



**Facultad
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URUGUAY

Study of factors that impact the engagement of visitors to informal science learning spaces

María Soledad Machado Corral

Postgraduate program in Chemistry, Education
Facultad de Química
Universidad de la República

Montevideo – Uruguay
March of 2025



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María Soledad Machado Corral

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RESUMEN

Este trabajo investiga los factores que impactan el involucramiento de visitantes en espacios de educación no formal en ciencias, particularmente en centros de ciencia.

La investigación se centra en el rol de las prácticas de facilitación y el diseño de exhibiciones, basándose en el trabajo previo de la autora sobre facilitación. Un componente clave de esta tesis es el refinamiento y validación de un Marco Conceptual de Facilitación ("Framework" de Facilitación), que identifica cuatro dimensiones fundamentales para una facilitación efectiva: Comfort, Información, Reflexión y Uso de la Exhibición. Además, se desarrolló una aplicación web llamada SOLEIL para optimizar la recolección y el análisis de datos en centros de ciencia.

La tesis emplea un diseño de investigación en múltiples etapas, incluyendo un Estudio Integral, que analiza un amplio conjunto de datos secundarios, y un Estudio Ampliado que incorpora un mayor número de variables mediante observaciones y encuestas en tres centros de ciencia. Ambos estudios utilizan métodos cuantitativos, incluyendo regresión ordinal, para identificar predictores significativos del involucramiento de los visitantes. La investigación también detalla el proceso de validación del Framework de Facilitación a través de la aplicación SOLEIL, demostrando su fiabilidad y utilidad para analizar interacciones entre visitantes y facilitadores. Los resultados ofrecen información sobre cómo las características y comportamiento de los visitantes, las estrategias de facilitación y las características de las exhibiciones interactúan para influir en los niveles de involucramiento. La tesis concluye proponiendo una serie de buenas prácticas para mejorar el involucramiento de los visitantes en centros de ciencia, que también pueden aplicarse a otros entornos de educación informal.

Palabras claves:

Involucramiento de visitantes, Centros de ciencia, Facilitación, Diseño de

exhibiciones, Aprendizaje informal.

ABSTRACT

This work investigates the factors that impact visitor engagement in informal science learning spaces, particularly science centers.

The research focuses on the roles of facilitation practices and exhibit design, building upon the author's previous work on facilitation. A key component of this thesis is the refinement and validation of a Facilitation Framework, which identifies four key dimensions of effective facilitation: Comfort, Information, Reflection, and Exhibit Use. Furthermore, a custom web-based application called SOLEIL was developed to streamline data collection and analysis.

The thesis employs a multi-stage research design, including a Comprehensive Study that analyzes a large secondary dataset of visitor interactions and an Extended Study that incorporates a wider range of variables through observations and surveys across three science centers. Both studies utilize quantitative methods, including ordinal regression, to identify significant predictors of visitor engagement. The research also details the validation process of the Facilitation Framework using the SOLEIL app, demonstrating its reliability and comprehensiveness for analyzing visitor-facilitator interactions. The findings provide insights into how visitor demographics, facilitation strategies, and exhibit characteristics interplay to influence engagement levels, and the thesis concludes by proposing best practices for enhancing visitor engagement in informal science education settings.

Keywords:

Visitor Engagement, Science Centers, Facilitation, Exhibit Design, Informal science learning.

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Chapter 1

Introduction

Informal science learning spaces, such as science centers, museums, zoos, aquaria, and botanical gardens, have emerged as vital venues for public engagement with science and lifelong learning. Unlike formal educational settings, these spaces offer visitors the freedom to explore at their own pace, select areas of personal interest, and engage in hands-on, interactive experiences that bridge the gap between theoretical knowledge and real-world phenomena. By providing dynamic, multisensory experiences, these venues not only display scientific artifacts but also create immersive environments that spark curiosity and foster sustained learning. As critical nodes in the broader ecosystem of public science communication, informal learning spaces empower diverse audiences to build knowledge, refine skills, and reshape attitudes toward science.

Visitor engagement in these settings is widely recognized as a key indicator of educational impact. Engagement extends beyond mere physical presence; it encompasses cognitive, emotional, and behavioral transformations. As visitors interact with exhibits, they often experience shifts in understanding, develop new skills, and sometimes even change their attitudes toward science. Several theoretical frameworks have been developed to understand this multifaceted phenomenon, with the Visitor-Based Learning Framework (VBLF) standing out as particularly useful in the context of this work. Developed by Barriault (Barriault and Rennie, 2019; Barriault and Pearson, 2010), the VBLF categorizes engagement into three levels: Initiation, Transition, and Breakthrough. These levels reflect progressively deeper involvement and learning, providing clear behavioral markers that allow researchers and practitioners to systematically assess visitor interactions and identify factors that catalyze or hinder

engagement.

The role of facilitators is central to these transformative experiences. Whether trained educators, volunteers, or subject experts, facilitators enrich the visitor experience by interpreting exhibit content, prompting critical thinking, and fostering dialogue. Their interventions can be pivotal in moving visitors from passive observation to active participation. This thesis builds on the author’s previous work (Machado Corral et al., 2021), which provided a preliminary analysis of the impact of facilitation on visitor engagement, underscoring the indispensable role of facilitators in informal science learning environments. Complementing the VBLF, the Facilitation Framework (FF) offers a detailed lens through which to examine facilitation practices. It identifies four key dimensions—Comfort, Information, Reflection, and Exhibit Use—that characterize effective facilitation. The application and validation of this framework form a central pillar of the present thesis, positioning it as both a theoretical extension and a practical tool for improving visitor engagement.

Exhibit design also plays a crucial role in shaping visitor engagement. Wideström (2020) proposes that effective exhibits can be understood along three axes: participation, virtuality, and collaboration. These dimensions describe the level of participation (from static to participative exhibits), the level of virtuality (from physical to virtual), and the level of collaboration (from individual to collaborative). Integrating these dimensions into the analysis of exhibit design helps researchers better understand how different exhibit characteristics contribute to visitor engagement and learning outcomes.

The convergence of these theoretical frameworks—the VBLF, the Facilitation Framework, and the Exhibit Dimensions—provides a comprehensive context for this thesis. By drawing on these diverse yet complementary perspectives, the research not only situates itself within a well-established academic tradition but also pushes boundaries by integrating innovative methodological approaches. This holistic perspective is essential for capturing the complex interplay between visitor behaviors, facilitation strategies, and exhibit design in informal science learning environments.

1.1. Operationalization of Key Terms

For clarity and precision in this study, it is necessary to define several key terms that form the conceptual backbone of the research.

- **Visitor:** In the context of this thesis, a “visitor” is defined as any individual who engages in free-choice learning within an informal science learning environment.
- **Exhibit:** An “exhibit” is conceptualized as an interactive module or display designed to foster visitor engagement and facilitate learning.
- **Facilitator:** A “facilitator” refers to a member of the science center’s staff or a trained volunteer who supports visitor interaction with exhibits. Facilitators are responsible not only for providing information but also for creating an engaging, supportive atmosphere that encourages visitors to explore, question, and reflect on their experiences.
- **Engagement Levels:** Engagement is operationalized using Barriault’s Visitor-Based Learning Framework (VBLF), which categorizes visitor engagement into three levels: Initiation, Transition, and Breakthrough. *Initiation* marks the beginning of the visitor’s interaction with an exhibit, characterized by initial curiosity and brief engagement. *Transition* represents a deeper involvement, where visitors begin to process information and form connections. *Breakthrough* engagement occurs when visitors achieve a high level of cognitive, emotional, and behavioral involvement, leading to significant learning outcomes.
- **Facilitation Dimensions** The Facilitation Framework (FF) identifies four key dimensions that underpin effective facilitation: *Comfort* (the creation of a welcoming and supportive environment), *Information* (the accurate and accessible transmission of content), *Reflection* (the encouragement of critical thinking and self-assessment), and *Exhibit Use* (guidance on how to interact with and benefit from the exhibit).

1.2. Research Rationale and Problem Statement

Despite the growing prominence of informal science learning spaces, assessing visitor engagement remains a challenging endeavor. One of the primary obstacles lies in capturing the nuanced and often transient interactions that characterize these environments. Unlike formal classrooms, where standardized assessments can be applied, informal settings demand methodologies that are sensitive to the spontaneous and heterogeneous nature of visitor behavior.

ior. Interactions at science centers can range from brief glances at signage to in-depth inter-generational discussions about an exhibit’s scientific concept prompted by a facilitator. The complexity of these interactions poses significant challenges for researchers attempting to quantify engagement in a meaningful way.

