze to adapt content placement [156]
Interruptions	Difficulty resuming tasks after interruptions	• AR cues [6, 7]
Multitasking	Hard to detect current cognitive workload	• Integrating LLM with feedforward neural network [2]
Cognitive load	Cognitive deficiencies	• The system captures sensory data and psychophysical states to discover triggers affecting stress [10] • AR assistance [161] • 3D models by helping users create mental images [138]
	Overwhelming tasks	• Full combination of visual/haptic effects [129] • Gaze visualisation [155]
	Different cognitive load	• Use eye-trackers to objectively measure different subtypes [85, 133] • AR-based adaptive training system that dynamically adjusts task difficulty based on real-time user performance [24, 152]
Affective		

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Table 4 – Continued from previous page

Factors	Specific Problems	Sensing and Adapting Strategies
Emotion	Lack of motivation	• ARCADIA comprises several gamified therapeutic activities, with a strong emphasis on fostering patient motivation [130] • AR bio-feedback without compromising the existing verbal, non-verbal, and paraverbal communication cues [149]
	Anxiety	• Playing on a real piano with real hand displayed in virtual scene [34] • An interaction paradigm enables humans to engage with technology in a way that closely resembles natural human behaviour and communication [136] • A humorous AR gag toy by applying emotional and universal design principles [139]
	Stress	• MR interaction with virtual animals [21, 86, 87] • Detecting user stress using only HMD head tracking (e.g., total displacement, speed) [35] • AR hypnosis [169]
	Mental fatigue	• Eye-tracking data from AR headsets can serve as a reliable fatigue indicator [99]
Social		
Crowds	Bystanders unknowingly occlude with MR interface	• "Always-on" visualization (projecting interface shadows on the floor) [53] • Sensing physical environment/people via computer vision and accommodates context using LLM reasoning to optimize UI placement [70]
Privacy and security	Indirect privacy leak	• AI-UPTA-S system detect shadow [140] • Linking physical and virtual spaces [102] • Sensing internal body voice propagation via a contact microphone [121]
	User location	• ARCore with lower structural complexity [44]
	Multiple/collaborative user interaction	• Using dummy bots/hidden chat boxes for unauthorized users [145] • Machine learning to automatically identify the occurrences of privacy risks in raw data captured by AR applications [28] • Sensing visual gestures and holograms [128] • TARPS is an out-of-the-box solution to add protection features to collaborative AR applications in a configurable manner [58]
Technological		
Small input/output	Restricted shoulder/head rotation	• HeadTurner actuates the resting surface to yield in pitch and yaw axes [163]
	Small and clipped FoV	• Adapting VR "amplified movement" techniques to AR allowed users to travel less distance in difficult search tasks [126]

To address Cognitive Load and Divided Attention, mitigation strategies have become proactive. Several studies utilise eye-tracking and neural networks to measure real-time mental fatigue or workload, dynamically adjusting task difficulty or providing high-priority warnings [48]. In the Affective domain, AR is being leveraged as a therapeutic tool. Strategies include using virtual animals in Mixed Reality to reduce stress [86] and employing "AR Hypnosis" or "gag toys" to mitigate anxiety. These systems often sense the user's internal state to tailor the emotional intervention.

Social mitigation strategies primarily focus on Privacy and Security. To protect users in public, researchers have developed systems that detect potential shadow leaks of private data [140] or use dummy bots to obscure sensitive information from unauthorised bystanders in collaborative settings [145]. Technological mitigations aim to overcome hardware limitations, such as restricted Fields of View. By amplifying movements, researchers allow users to navigate large virtual datasets without requiring excessive physical rotation, effectively bypassing the physical constraints of current AR headsets [126].

4.3.2 Participants and Environments. Across the 72 analysed papers, recruitment strategies typically enrolled 10-50 participants, with an average sample size of approximately 24 per study. A significant portion of research relies on university students (47.2%), and 19.4% of studies targeted specialised populations, including geriatric inpatients with mild cognitive impairment, people with low vision, mental health patients, military personnel, and front-line workers. General adult populations were recruited in approximately 13.9% of the cases.