Building on the insights from our earlier work, which identified key facilitation dimensions that significantly influence visitor engagement, this thesis recognizes that while those findings have laid important groundwork, they also expose critical gaps. Our previous research provided valuable evidence supporting the idea that facilitation can enhance the visitor experience, and also categorized facilitation strategies into four Dimensions: Comfort, Information, Reflection, and Exhibit Use. However, that study primarily focused on exploring the relationship between the presence of a facilitator and changing levels of engagement, and did not fully explore how the experience is mediated by exhibit design or visitor characteristics such as prior knowledge.

The inherent variability of visitor experiences, compounded by diverse exhibit designs and the evolving nature of facilitation practices, calls for a more comprehensive and systematic approach. There remains a need to integrate multiple factors, ranging from the physical characteristics of exhibits to the specific behaviors of visitors and facilitators, into a cohesive analytical framework. Such an approach would not only address the shortcomings of earlier research but also provide a more holistic understanding of the dynamics at play in informal science learning settings.

Addressing these gaps is of paramount importance. A systematic approach that combines the theoretical rigor of frameworks like the VBLF with the methodological innovations enabled by digital tools is necessary to comprehensively assess visitor engagement. This thesis is positioned to meet that need by building upon previous work while incorporating cutting-edge digital methodologies. By doing so, it aims to generate a more detailed and dynamic understanding of how exhibit design, facilitation strategies, and visitor characteristics interact to produce meaningful learning outcomes. Ultimately, this research seeks to offer actionable insights that can inform the development of best practices for enhancing visitor engagement in informal science education settings.

1.3. Research Objectives and Questions

The overarching objective of this thesis is to comprehensively investigate the factors that impact visitor engagement in science centers, with a particular focus on the roles of facilitation and exhibit design. In alignment with and as an extension of our prior work, this study endeavors to unravel the complex interplay between visitor behaviors, exhibit characteristics, and facilitation strategies. By adopting a systematic and multifaceted approach, the thesis aims to deepen our understanding of what drives engagement and how these insights can be operationalized to enhance learning outcomes.

To achieve this general objective, the research sets forth several specific objectives:

- To generate, adapt, and validate instruments for measuring visitor behaviours, facilitator strategies, and exhibit characteristics in the context of informal science learning.
- To develop and leverage digital tools for efficient, scalable data collection and analysis, thereby overcoming the limitations of traditional observational methods.
- To suggest best practices for informal science education settings that can be readily adopted by science centers and similar institutions.

Central to the inquiry are several core research questions that guide the investigation:

- What specific facilitation strategies are most effective in promoting higher levels of visitor engagement, and how do these strategies interact with different visitor demographics and exhibit characteristics?
- How can digital tools be optimized to streamline the collection and analysis of complex observational data in informal science learning environments?
- What are the best practices for integrating facilitation strategies with exhibit design to foster learning experiences among diverse visitor groups?

The expected contributions of this research are multifold. Theoretically, the study aims to extend existing frameworks by incorporating new dimensions of analysis that capture the dynamic nature of visitor engagement. Practically, it is anticipated that the findings will offer concrete recommendations for exhibit

design and facilitation practices, thereby directly benefiting science centers and other informal learning institutions. Methodologically, the integration of digital tools is expected to set a new benchmark for how visitor engagement research can be conducted, offering a scalable and replicable model for future studies. By addressing these objectives and research questions, this thesis endeavors to bridge the gap between theoretical constructs and practical applications, ultimately contributing to the advancement of informal science education.

1.4. Research Design Overview

This thesis employs a multi-stage research design to comprehensively investigate the factors impacting visitor engagement in science centers, bringing together the development of research tools and their application in empirical studies. One component of the research involves developing the SOLEIL app and refining and validating the Facilitation Framework, which were done in parallel to support data collection and analysis. The SOLEIL app is a custom digital tool designed to streamline data collection and enable real-time coding and analysis, while the Facilitation Framework was validated through observational studies and inter-rater reliability assessments to ensure its robustness and applicability across diverse contexts. In the other component of the research, the Comprehensive Study and the Extended Study explore visitor engagement. The Comprehensive Study analyzes a large dataset of visitor interactions, examining demographic characteristics, visitor behaviors, and exhibit attributes to identify key predictors of engagement. Building on this, the Extended Study applies the tools developed earlier, incorporating additional variables (e.g., visitor familiarity and motivation) to offer a more nuanced understanding of the interplay between facilitation strategies, exhibit design, and visitor engagement.

1.5. Structure of the Thesis

The thesis is organized into several chapters, each building upon the previous work and contributing to a holistic understanding of visitor engagement in informal science learning environments. The opening chapter, this **Introduc-**

tion, sets the stage by outlining the context, rationale, objectives, and theoretical frameworks underpinning the research. The subsequent chapter presents a comprehensive **Literature Review** of relevant literature, detailing existing studies on visitor engagement, facilitation practices, and exhibit design, while also identifying key research gaps. Following this, the **Methodology** chapter describes the research design, data collection methods, and analytical techniques employed in the Comprehensive and the Extended Study, the development of the SOLEIL app, and the validation of the Facilitator framework. The **Tools** chapter includes the development of the SOLEIL app, detailing its features and functionalities, and the refinement and validation processes of the Facilitation Framework. The following chapters, **Comprehensive Study** and **Extended Study**, present the findings from each study, highlighting critical trends and patterns in visitor behavior and engagement. Finally, the **Conclusion** chapter synthesizes the results, draws connections with the broader field, outlines the contributions of the research, and proposes directions for future study.

Chapter 2

Literature Review

Visitor engagement in informal science learning spaces, such as science centers, plays a pivotal role in enhancing educational experiences and outcomes. This literature review examines the multifaceted factors influencing visitor learning and engagement in informal science spaces, in particular, in science centers. It focuses on the crucial role of facilitators and their employed strategies, as well as the assessment tools and frameworks used to gauge the effectiveness of these spaces. The review synthesizes existing research on the various factors that influence engagement, providing a comprehensive foundation for understanding how these elements interact, highlighting areas of consensus and identifying research gaps.

The first section explores the unique characteristics and significance of informal science learning environments, particularly science centers, highlighting how they differ from formal education settings. The second section reviews the methods and tools used to research visitor engagement in these spaces, including theoretical frameworks and assessment techniques. The third section examines the various social, environmental, and demographic factors that influence engagement, such as visitor backgrounds, social interactions, and exhibit design. The fourth section focuses on facilitation practices, analyzing the role of science center staff in enhancing visitor experiences and learning outcomes. The fifth section delves into exhibit design, outlining key characteristics that foster engagement and learning. Finally, the sixth section identifies gaps in the literature, emphasizing the need for further research on underexplored aspects of visitor engagement and assessment methodologies.

2.1. Informal Science Learning Environments

Informal science learning environments encompass a wide range of settings, including museums, zoos, aquariums, botanical gardens, and science centers, where learning occurs outside the traditional classroom. These venues play a crucial role in enhancing public understanding of science by providing engaging, accessible, and enjoyable educational experiences. Informal learning spaces are designed to stimulate curiosity and foster lifelong learning by allowing visitors to explore scientific concepts at their own pace through hands-on, interactive activities (Falk and Dierking, 2000; National Research Council, 2009).

Science centers, in particular, are central to this mission. They offer thematic, interactive exhibits that encourage visitors to actively engage with scientific ideas and phenomena (Falk and Storksdieck, 2005; Rennie et al., 2007). According to the National Research Council (2009), science centers are vital components of the science education infrastructure, supporting a wide array of learning outcomes, such as nurturing curiosity, promoting scientific thinking, and fostering an understanding of scientific processes. Falk and Dierking (2000) emphasize that learning in these environments is deeply rooted in the personal, social, and physical contexts of visitors, making science centers uniquely positioned to cater to diverse learning needs and styles.

The evolution of science centers has been marked by significant shifts in both their educational philosophy and exhibit design. Rennie et al. (2007) trace this progression from "first-generation" museums, which primarily focused on static displays and collections, to "third-generation" centers that feature thematic, interactive exhibits aimed at engaging visitors in active learning processes. This transition reflects a broader shift in educational theory from behavioral to cognitive and, more recently, to sociocognitive and sociocultural approaches (Rennie et al., 2007). Falk and Storksdieck (2005) underscore this shift by highlighting the importance of contextual factors in shaping visitor experiences and learning outcomes. The development of sophisticated frameworks like the Visitor-Based Learning Framework (VBLF) by Barriault and Pearson (2010) further exemplifies the ongoing efforts to better understand and enhance visitor engagement and learning.