The research settings were predominantly controlled laboratory environments (72.2%), allowing for precise manipulation of variables. However, 15.3% of research was conducted "in the wild" to test ecological validity, utilising diverse locations such as mental health day-care centres, therapeutic kitchens, city streets with connected vehicles, and staircases. 5.6% of the research adopted a hybrid approach, validating initial results in the lab before moving to real-world environments like office corridors or outdoor balconies.

4.3.3 Evaluation Methods. As shown in Table 5, Behavioural and Environmental factors primarily rely on standard HCI metrics such as completion time, error rates, and throughput. However, the Behavioural category is more detailed in its use of specialised physical scales, such as the Borg CR10 for perceived exertion and Social Comfort ratings to assess the viability of interaction in public spaces. In contrast, Environmental evaluations are more localised, focusing on spatial metrics such as accuracy to determine how effectively the system reconciles virtual content with physical constraints.

Table 5. Summary of the subjective and objective measures for each category.

Factors	**Objective Measures**	**Subjective Measures**
Behavioural	movement/completion/reaction time, error rate/accuracy/deviation, throughput, walking speed, head/eye movement	NASA-TLX, SUS, SSQ, Borg CR10, user experience questionnaire, user preference rating, perceived safety/usability, SEQ, social comfort
Environmental	completion time, error rate/accuracy, distance, position	NASA-TLX, SUS, SSQ
Attentional	error rate/accuracy, completion time, eye/head movement, heart rate	NASA-TLX, SUS, SSQ, MFI-20, custom perception/usability questionnaire
Affective	resumption time, error rate/accuracy, heart rate	NASA-TLX, SSQ, valence, arousal, MFI-20, short stress state questionnaire, modified technology anxiety scale, K-POMS-B, total mood disturbance, user experience questionnaire, self-assessment manikin
Social	error rate/accuracy, F1 score, completion time	NASA-TLX, SUS, custom acceptance questionnaire
Technological	response time	NASA-TLX, SUS, fast motion sickness, user preference questionnaire

A significant shift occurs when moving into Attentional, Affective, and Social domains, where metrics move beyond simple task performance to capture the user's internal state. While NASA-TLX and SUS remain widely used across all categories as baseline measures for mental workload, the Affective category introduces highly specialised psychological instruments such as the Self-Assessment Manikin (SAM) and the Profile of Mood States (K-POMS-B) to quantify emotional shifts. Interestingly, heart rate and eye-movement data serve as common objective bridges between the Attentional and Affective categories, suggesting that physiological monitoring is a shared priority for researchers addressing cognitive and emotional impairments. Conversely, Technological and Social evaluations are more specialised; the former focuses on hardware-related issues, such as the Fast Motion Sickness scale [52], while the latter prioritises data-integrity metrics, such as F1 scores, alongside custom acceptance questionnaires to evaluate the interpersonal implications of MR use.

5 DISCUSSION

We synthesise key considerations for conducting situational impairments research from a general methodological perspective, where prior research often overlooks these issues. We then examine how situational impairments studies are typically evaluated and identify recurring methodological flaws that can undermine their validity and interpretability.

5.1 Key Considerations for Situational Impairments Research

5.1.1 Identify Situational Impairments using Empirical Evidence. Much of the current literature prioritises proposing solutions before the underlying problem is adequately characterised. Of the 109 publications reviewed, only 37 were classified as Understanding and Modelling studies (33.9%). Although situational impairments are presumed to arise from everyday situations, environments, and contexts, researchers should empirically demonstrate and justify that these conditions measurably degrade performance [108]. Besides, without a foundational understanding and robust modelling of these impairments, the development of reliable sensing and adaptive mechanisms remains constrained to surface level problems. These empirical models could provide the necessary logic for adaptive interfaces to transition from reactive error-correction to proactive environmental awareness.