Learning in informal science settings is distinct in its flexibility, visitor-centered approach, and emphasis on experiential learning. These environments

allow visitors to explore scientific concepts in a self-directed manner, fostering intrinsic motivation and personal relevance (Falk and Dierking, 2000). The interactive and hands-on nature of exhibits in science centers, as described by Allen and Gutwill (2004), promotes active engagement and deeper understanding by encouraging visitors to manipulate objects, test hypotheses, and observe outcomes. Rennie’s work emphasizes that informal learning is not limited to cognitive gains but also includes affective and social dimensions, such as enjoyment, curiosity, and social interaction (Rennie, 2014). Davidsson and Jakobsson (2012) further highlight the importance of social interactions and collaborative learning in these settings, where visitors often learn through discussions and shared experiences with others. This holistic approach to learning, which integrates cognitive, emotional, and social aspects, makes informal science learning environments uniquely effective in promoting a comprehensive understanding of science and fostering a lifelong interest in scientific inquiry.

2.2. Assessing Visitor Engagement in Science Centers

2.2.1. Theoretical frameworks

Theoretical frameworks in informal science learning settings play a crucial role in guiding the design and assessment of visitor experiences. Constructivism, largely influenced by Jean Piaget, posits that learning is an active process where individuals construct new knowledge based on their experiences and prior understanding. This approach emphasizes the role of active participation and personal meaning-making in the learning process (Durbin, 1996; Rennie et al., 2007).

Experiential learning, supported by John Dewey, further highlights the importance of hands-on experiences and reflection. Dewey argued that learners gain the most from experiences that are directly tied to their interests and can be reflected upon to form new knowledge (Hein, 2004; Rennie et al., 2007). Science centers embody these principles by offering interactive exhibits that encourage exploration, experimentation, and personal engagement with scientific concepts (Rennie et al., 2007). These settings foster an environment where visitors can engage deeply with scientific phenomena, reinforcing the idea that

learning is an active, participatory process (Falk and Dierking, 2000).

In addition to constructivism and experiential learning, sociocultural theories have also influenced the understanding of learning in science centers. Vygotsky’s concept of the Zone of Proximal Development (ZPD) underscores the importance of social interaction, scaffolding, and collaboration in supporting learning (Ash et al., 2012; Rennie et al., 2007). This perspective is applied in science centers to design exhibits and facilitation strategies that promote peer learning and guided discovery (Davidsson and Jakobsson, 2012; Rennie et al., 2007; Shaby, Ben-Zvi Assaraf, and Tal, 2019b).

2.2.2. Tools and methods for assessing visitor engagement

Engagement in the context of informal science learning environments, such as science centers, is defined as the degree to which visitors are actively involved, emotionally invested, and behaviorally interacting with exhibits and activities (Brown et al., 2019; Rennie and Howitt, 2020; Shaby, Ben-Zvi Assaraf, and Tal, 2019a). It encompasses cognitive, emotional, and behavioral dimensions. Cognitive engagement refers to the mental processes involved in understanding and learning scientific concepts, including curiosity, critical thinking, and reflection (Block et al., 2015). Emotional engagement involves the feelings and attitudes elicited by exhibits, such as excitement, wonder, and a sense of achievement (Long et al., 2022; Shaby, Ben-Zvi Assaraf, and Tal, 2019a). Behavioral engagement pertains to the physical actions visitors take, such as manipulating exhibits, participating in interactive activities, and discussing their experiences with others (Falk and Storksdieck, 2005). Engagement is a crucial proxy for learning outcomes, as it indicates how effectively visitors are interacting with and absorbing the educational content presented in informal settings (Rennie and Johnston, 2004). It is also related to meaning-making and building knowledge (Rennie and Howitt, 2020). Furthermore, engagement can lead to increased interest in science, fostering a positive attitude towards lifelong learning and scientific inquiry (Longnecker et al., 2022; National Research Council, 2009; Rennie et al., 2007). Thus, understanding and enhancing engagement is critical for science centers to achieve their educational missions.

Assessing visitor engagement in science centers involves a variety of tools and methods tailored to capture the complexities of informal learning. National Research Council (2009) discusses several methods for studying learning in informal environments, including structured self-reports, interviews, focus groups, and tracking visitor movement through exhibits. This report emphasizes the need to understand the relationship between visitors' thoughts and behaviors and stresses the importance of considering the context in which learning occurs. Traditional tools include observations, surveys, and interviews, which provide both qualitative and quantitative data on visitor interactions and experiences (Rennie and Johnston, 2004). Observational studies involve systematically recording visitor behaviors and interactions with exhibits to understand engagement patterns (Falk and Storksdieck, 2005). Surveys and questionnaires collect visitor feedback on their experiences, satisfaction, and learning outcomes, providing valuable quantitative and qualitative data (King et al., 2015). Interviews offer in-depth insights into visitors' thoughts, motivations, and reflections, complementing the quantitative data with rich qualitative information (Davidsson and Jakobsson, 2012). In recent years, researchers have started to use digital tools, such as interactive feedback systems and eye-tracking technologies, which provide detailed data on how visitors interact with exhibits, revealing patterns of attention and engagement that are not easily captured through traditional methods (Damala et al., 2019; Emerson et al., 2020; Krogh-Jespersen et al., 2020; Rainoldi et al., 2018).

Each assessment method has its strengths and weaknesses, making it essential to choose the appropriate tools based on the research questions and context. Observational studies are robust in capturing real-time visitor behaviors and interactions, providing rich, contextual data. However, they can be labor-intensive and subject to observer bias, requiring trained observers and standardized protocols to ensure reliability (Ash et al., 2012; Monteiro et al., 2018). Surveys are efficient for collecting large amounts of data quickly and can be easily administered to diverse audiences. Nevertheless, they may suffer from response bias and often lack the depth needed to understand the nuances of visitor experiences (Andre et al., 2017). Interviews provide rich, detailed insights into visitors' thoughts and motivations, offering a deep understanding of their experiences. However, they are time-consuming and may not be easily generalizable due to the small sample sizes typically involved (Pattison et al., 2019). Cutting-edge digital tools allow researchers to track visitor be-

havior in real-time and gather nuanced data on engagement, offering valuable insights for improving exhibit design and educational impact. However, many advanced technologies are expensive, difficult to install and maintain, and are limited by the technology powering them (Cuellar et al., 2020; Rainoldi et al., 2018).

Therefore, by using multiple data collection methods, researchers can bypass some of their limitations and gain a more comprehensive view of how visitors engage with exhibits and what factors influence their learning. The National Research Council (2009) report advocates for a holistic view of learning, which takes into account both cognitive and behavioral aspects of the visitor experience. Integrating advanced technologies with robust theoretical frameworks, can provide a deeper understanding of the complex, multifaceted nature of informal learning environments. This, in turn, can inform the design of more effective and engaging exhibits and experiences, ultimately enhancing the educational impact of science centers and other informal learning environments (Institute of Museum and Library Services, 2005).

2.2.2.1. Visitor experience frameworks

Several researchers have developed frameworks and tools that provide a multifaceted approach to understanding visitor learning in science centers. They combine observational methods, quantitative assessments, and sociocultural perspectives to offer a rich understanding of how visitors interact with exhibits, facilitators and each other, and how they engage in the learning process.

Arguably one of the most important theoretical frameworks in this field is Falk and Dierking’s 2013, 1992, 2000 Contextual Model of Learning, which emphasizes the interplay of personal, social, and physical contexts, as well as the role of time, in shaping visitor experiences (see Fig. 2.1). The model suggests that learning in informal settings is not just about knowledge acquisition but also about how visitors interact with their environments and with one another, across the span of their visit and beyond. It highlights the dynamic nature of visitor learning, where the context in which learning occurs plays a crucial role in shaping how visitors engage with scientific concepts. By considering the broader social and physical environment, the model helps researchers understand the factors that influence learning beyond just the content of exhibits.

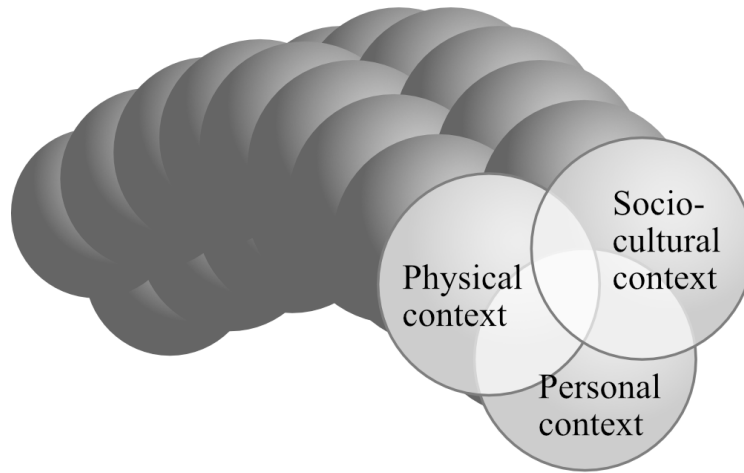


Figure 2.1: Falk and Dierking’s Contextual Model of Learning, adapted from Falk and Dierking (2013)

Another influential framework is the Visitor-Based Learning Framework (VBLF, Table 2.1). It was developed by Barriault (1999), refined with Pearson (Barriault and Pearson, 2010) and later adapted to zoos and aquaria with Rennie (Barriault and Rennie, 2019). This framework categorizes visitor engagement into three levels: Initiation, Transition, and Breakthrough. Each level is defined by observable visitor behaviors that indicate different stages of learning and engagement. The VBLF is particularly useful in assessing the impact of exhibits on visitor learning, emphasizing the learning potential of exhibits rather than focusing solely on cognitive gains or visitor demographics (Barriault and Pearson, 2010). The VBLF has been adopted in several science centers, where it serves as a practical tool for staff to observe and assess the ways visitors interact with exhibits (McCubbins, 2016; Monteiro et al., 2018). The framework is not only valuable for assessing engagement but also for staff training, making it a key resource for science centers that want to enhance the learning experience (Barriault and Pearson, 2010).

The VBLF usefulness can be further enhanced with the use of Visitor Engagement Profiles (VEPs, Fig. 2.2), plotting the percentage of visitors that reach each category of engagement (Barriault and Rennie, 2019; Barriault and Pearson, 2010). The baseline for a VEP is the number of visitors who approach an exhibit and pay attention to it, excluding those who do not stop to interact. Therefore, the VEP focuses on the learning behaviors visitors demonstrate after choosing to engage, rather than assessing an exhibit’s attracting power.

Table 2.1: Barriault’s Visitor-Based Learning Framework (VBLF); adapted from Barriault and Rennie (2019)

Engagement level	Learning behaviors
Initiation	1. Doing the activity. 2. Observing the exhibit or other visitors engaging in the activity.
Transition	3. Repeating the activity. 4. Expressing emotional response in reaction to engaging in the activity.
Breakthrough	5. Referring to past experiences while engaging in activity. 6. Seeking and sharing information. 7. Being engaged and involved: testing variables, making comparisons, using information gained from activity.

Furthermore, VEPs can be used to compare visitor experience across multiple exhibits.

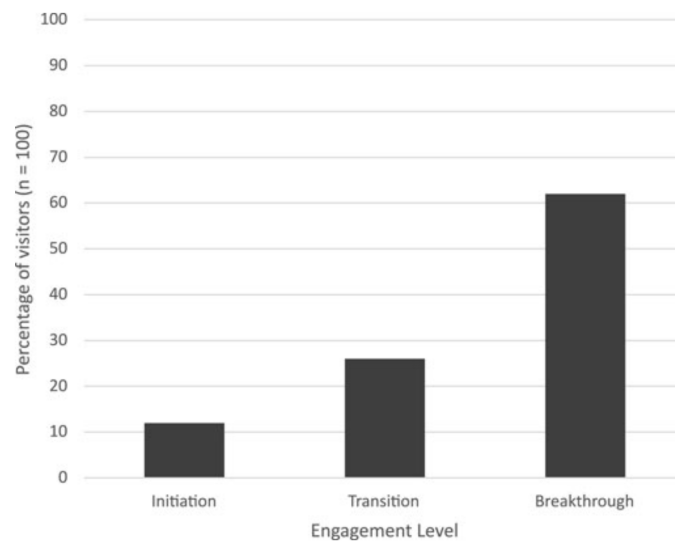


Figure 2.2: Example of a Visitor Engagement Profile (VEP)

Davidsson and Jakobsson (2012) apply a sociocultural approach to studying science centers, using the concepts of mediated action and mediational means to analyze how exhibits engage visitors and guide them in transforming experiences into knowledge (Fig. 2.3). This framework highlights the role of external resources—such as artifacts, physical objects, and human interactions—in shaping the learning process. It draws on Vygotsky’s sociocultural

theory, emphasizing how learning is mediated by interactions with others and the surrounding environment. This approach provides valuable insights into how exhibits, as well as the facilitators and social context within science centers, contribute to the learning process.

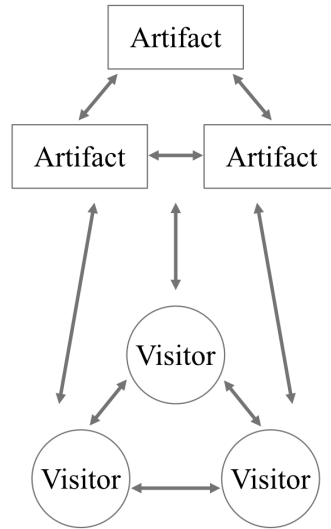


Figure 2.3: Davidsson and Jakobsson’s model of learning and development, adapted from Davidsson and Jakobsson (2012)

Leister et al. (2015) introduced the Visitor Engagement Installation (VEI) profile, which assesses installations along six dimensions: competition, narrative, interaction, physical, visitor control, and social (Fig. 2.4). Unlike observational frameworks, the VEI profile uses measurable values from installations, sensors, and cameras to assess engagement in real time. This tool provides a more focused, installation-centric approach by evaluating the attractiveness, usability, and educational value of exhibits. By using technology to track engagement, the VEI profile offers a more quantifiable method for understanding visitor interaction with exhibits.

Researchers at the Exploratorium developed the Active Prolonged Engagement (APE) framework (Humphrey and Gutwill, 2005), which includes descriptions of behavioral markers for four types of engagement (Table 2.2). Intellectual Engagement is about the connections visitors make to their existing knowledge, the conceptual understandings they gain, and the questions they have. Social Engagement recognizes that museum visits are often social activities that should be encouraged. Physical Engagement includes the ways that visitors interact with the tangible parts of the exhibits. Finally, while Emo-

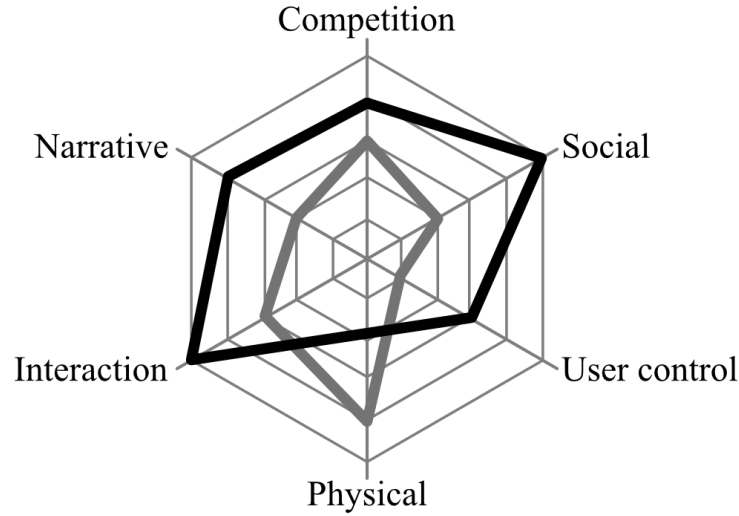


Figure 2.4: Leister’s Visitor Engagement Installation (VEI) profile, adapted from Leister et al. (2015)

tional Engagement may not directly reflect content-knowledge understanding, researchers state it plays an important role in interest development (Humphrey and Gutwill, 2005; Long et al., 2022).