Understanding why the degradation occurs is essential as it allows future work to target specific contributing mechanisms (e.g., attentional interference, perceptual limitations, motor constraints) rather than treating the impairment factor as a single undifferentiated phenomenon. For example, empirical studies examining MR interaction while walking compare different anchoring strategies (e.g., head-anchored versus hand-anchored interfaces) and report their effects on task performance [100]. However, anchoring choices can influence different aspects of interaction. For example, head-anchored interface may reduce the impact of hand tremor and improve target stability, but it can also increase the risk of attentional diversion from the real world. In contrast, a hand-anchored interface may better support environmental awareness and opportunistic glances, yet it typically demands higher motor stability and may be more susceptible to motion-induced jitter. Understanding different mechanisms behind the effect enables interventions to address the core causes of performance decline, rather than merely mitigating surface-level effects.

Empirical identification can be supported through field observations [162], controlled manipulations of factors (e.g., motion, noise, glare, divided attention) [66, 116], or mixed-method approaches that connect subjective reports to objective behavioural changes [64]. Such grounding clarifies what the impairment is, how it affects, and under which conditions it emerges, providing a defensible foundation for subsequent design and evaluation.

5.1.2 Design for Long Term Use. Many proposed solutions are presented as short-term prototypes and evaluated over a brief user study (e.g., a one-hour lab session). However, situational impairments are typically recurrent and episodic, arising intermittently across everyday routines rather than within a single bounded interaction [160]. Consequently, solutions should be assessed not only for immediate effectiveness but also for sustained usability, learnability, and long-term acceptability [144]. This includes examining how users adapt over time, whether they integrate the mitigation into everyday use, compensate in unexpected ways, or abandon the feature once the initial novelty wears off.

Long-term evaluation is particularly important because mitigations may impose costs outside impaired moments. For example, a head-pointing technique can be proposed to support hands-free interaction while walking and to reduce selection errors caused by hand tremor [125]. However, head pointing typically requires users to visually fixate on targets to confirm selection, which can divert attention away from the real world and introduce new safety or situational-awareness challenges. In practice, users may also need to switch between head pointing and hand pointing depending on context. Researchers should therefore consider the "always-on" problem of a design: whether it disrupts established workflows, demands sustained attention, or requires frequent configuration. Relatedly, learning retention is also important. If a solution relies on a new interaction paradigm, it is essential to assess whether users can remember and reliably execute the interaction after extended gaps, and whether the interface supports reacquisition when users return to it.

Where possible, studies should examine the persistence of benefits across multiple sessions and contexts, reporting whether performance gains remain stable, improve with practice, or diminish over time. Such longitudinal evidence provides a clearer account of real-world viability and helps distinguish interventions that are merely effective in short demonstrations from those that remain useful and low-cost in sustained everyday use.

5.1.3 Validate in Real World Scenarios. Most situational impairments studies are conducted in laboratory settings. Of the 109 papers identified, only 23 publications were analysed in real-world settings (21.1%). Lab experiments are valuable for isolating mechanisms and establishing causal relationships, but they often underrepresent the variability and practical constraints [66]. For example, when evaluating an obstacle warning system, researchers map detected hazards to a predefined database and test the system in only a small set of situations [97]. While such studies were conducted in-the-wild, the setting remains highly controlled: the range of hazards is constrained, the scenarios are limited, and the environment is simplified relative to the diversity of real-world conditions. As a result, effects observed in the lab may overestimate benefits, miss failure modes, or fail to capture the conditions under which a mitigation is truly needed.

To strengthen ecological validity, researchers should test whether the observed problems and proposed benefits hold under realistic constraints in dynamic situations, environments, and contexts [116]. In-the-wild deployments, diary and experience-sampling studies, and opportunistic evaluations can reveal edge cases that controlled protocols overlook, and can help distinguish robust improvements from artefacts of simplified tasks or artificially stable conditions. These approaches also capture practical factors and the trade-offs users make in real-world scenarios.

When full field deployment is infeasible, studies should still approximate real-world complexity. This can be achieved through scenario-based tasks with meaningful stakes, realistic stimuli, and systematic context manipulations that mimic naturally occurring conditions (e.g., walking while interacting, background noise, variable lighting). Importantly, researchers should report how closely experimental conditions resemble the intended real context and justify the realism of their method. Such steps improve generalisability and provide clearer evidence that findings translate beyond the lab.