Long et al. (2022) build on the APE and VBLF frameworks to create the Active Prolonged Engagement eXpanded (APEX) framework, which provides a more detailed analysis of visitor engagement (Table 2.3). This framework seeks to provide insight into visitor interactions and engagement at both micro (moment-by-moment) and macro (across multiple groups) levels. The APEX also adds a temporal component that is missing from APE and VBLF, as it seeks to understand the transition between different levels of engagement. The APEX framework provides more information about how participants navigate varying stages of engagement over time, as well as what behaviors precede transitions between stages of engagement.

In the realm of facilitation, Harlow (2019) outlined a framework for practice-based facilitation, which focuses on how facilitators can observe and deepen visitor engagement with exhibits. The Practice Inferred x Engagement Levels (PIxEL) matrix builds on Barriault’s VBLF but differs in its exhibit-specific approach. While the VBLF categorizes engagement into three general levels, the PIxEL matrix defines specific visitor activities and observable behaviors as “engagement levels”. Additionally, the PIxEL matrix provides facilitators with three distinct pathways to navigate their interactions with visitors:

Table 2.2: Exploratorium’s Active Prolonged Engagement framework, adapted from Humphrey and Gutwill (2005)

Engagement	Description
Physical	Visitors physically interact with an exhibit. Includes dwell time, reading labels, where they sit or stand, what buttons they push, and the sequence of activities.
Intellectual	Visitors engage with their minds. Includes making connections to existing knowledge, conceptual understandings, and questions.
Social	Visitors influence other visitors’ experiences at exhibits. Includes conversations, observation, guidance, cooperation, and competition among visitors using an exhibit at the same time, as well as deliberate teaching/learning behavior.
Emotional	The nature and intensity of the affect (positive or negative) exhibited by visitors during the engagement and immediately after.

Table 2.3: Long’s Active Prolonged Engagement eXpanded (APEX) framework, adapted from Long et al. (2022)

Engagement	Code
Physical	Isolated manipulation
	Investigative manipulation
	Integrated manipulation
Intellectual	Seeking knowledge
	Sharing knowledge
	Applying knowledge
Social	Discord
	Harmony
	Independent
	Collaborative
	Active/Passive
	Equal partners
Emotional	Positive emotion
	Neutral emotion
	Negative emotion

maximizing engagement, expanding understanding, and deepening the visitor’s use of the exhibit (Fig. 2.5). The framework is designed to help facilitators create visitor-centered experiences that are grounded in STEM practices and can be adapted for other disciplines. It underscores the importance of facilitators in guiding visitors toward a deeper understanding of scientific concepts, showing how active facilitation can enhance the learning experience in science centers.

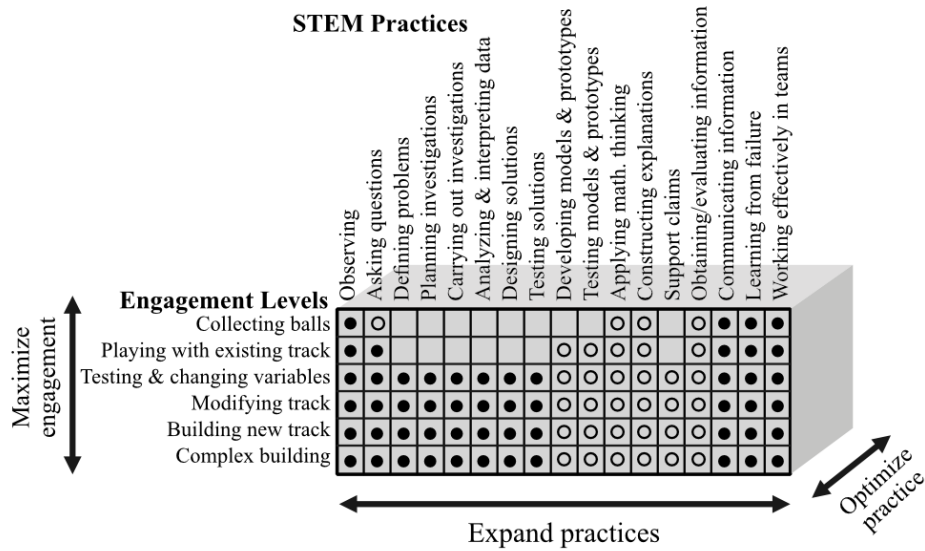


Figure 2.5: Harlow and Skinner’s Practice Inferred x Engagement Levels (PIxEL) framework, adapted from Harlow (2019)

Finally, Machado Corral et al. (2021) explored how interactions with interpretative science center staff influence visitor engagement and learning behaviors using the VBLF. This research identified four Facilitation Dimensions—Comfort, Information, Reflection, and Exhibit Use—that impact the effectiveness of facilitators in promoting engagement and learning (Table 2.4). This research underscores the critical role of facilitators in guiding visitor engagement, suggesting that trained staff can significantly enhance the learning experience by fostering a supportive and interactive environment.

2.2.3. Visitor Engagement: social, environmental and demographic factors

Several factors influence visitor engagement in science centers, reflecting the complex interplay between individual, social, and environmental elements.

Table 2.4: Machado Corral’s Facilitation Framework, adapted from Machado Corral et al. (2021)

Dimension	Facilitator behavior
Comfort	Encouraging language Welcoming Laughter, joy Focus on visitor
Exhibit use	Showing how to use the exhibit Telling how to use the exhibit Insight into exhibit use Using the exhibit along with the visitor Providing technical assistance
Information	Giving context and explanation Giving explanation Giving context Tells a story Explaining how the exhibit works Fun facts
Reflection	Making connections Calling attention to phenomena Proposing a challenge or experiment Inviting reflection Asking a trigger question Asking for a guess or a hypothesis

Personal interest and prior knowledge play significant roles: visitors with a strong interest in science or prior exposure to scientific concepts are more likely to engage deeply with exhibits (Falk and Storksdieck, 2005). Furthermore, they often seek out specific exhibits that align with their interests and spend more time exploring and interacting with them (Massarani, Scalfi, et al., 2021).

Social interactions also profoundly affect engagement. Family dynamics, peer interactions, and the presence of facilitators can significantly enhance the learning experience by providing social scaffolding and shared meaning-making opportunities (Ash et al., 2012; Ellenbogen et al., 2004; Franse et al., 2021; Massarani, Norberto Rocha, et al., 2021). Families visiting science centers often engage in collaborative exploration, with parents and children discussing exhibits and interpreting information together. This collaborative engagement helps to deepen understanding and create shared learning experiences that are memorable and impactful (Davidsson and Jakobsson, 2012). Facilitators play a vital role in this process by guiding visitors through exhibits, encouraging ex-

ploration, and linking exhibit content to visitors' prior knowledge and interests (Franse et al., 2021; Machado Corral et al., 2021; Pattison et al., 2018).

Demographic factors also impact visitor engagement. Age is a primary determinant, with younger children and older adults engaging differently with exhibits. Young children, for example, tend to engage with exhibits through physical interaction, exploration, and play. Their learning is often facilitated by sensory experiences and hands-on activities that stimulate curiosity and experimentation (Block et al., 2015). In contrast, older children and teenagers may prefer exhibits that offer cognitive challenges and opportunities for critical thinking and problem-solving (Allen and Gutwill, 2004; Andre et al., 2017). Adults, particularly those with higher educational backgrounds, often engage more deeply with informational text and reflective activities, seeking to understand complex scientific concepts and their real-world applications (Falk et al., 2016).

The visitor's gender and academic level also play a role in shaping engagement. Research indicates that females are slightly more likely to visit museums and engage in introspective activities, such as reading exhibit texts and reflecting on their experiences (Chang, 2006). Males, on the other hand, often prefer exhibits that offer interactive, hands-on experiences and cognitive challenges (Kirchberg and Tröndle, 2012). Educational level and cultural background further influence how visitors interact with exhibits. Visitors with higher educational backgrounds typically exhibit deeper cognitive engagement and greater knowledge gains, as they are better equipped to understand complex scientific concepts and make connections between new information and existing knowledge (Falk et al., 2016). Cultural background can also shape visitors' perceptions and interactions with exhibits, influencing what they find relevant and interesting (National Research Council, 2009). For instance, exhibits that connect scientific concepts to everyday life and cultural practices can resonate more deeply with visitors from diverse cultural backgrounds, enhancing their engagement and learning (Dawson, 2019).

Even though there's evidence to support the idea that demographic characteristics influence engagement, science center visitors tend to be a relatively homogeneous group. Research indicates that high-income, highly educated individuals who have ample free time are overrepresented among science center visitors, highlighting a need to broaden accessibility and appeal (Ash et al., 2012; Dawson, 2019; Rennie et al., 2007). Strategies to enhance engagement

across different demographic groups include designing exhibits that connect with visitors' everyday lives, employing multilingual signage, and creating programs that specifically target underrepresented communities (Dawson, 2019; Drotner et al., 2018; Durall et al., 2021).

2.2.4. Facilitation Practices

Facilitators in science centers play a critical role in enhancing visitor engagement and learning. They are staff members or volunteers who interact with visitors to guide their exploration, provide information, and foster a deeper understanding of scientific concepts. The role of facilitators extends beyond merely explaining exhibits; they actively engage visitors in discussions, encourage curiosity, and help bridge the gap between complex scientific ideas and the visitor's prior knowledge (Block et al., 2015). For instance, at the Exploratorium in San Francisco, facilitators use interactive demonstrations to explain complex scientific concepts in a fun and engaging way. These sessions not only attract large audiences but also result in high levels of engagement and retention of information (Block et al., 2015). Facilitators are essential in creating a welcoming and supportive learning environment, making science accessible and enjoyable for a diverse audience.

Machado Corral et al. (2021) provides a comprehensive analysis of the impact of facilitators on visitor engagement and learning in science centers. This research highlights the critical role that facilitators play in enhancing the visitor experience, using the Visitor-Based Learning Framework (VBLF) to categorize and assess visitor behaviors. The study demonstrates that the presence of facilitators significantly increases the percentage of visitors achieving higher levels of engagement.

Personalized interactions are crucial for effective facilitation. Facilitators who tailor their approach based on the visitor's age, background, and interests can create more meaningful and impactful learning experiences. For example, facilitators might use simpler language and more basic concepts when interacting with young children, while engaging adults in more complex discussions about the scientific principles behind an exhibit (Block et al., 2015). Furthermore, identifying and using effective facilitation techniques can significantly enhance visitor engagement and learning outcomes. One key technique is asking open-ended questions that encourage visitors to think critically and

explore scientific concepts in greater depth (Machado Corral et al., 2021; Massarani, Norberto Rocha, et al., 2021). By prompting visitors to articulate their thoughts and make connections, facilitators can foster a more interactive and reflective learning experience. Previous work (Machado Corral et al., 2021) identifies four key dimensions of effective facilitation: Comfort, Information, Reflection, and Exhibit Use. Facilitators who excel in creating a comfortable environment help visitors feel welcomed and supported, which is essential for encouraging exploration and interaction. Providing accurate and relevant information is crucial for helping visitors understand complex scientific concepts and see the relevance of exhibits to their own lives. Facilitators also play a vital role in prompting visitors to reflect on their experiences, fostering deeper cognitive engagement. Lastly, effective use of exhibits involves guiding visitors in how to interact with exhibits in ways that maximize learning opportunities. Despite the many benefits of facilitation, there are several challenges and limitations that science centers must navigate. One major challenge is the need for continuous training and professional development for facilitators. Effective facilitation requires a deep understanding of both scientific content and pedagogical techniques, which can be difficult to achieve and maintain without ongoing support (Massarani, Norberto Rocha, et al., 2021). Additionally, facilitators must be adept at adapting their approaches to a diverse audience, which requires flexibility and cultural sensitivity. Another limitation is the potential for variability in the quality of facilitation. Since facilitation relies heavily on the skills and knowledge of individual facilitators, there can be significant differences in the visitor experience depending on who is providing the facilitation. This variability can make it challenging to ensure a consistently high-quality experience for all visitors. Moreover, resource constraints can limit the availability of facilitators, particularly in smaller or underfunded science centers (Massarani, Scalfi, et al., 2021; Monteiro et al., 2018). This can reduce the opportunities for personalized interactions and diminish the overall impact of facilitation on visitor engagement and learning.

2.3. Exhibit Design and Characteristics That Foster Engagement

Exhibit design is fundamental to the success of science centers, as it directly influences visitor engagement, learning, and overall experience. Well-designed exhibits can stimulate curiosity, facilitate hands-on learning, and make complex scientific concepts accessible and enjoyable. Effective exhibit design not only captures the interest of diverse audiences but also provides multiple pathways for interaction, catering to different learning styles and preferences (Hein, 1998; Wideström, 2020). The primary goal of exhibit design in science centers is to create immersive, interactive environments that encourage visitors to explore, experiment, and reflect on scientific phenomena.

Engaging exhibits typically share several key characteristics: interactivity, accessibility, and relevance. Interactivity is perhaps the most crucial element, as it transforms passive observation into active participation. Allen (2004) argues for a research-driven approach to museum exhibit design to create environments that are both engaging and educational. She proposes exhibits should be easily understandable (“immediate apprehendability”), they should connect to broader scientific themes (“conceptual coherence”) and accommodate different learning styles. Interactive exhibits encourage visitors to manipulate objects, conduct experiments, and engage with digital interfaces, leading to deeper cognitive and emotional engagement (Block et al., 2015; Rainoldi et al., 2020). However, too many interactive elements could lead to a confusing or overwhelming experience, especially when there’s no clear hierarchy or when they lead to visitors interfering with one another (Allen and Gutwill, 2004). Accessibility ensures that exhibits are inclusive and can be enjoyed by visitors of all ages, abilities, and backgrounds. This includes physical accessibility features, such as ramps and tactile elements, as well as providing content in multiple languages and formats (Durall et al., 2021). Relevance involves connecting exhibit content to visitors’ everyday lives and interests, making scientific concepts more relatable and meaningful (Davidsson and Jakobsson, 2012).

Technology and digital media play an increasingly vital role in modern exhibit design, offering new possibilities for interaction and engagement. Virtual Reality, Augmented Reality, and interactive digital displays can create immersive environments that allow visitors to explore scientific phenomena

in ways that would be impossible in the physical world alone (Block et al., 2015; Wideström, 2020). For example, virtual reality can transport visitors to distant planets or inside the human body, while augmented can overlay digital information onto physical exhibits, enhancing the learning experience. These technologies can also facilitate personalized learning experiences, adapting content to the visitor’s level of knowledge and interest (Rainoldi et al., 2020). However, integrating technology into exhibits requires careful consideration to ensure it enhances, rather than detracts from, the educational goals of the exhibit (Allen and Gutwill, 2004; Drotner et al., 2018).

Wideström (2020) introduces a classification framework, intended to contribute to the design and analysis of interactive science center exhibitions. The model uses three dimensions to classify exhibits:

- Level of participation: Ranges from static content (predetermined, users discover it) to participatory content (co-created by users).
- Level of virtuality: Ranges from physical space to virtual space.
- Level of collaboration: Ranges from individual interaction to collaborative interaction.

Each dimension can be thought of as an axis, so an exhibit can be classified in either of the extremes or somewhere in the middle. For example, an exhibit like the classic “bed of nails”, which consists only of physical elements would be classified as “Physical”, and a completely virtual experience like a computer game would be classified as “Virtual”. Meanwhile, an exhibit that combines physical and virtual elements, like augmented reality or a computer display that tallies how many times a car has gone around a racetrack, would be classified as “Physical/Virtual”.

An exhibit can be classified in an integral way by combining the three dimensions, and these three dimensions can be represented with a 3x3x3 matrix or the “rubik’s cube model”, where each corner represents an “extreme” type of exhibit and the edge pieces represent the hybrids (Fig. 2.6). For example, a one-person physical puzzle would be classified as “Static, Physical, Individual”, while an escape room with a quest would be “Static, Physical, Collaborative” and a 3D-modelling sandbox would be “Participatory, Virtual, Individual”.