5.1.4 Proposing Unified Solutions Across Situational Impairments. Situational impairments are highly diverse, yet many share common functional consequences such as reduced attention, limited dexterity, degraded perception, or constrained interaction opportunities. Rather than proposing one-off fixes for narrow contexts, researchers should consider whether a solution targets an underlying limitation that generalises across multiple impairments (e.g., reducing precision demands, lowering visual load, enabling robust interaction under motion) [75]. Recent work has begun to move in this direction by demonstrating that a single approach can identify a wide range of situational impairments states concurrently [75]. Building on such advances in detection, future research can shift from mitigating impairments one at a time toward developing interventions that support users across multiple conditions within a unified framework.

5.1.5 Framing Research through the Lens of Situational Impairments. Although many studies aim to address real-world constraints that limit user performance, they are not always framed as situational impairments research, often because the construct itself is not clearly defined or recognised. For example, work on adaptive user interfaces is frequently framed as context-aware computing, even when it is effectively addressing situational impairments [70]. In our corpus of 109 papers, only 8 papers explicitly mentioned situational impairments or situational awareness in the keyword or abstract. This lack of explicit positioning makes it harder for findings to accumulate into a coherent body of knowledge, as relevant contributions remain scattered across different areas such as MR interaction, accessibility, safety, or context-aware computing [70]. Bringing situational impairments "into the field" therefore involves more than evaluating technologies in realistic settings. It also requires clearly articulating how the studied constraints constitute situational impairments, which mechanisms drive the performance degradation, and how the proposed intervention addresses those mechanisms. A field-oriented framing helps ensure that studies start from authentic real-world challenges and end with solutions that are deployable, meaningful, and comparable across the broader situational impairments literature.

5.1.6 Extending Situational Impairments Research to Different Contexts. Although situational impairments research is typically categorised by situational, environmental, and contextual factors, its underlying mechanisms often overlap with challenges faced by older adults and people with disabilities (e.g., low vision). Leveraging this overlap, situational impairments research can be broadened beyond short-term environmental and contextual disruptions to inform inclusive designs that remain effective across a wider range of user capabilities. For instance, a stair warning system designed to mitigate momentary inattention can also support older users by providing timely cues that reduce fall risk and decision uncertainty during everyday mobility [84]. This positions situational impairments as a lens for robust, inclusive design, where the research could focus on interventions that lower perceptual load, reduce precision demands, and offer multimodal support that generalises to both temporary impairments and longer-term capability changes.

5.2 Task Usage and Evaluation

Situational impairments research is ultimately grounded in effects observed while participants complete tasks [11, 113]. A standard experimental workflow typically involves (1) identifying the variable or construct of interest, (2) selecting tasks that validly elicit or operationalise that construct, and (3) evaluating performance and experience using appropriate measures. At each of these stages, methodological missteps can bias results or weaken interpretation [4]. The following sections summarise common pitfalls at each step and provide practical guidance for designing tasks and evaluations that more reliably support defensible theoretical claims.

5.2.1 Distinguish Observed and Latent Variables. Experimental design often requires using observed variables to draw inferences about latent variables, underlying constructs that are theoretically meaningful but not directly measurable [151]. For instance, a researcher is interested in the effects of distraction, yet evaluate it through observable variables such as reaction time, while the latent mechanism driving this change is an increase in cognitive load [16]. The appropriate causal logic is typically: an experimental condition (e.g., distraction) influences a latent construct (e.g., cognitive load), which in turn shapes an observed metric (e.g., reaction time). Reaction time is better understood as an empirical trace rather than the construct of interest itself. Accordingly, analysis and discussion should emphasise the hypothesised latent effect behind the phenomenon, recognising that reported metrics are often abstractions of hidden internal states [151]. Therefore, it makes measurement assumptions transparent, acknowledges potential sources of error or confounding, and provides a clearer basis for replication and validation. In this way, researchers strengthen the interpretability of their findings and the credibility of the claimed causal pathway.