Designing exhibits that engage diverse audiences and accommodate different engagement levels presents several challenges. Science centers attract visitors of all ages, educational backgrounds, and cultural contexts, each with

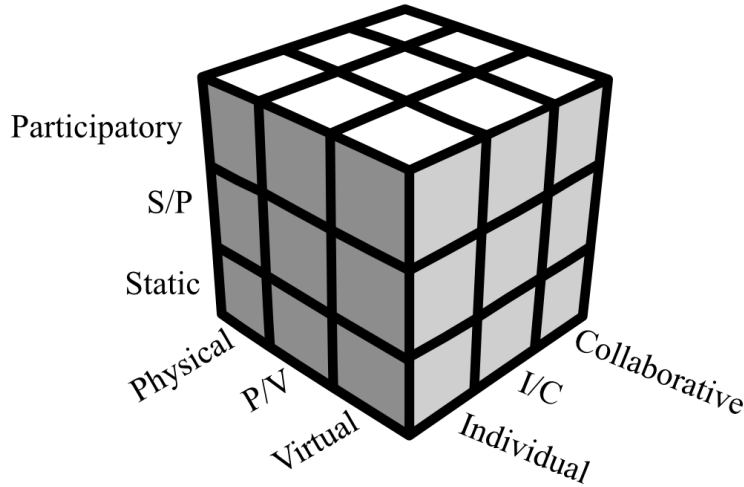


Figure 2.6: Wideström’s model for classifying the three dimensions of interaction with exhibits, adapted from Wideström (2020)

unique needs and interests. To address this diversity, exhibit designers must create flexible and adaptable exhibits that offer multiple entry points and pathways for exploration (Durall et al., 2021; Wideström, 2020). Additionally, balancing educational content with entertainment value is essential to maintain visitor interest while ensuring the integrity of the scientific information presented (Davidsson and Jakobsson, 2012). This balance is particularly challenging in highly participatory exhibits, where visitor contributions can vary widely in quality and accuracy (Ash et al., 2012; Wideström, 2020).

Furthermore, ensuring physical and cognitive accessibility can be difficult. Exhibits must be designed to be navigable for individuals with disabilities while also being intellectually stimulating for those with varying levels of prior knowledge. This often requires innovative design solutions that blend physical and digital elements to create inclusive learning environments (Rainoldi et al., 2020). Additionally, ongoing evaluation and feedback from diverse visitor groups are crucial for refining exhibits and making them more engaging and effective over time (Block et al., 2015).

2.4. Gaps in the Literature

Despite growing interest in visitor engagement, research on how different demographic groups interact with science center exhibits remains relatively

scarce, leaving many questions unanswered. One significant gap is the limited understanding of how different demographic groups engage with science center exhibits. While studies have examined age, gender, and educational background, there is a need for more comprehensive research on how cultural background, socioeconomic status, and prior experiences influence engagement with exhibits (Block et al., 2015; Durall et al., 2021). Understanding how different demographic groups engage with exhibits is crucial for designing inclusive and accessible learning environments. Without this knowledge, science centers may inadvertently create exhibits that do not resonate with or adequately support the learning needs of all visitors (Davidsson and Jakobsson, 2012). Additionally, the impact of social interactions, particularly peer and family dynamics, on visitor engagement has not been fully explored. Although some studies have investigated the role of facilitators, there is a lack of research on the specific techniques and strategies that are most effective in different contexts (Machado Corral et al., 2021; Pattison, Randol, et al., 2017; Rennie et al., 2007).

Another gap lies in the assessment methodologies used to measure engagement. Traditional methods such as surveys and observations provide valuable insights but often fail to capture the nuanced, dynamic nature of visitor interactions with exhibits. There is a need for innovative assessment tools that can provide real-time data on visitor engagement and allow for more detailed analysis of engagement patterns over time (Ash et al., 2012). Furthermore, the integration of digital technologies in exhibits presents new challenges and opportunities for assessment that have not been fully addressed in the literature (Rainoldi et al., 2020).

Addressing these gaps in research is essential for advancing the field of informal learning and enhancing the educational impact of science centers. The present research aims to fill these gaps by focusing on three key areas: studying the factors that impact engagement, exploring the role of social interactions with a focus on facilitation, and the development of innovative assessment tools. By conducting comprehensive studies on how different types of visitors engage with exhibits, facilitators and each other, this research will provide valuable insights that can inform the facilitation process and the design of exhibits that are not only efficient in terms of learning, but also inclusive and accessible.

2.5. Conclusion

This literature review has explored the various factors that shape visitor engagement in science centers, including the unique characteristics of informal learning environments, the role of facilitators, and the influence of social, environmental, and demographic factors. Theoretical frameworks and assessment tools provide a foundation for understanding engagement, yet research continues to evolve as new methodologies and technologies emerge. While existing studies highlight the importance of interactive exhibits and facilitation strategies in enabling visitor learning in science centres, there is still a need to refine engagement assessment methods and develop more inclusive approaches that account for diverse visitor experiences.

Addressing these gaps is essential for advancing the field and ensuring that science centers remain effective and accessible learning spaces for all visitors. By deepening our understanding of visitor engagement, we can design exhibits and facilitation strategies that foster meaningful interactions and enhance learning outcomes. This work contributes to the broader conversation on improving science communication and education in informal settings. In the next chapter, we will discuss the methods used in this study, followed by an analysis of the results and their implications.

Chapter 3

Methodology

This chapter provides a comprehensive overview of the methodologies employed in this research to investigate visitor engagement in science centers. This work is divided into four stages: (1) the development of the SOLEIL app, (2) the validation of the Facilitation Framework, (3) the Comprehensive Study, and (4) the Extended Study. Each stage employs distinct methods to explore various aspects of the visitor experience. The following sections detail the study design, sample selection, measurement tools, and data collection and analysis procedures used in each stage.

The Comprehensive Study is an extensive investigation into the factors that influence visitor engagement at science centers, and stands as a substantial piece of research on its own. However, the insights gained from this initial study paved the way for further exploration. Motivated by the findings of the Comprehensive Study, we decided to extend our research by including other variables in the analysis, which led to the development of SOLEIL, a specialized web-based app. This app was designed to streamline the collection of extensive data, simplifying the process of gathering large volumes of information, including additional details. It also served to validate and update the Facilitation Framework. Both these tools, plus a visitor survey, were used to conduct the Extended Study. The Extended Study allowed us to delve deeper into the nuances of visitor engagement, taking into account not only the presence of a facilitator, but also the facilitation practices employed, providing a more granular understanding of the phenomena observed.

Before moving on to the following sections, we will briefly revisit the definitions of some terms introduced in Chapter 1, as they are used for the purposes



Figure 3.1: An example of a group of visitors interacting with a facilitator at an exhibit

of this study (Fig. 3.1). “Visitors” are people who choose to visit a science center and participate in the activities they offer, engaging in free-choice learning (*i.e.*: they are not part of school visits or guided tours). “Exhibits” are interactive modules or experiences that engage visitors (usually hands-on, but not exclusively). Finally, “facilitator” is a member of staff (both paid and volunteer) who is trained for and tasked with interacting with visitors.

Research Sites

The research for this PhD was conducted across four science centers, each playing a crucial role in different phases of this work (Fig. 3.2). Table 3.1 summarizes which science center was involved in each stage of the research.

Science North is the largest science center in Canada, receiving over 200,000 visitors per year. It is located in Sudbury, Ontario and opened its doors to the public in 1984. The research team from this center kindly allowed us to access the tabulated data from hundreds of exhibits, which was the basis for the Comprehensive Study, as well as video from their archives, which was used for the validation of the Facilitation Framework. Furthermore, they allowed us to conduct new visitor observations and surveys, which were the basis of the Extended Study.

Centro Cultural de la Ciencia is located in Buenos Aires, Argentina, receiving over 200,000 visitors per year. It was inaugurated in 2015, with the main objective of promoting access to science culture to all audiences. This center was selected as an independent science center, to collect video from facilitators, which was used for updating and validating the Facilitation Framework.

Finally, two science centers in Uruguay kindly allowed us to conduct visitor observation and surveys for the Extended Study. Espacio Ciencia is the largest

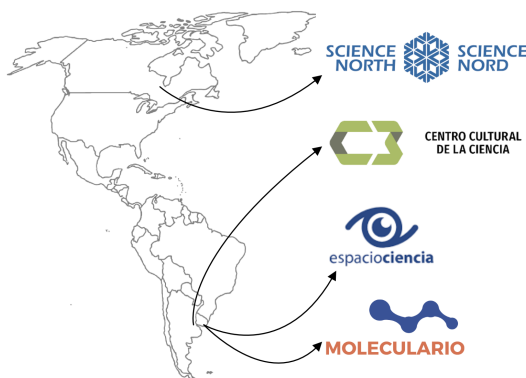


Figure 3.2: Geographical location of the four research sites: Science North (Canada), Centro Cultural de la Ciencia (Argentina), Espacio Ciencia and Moleculario (Uruguay)

Table 3.1: Locations of different stages of this thesis research

	Comprehensive study	Validation of the Facilitation Framework	Extended Study
Science North	X	X	X
Centro Cultural de la Ciencia		X	
Espacio Ciencia			X
Moleculario			X

science center in Uruguay, receiving 50,000 visitors per year. It is located in Montevideo and it was inaugurated in 1995. Moleculario is a micro-science center that functions in the School of Chemistry, Universidad de la República, inaugurated in 2016, receiving around 800 visitors per year.