5.2.2 Select the Appropriate Task. Selecting an appropriate task is the first step in ensuring construct validity when studying situational impairments, because the task must operationalise the factors that is hypothesised to be impaired [11]. As summarised in Table 1, when the research objective is to investigate how attention function is modulated by specific variables (i.e., attentional impairments), tasks such as the N-back or Stroop task are most appropriate. These tasks are grounded in cognitive psychology; the N-back targets the manipulation of working memory, while the Stroop task isolates the interference effect and inhibitory control. In contrast, when situational factors are expected to degrade physical behaviour or interaction efficiency, Fitts' Law task and text entry task provide the necessary theoretical framework. Fitts' Law explicitly models motor performance through the relationship between movement time, distance to the target, and target width, enabling quantification via completion time, throughput, and accuracy/error rate rather than internal cognitive processing [78–80, 167]. Similarly, text entry/voice dictation tasks can sensitively reflect interaction impairment using words per minute and word error rate, along with corrected versus uncorrected error rates [131, 168]. By selecting tasks from Table 1 according to the impairment category, researchers can better understand how different categories of situational impairments affect performance on tasks that evaluate specific functions.

5.2.3 Align Measurement with Construct. In research on situational impairments, rigorous measurement relies on ensuring that the chosen instruments capture the specific construct that the study aims to explain. Without this alignment, observed effects may be attributed to the wrong mechanism. A common methodological pitfall is the conflation of distinct theoretical constructs [4]. For example, researchers frequently confuse mental workload with cognitive load [4]. The NASA-TLX is a widely used subjective, multidimensional instrument that quantifies mental workload across several dimensions (e.g., mental demand, temporal demand, effort, frustration). Yet, a substantial portion of the literature (approximately 65%) cites NASA-TLX as if it were a direct measure of cognitive load. This is partly because, in everyday language, "workload" and "load" are often used interchangeably, and the NASA-TLX subscales such as mental demand and effort seem to align intuitively with cognitive processing demands [4]. This slippage matters because the two constructs are conceptually and mechanistically different. Cognitive load typically refers to the total mental effort required by working memory during information processing and learning. In contrast, mental workload characterises the cost an operator incurs to maintain a given level of performance under task and environmental demands, reflecting not only cognitive demands but also time pressure, motivational factors, and perceived strain. When instruments are treated as interchangeable proxies, researchers risk a construct-measurement misalignment: the data collected primarily reflect perceived workload, while the theoretical claims are framed in terms of working-memory load. Such a mismatch can distort interpretation, weaken internal validity, and lead to misleading conclusions in subsequent studies.

5.2.4 Follow Standardized Evaluation. In situational impairments research, standardized evaluation is essential for producing results that are comparable across studies and interpretable against benchmarks. Researchers often do not use psychometric tools correctly [4]. For example, the NASA-TLX was developed as a multidimensional instrument intended to aggregate six sub-scales into a single weighted average to represent overall workload. However, many researchers skip this calculation and evaluate the sub-scales separately, which deviates from the tool's intended design (approximately 70%). Similarly, while the SUS is a standard measure for usability, researchers frequently neglect to compare results against common grading criteria [63]. Instead of using established thresholds to determine if a system is truly usable, studies often only compare differences between groups. This fails to provide the necessary context to know if a system is actually functional or just slightly better than a flawed alternative. Therefore, researchers should apply standardized scoring procedures and benchmark results against established criteria to support valid, actionable conclusions.

5.3 Limitations

While our systematic review followed the PRISMA guidelines through iterative query searches, several limitations regarding the corpus and scope must be acknowledged. First, although we are confident in the representativeness of the selected articles, this survey cannot be treated as an exhaustive list of every study in the domain, as some relevant works may have been inadvertently omitted, particularly due to variations in titling or keyword conventions across different research communities [166]. Thus, this corpus should be viewed as a representative subset of the field rather than an exhaustive catalogue of every situational impairments study in MR.

Additionally, we primarily focused on the core situational factors established by Wobbrock [160], as these represent the most documented and validated triggers of situational impairments in HCI. However, we recognize that as MR technology evolves, additional factors—such as specific physiological conditions, long-term cognitive adaptations, or complex legal and ethical constraints—will certainly emerge. We chose to prioritize these well-established categories to provide a clear, standardized baseline for the community, but we acknowledge that further research is needed to explore the less common situational variables.

Finally, our analysis is strictly restricted to the context of MR. For the purposes of this work, we define MR as experiences delivered via head-mounted displays (HMDs) that feature interactive virtual objects superimposed on the physical world (detailed in Section 2.1). While situational impairments also affect "Heads-Down" computing (e.g., smartphones) and other spatial formats (e.g., large-scale projections or CAVE systems), we focused on HMD-based MR due to its unique "Heads-Up, Hands-Free" interaction paradigm and the specific challenges of ego-centric spatial awareness. Consequently, solutions identified here may require re-evaluation or adaptation before they can be applied to other display modalities.

6 CONCLUSION

In this survey, we systematically reviewed publications on situationally induced impairments and disabilities in MR. We highlight the need to move MR beyond controlled laboratory settings and into diverse everyday contexts by identifying how situations, environments, and contextual constraints introduce unique challenges. We examine how different impairments degrade user performance and synthesise a taxonomy of sensing and adapting strategies proposed in prior work. We also reflect on current evaluation practices by organising commonly used objective and subjective measures and discussing recurring methodological limitations. Finally, we outline key considerations for researchers, developers, and designers, and propose future research directions for creating and assessing solutions that are empirically grounded, ecologically valid, and generalisable across situational impairments.

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A Systematic Query Search Table

Table 6. Detailed search categories and specific keywords used for database searches, and the initial number of publications identified in each online database (ACM, IEEE, Springer, Scopus). * denotes any number of unknown characters (wild cards).

Categories	Factors	Keywords	ACM	IEEE	Spr.	Sco.
Behavioural	Walking	walk*, obstacle*, locomotion	49	62	34	112
	Driving	drive, driving, ride, riding	168	86	44	135
	Encumbrance	encumbrance, hands-busy, hands-free, carry*, free-hand	30	17	8	36
	Operating machinery	operat* machine*	5	0	5	20
	Out of reach	out of reach, far, further	60	12	23	0
Environmental	Vibration	vibrat*	15	53	53	11

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Table 6 – Continued from previous page

Categories	Factors	Keywords	ACM	IEEE	Spr.	Sco.
	Cold temperatures	temperature*, hot, cold	24	106	159	22
	Ambient noise	nois*	57	167	54	27
	Rainwater, humidity	rain*, humid*	0	9	6	5
	Ambient light	light*, dark*, bright*, dim, glare, illumina*	165	148	121	348
	Coloration	colo*	88	97	225	205
	Smoke, fog, smog, haze	smok*, fog*, smog, haze	5	7	9	20
	Difficult terrain	terrain*, stair*	10	6	9	19
	Confinement	confine*, constrain*	58	83	114	35
	Extraneous forces	force*	33	60	39	56
Attentional	Divided attention	divided attention, distract*, eyes-busy, eyes-free	14	9	4	1
	Interruptions	interrupt*	3	1	2	3
	Multitasking	multitask*	6	6	3	12
	Cognitive load	cogniti*, overload	116	98	160	413
Affective	Emotion	affective, emotion*, stress, anxiety, fear, fatigue*, ex-haust*, haste, elat*, intoxicat*	126	60	146	276
Social	Conversation	conversation*	41	43	38	50
	Crowds	crowd*	38	36	36	38
	Social norms	social norm*	35	35	35	35
	Laws, policies	law*, polic*, procedure*	57	54	96	71
	Privacy	priva*, security	58	46	46	60
Technological	Small input/output	small, tiny	50	60	153	54
	Lack of power	power, battery	64	122	60	112
	Lack of connectivity	connect*, wi-fi	53	53	54	79

B List of Relevant Publications

Table 7. Summary of understanding and modelling studies and sensing and adapting strategies, organised by SIIDs category and factor. – denotes no relevant studies were identified.

Factors	Understanding and Modelling Studies	Sensing and Adapting Strategies
Behavioural		
Walking	Li et al. [66]; Chen et al. [20]; Zhou et al. [171]; Shin et al. [124]; Li et al. [69]; Nenna et al. [88]; Rasch et al. [100]; Sünderkamp et al. [137]; Goodge et al. [40]	Suma et al. [134]; Shin et al. [125]; Pei et al. [97]; Jannat et al. [49]; Maman and Szpiro [81]; Chang et al. [17]; Lages and Bowman [59]; Nescher and Kunz [89]; Liu and Lindlbauer [74]; Fox et al. [36]; Lee and Woo [61]; Połap et al. [98]; Clérigo et al. [25]; Wang et al. [153]
Driving	Sasalovici et al. [116]	Bram-Larbi et al. [13]

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Factors	Understanding and Modelling Studies	Sensing and Adapting Strategies
Encumbrance	Li et al. [66]	Caillet et al. [15]; Taima et al. [141]; Liu et al. [75]; Li et al. [67]; Lu et al. [77]; Drewes et al. [31]; Wilson et al. [157]; Shen et al. [122]; Datcu and Lukosch [27]; Sadri et al. [104]; Ban et al. [8]
Operating machinery	–	–
Out of reach	Sun and Varshney [135]; Kim et al. [57]; Kim et al. [56]	Riechmann-Thom and Rexilius [103]; Tamboli et al. [142]
Environmental		
Vibration	–	–
Cold temperatures	–	–
Noise	Li et al. [64]; Gottsacker et al. [41]; Sinlapanuntakul et al. [127]; Derby et al. [29]	Liu et al. [75]; Sekiguchi et al. [120]
Rainwater, humidity	–	–
Light	Gutiérrez et al. [43]; Liu et al. [72]; Erickson et al. [32]; Choi et al. [23]; Gabbard et al. [37]; Alesawy et al. [3]	Liu et al. [75]
Colouration	Wang et al. [154]; Shin et al. [123]; Guo et al. [42]; Bautista et al. [9]; Liu et al. [71]; Chen et al. [19]; Yamin et al. [164]	Marino et al. [82]
Smoke, fog, smog, haze	–	–
Difficult terrain	–	Miura et al. [84]; Zhao et al. [170]
Confined space	–	Kim et al. [55]; Suma et al. [134]; Riechmann-Thom and Rexilius [103]; Ouedraogo et al. [95]
Force	–	Lopes et al. [76]; Youn et al. [165];
Attentional		
Divided attention	Zhou et al. [171]; Chandio et al. [16]; Chang et al. [18]; Baek et al. [5]	Chen et al. [21]; Liu et al. [75]; Wecker and Yigitbas [156]; Clérigo et al. [25]
Interruptions	Bahnsen et al. [7]; Bahnsen et al. [6]	Liu et al. [75]; Li et al. [70]
Multitasking	Abbas and Jeong [1]; Nenna et al. [88]; Rasch et al. [100]	Abbas et al. [2]; Liu et al. [75]

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Table 7 – Continued from previous page

Factors	Understanding and Modelling Studies	Sensing and Adapting Strategies
Cognitive load	Hou et al. [48]; Nenna et al. [88]	Beato et al. [10]; Stuhlmacher and Bodensiek [133]; Smith et al. [129]; Wang et al. [155]; Liu et al. [75]; Mohanty et al. [85]; Bram-Larbi et al. [13]; Wolf et al. [161]; Chu et al. [24]; Wang et al. [152]; Suzuki et al. [138]
Affective		
Emotion	Bahnsen et al. [6]; Fang et al. [33]	Soler-Dominguez et al. [130]; Fanger et al. [34]; Sun and Nakajima [136]; Na and Dong [86]; Na et al. [87]; Ferrarotti et al. [35]; Szentirmai [139]; Zhao et al. [169]; Psyllosa et al. [99]; Valente et al. [149]
Social		
Conversation	–	Liu et al. [75]; Li et al. [70]; Sekiguchi et al. [120]
Crowds	–	Khan et al. [53]; Li et al. [70]
Social norms	–	–
Laws, policies	–	–
Privacy and security	Guzman et al. [44]; Sajid et al. [105]	Tabet et al. [140]; Guzman et al. [44]; Tran et al. [145]; Reilly et al. [102]; de C. Costa et al. [28]; Shang and Wu [121]; Sluganovic et al. [128]; Krings and Yigitbas [58]
Technological		
Small input/output	–	Wu et al. [163]; Shin and Kim [126]
Lack of power	–	–
Lack of connectivity	–	–

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