3.1. Development of a Custom App (SOLEIL)

To address the need for innovative assessment tools identified in the literature review and the objective of developing tools for data collection and analysis, we developed a web-based, open-source application designed to provide a simple, intuitive, and cost-effective solution for visitor research. The

app uses the VBLF to record visitor engagement, and the FF to record facilitator behaviors and strategies. Additionally, it allows the user to collect data on various other variables, including dwell time and characteristics of visitors, facilitators, and exhibits. The app was developed iteratively, using a combination of modern web technologies for both the front-end and back-end, ensuring a robust and user-friendly experience.

Methodology

In the front-end, we used HTML and CSS for the structure and styling, respectively. We employed React, a powerful JavaScript library, to build the user interface. React’s component-based architecture allowed us to create a dynamic and responsive application, essential for handling complex data visualizations and interactions. Also, in order to enhance the analytical capabilities of the app, we integrated the *stats.js* library, which provided essential statistical functions. Specifically, the app calculates inter-rater reliability using the percentage of agreement and Cohen’s kappa (McHugh, 2012), which is important for assessing the consistency and reliability of the data collected through the coding process. These measures ensure that the interpretations of visitor and facilitator behaviors remain objective and reproducible.

We built the back-end of the app using Google Firebase, a comprehensive platform for developing web applications. We built a series of interconnected databases, allowing for real-time data storage and synchronization, as well as integrating the diverse types of data we collected. Firebase’s real-time database enabled us to provide instantaneous updates and access to data, facilitating seamless integration with the front-end. Furthermore, we implemented secure login mechanisms to ensure that only authorized users could access and input data.

3.2. Validation of the Facilitation Framework

In line with the objective to generate, adapt and validate instruments that allow researchers to measure different characteristics of visitors, facilitators and exhibits, we validated the Facilitation Framework (Machado Corral et al., 2021). To ensure the robustness and applicability of the framework we undertook a two-stage validation process. This process involved collecting and coding data from two different sources and verifying the consistency and

comprehensiveness of the framework with two pairs of coders.

Methodology

Stage 1: Centro Cultural de la Ciencia Data Collection and Coding

In the first stage, we collected data from Centro Cultural de la Ciencia. Our goal was to apply the original Facilitation Framework to this new dataset to assess its validity outside the initial context, Science North. We coded the interactions using the original facilitation framework to determine if the existing codes were sufficient, redundant, or if new codes would emerge.

We gathered observational data, collecting video and audio focusing exclusively on visitor-facilitator interactions at 4 exhibits over two weekends in April 2022. The four exhibits that comprise this sample can be described as follows:

1. El color del calor (“The color of heat”): This exhibit has a big screen where visitors can see themselves captured through an infrared camera. They have different objects at their disposal to see how heat transfer works on different materials.
2. Código Ensamble (“Code join”): This is a table-top interactive screen, where visitors create music by placing different tokens in different places. Each token is associated with an instrument and a color, and the placement on the table determines the tempo.
3. Mesa caótica (“Chaotic table”): In this exhibit, visitors explore chaotic patterns by throwing steel balls into a hyperbolic funnel, and watch them accelerate and decelerate before dropping into the center hole.
4. Cuestión de peso (“A matter of weight”): This exhibit consists of a motorcycle hanging from the ceiling and a simple computer interactive. Visitors are invited to guess how much it weighs. After they input their guess, they can see where their guess is in the context of a histogram of all the guesses from previous visitors to the exhibit.

The facilitators signed consent forms, providing explicit consent after being fully informed about the study and assured their participation would involve no risk or benefit for them. Visitors in these videos gave their implicit consent, following (Gutwill, 2003) guidelines: cameras and microphones were fully visible, signs indicating they were being filmed for research were placed in several locations and were fully visible, the principal investigator was present and

clearly identified, and any visitors who declined to be filmed or have their footage kept were accommodated by turning off the camera or deleting the footage. No visitors declined to be filmed, and one facilitator declined to participate afterwards, therefore their footage was promptly deleted. The research was reviewed and approved by the Facultad de Química’s Committee involving human subject research (Exp. N^o 101900-000019-22).

We used DaVinci Resolve software to create separate video segments that showed visitors interacting with facilitators. Each segment begins when the facilitator walks into the space of the exhibit being recorded, or is brought there by a visitor, and ends when the facilitator walks out of that space. This created a pool of 83 clips of visitor-facilitator interactions (approximately 9 hours of footage) which were analyzed using the SOLEIL app described in the previous section. Table 3.2 shows the distribution of unique facilitators and visitors in the sample.

Two coders (the principal investigator aka Coder 1, and a senior Moleculario facilitator aka Coder 2) reviewed and analyzed the collected data, categorizing and coding the interactions using the Facilitation Framework as a guide. During this process, we paid close attention to whether the existing codes captured all aspects of the interactions or if there were behaviors that required new codes, or codes that were redundant. We then discussed the codes and themes at length to minimize observer bias, and to verify that the themes that emerged were representative of the data we observed. Since both Coder 1 and Coder 2 are experienced facilitators, we consciously brought this perspective to the data analysis when coding facilitator behaviours.

Stage 2: Independent Validation

After revising and refining the Facilitator Framework based on the findings from Centro Cultural de la Ciencia, we proceeded to the second stage to further validate the updated framework. We recruited a new, independent coder

Table 3.2: Distribution of facilitators and visitors in the sample

	Unique facilitators	Visitors
Exhibit 1	7	41
Exhibit 2	10	68
Exhibit 3	8	62
Exhibit 4	9	46
Total	31	217

(a graduate student, Coder 3) to ensure objectivity and reliability in the validation process. We selected this coder because they had no prior involvement with the Facilitator Framework. Coder 1 provided comprehensive training on how to use the app and the updated framework.

Coders 1 and 3 then watched a different set of videos, collected by the research team from Science North, which comprised a pool of 75 visitor-facilitator interactions at 11 different exhibits. The facilitators and visitors shown in these videos had also given their consent for the recordings, but for the purposes of our research, these videos were treated as secondary data since we did not collect it and were given permission by Science North to use the data. We applied the new and improved Facilitator Framework to these videos, coding the interactions to test if the revised framework was robust and applicable across different contexts. We established inter-rater reliability using both the percentage of agreement and Cohen’s kappa for each individual code and for each Facilitation Dimension as a whole.

3.3. Comprehensive Study

One of the objectives of this thesis was to identify the variables related to visitors and exhibitions that influence visitor engagement. Therefore, this Comprehensive Study aims to investigate the factors influencing visitor engagement at science centers through a comprehensive analysis of secondary data and ultimately creating a predictive model for these factors and visitor engagement.

Methodology

Science North’s exhibit evaluation and research team has years of experience applying the VBLF (Barriault and Rennie, 2019; Barriault and Pearson, 2010) to assess and improve their exhibits. Since 2008, the science center has video recorded and analyzed video data to produce Visitor Engagement Profiles (VEP) for hundreds of individual exhibits. The VBLF and VEP for exhibits are part of the institution’s formal exhibit evaluation practices and have become part of Science North’s organizational measures of success (Barriault and Pearson, 2010; Monteiro et al., 2018). For this reason, Science North served as the primary site for the Comprehensive Study, due to its extensive repository of tabulated data from multiple exhibits, spanning several years,

which provided a robust foundation for our initial ordinal regression analysis.

This study aims to thoroughly explore the extensive data contained in the tabulated records from Science North. This data, previously utilized primarily for the creation of Visitor Engagement Profiles (VEPs), holds a wealth of additional information that was yet to be fully explored. Attributes recorded included visitor gender, age group, group type (whether visitors are alone or in a group), and behaviors (as defined by the VBLF), photo-taking, signage reading, and visitor-facilitator interaction, as well as exhibit type (the level of participation, virtuality and collaboration, as defined by Wideström, 2020). By delving deeper into this rich dataset, we seek to uncover new insights and enhance our understanding of visitor engagement at science centers.

Sample

Research staff from Science North manually coded visitor behaviors and dialogue using the VBLF as the coding protocol, generating detailed spreadsheets filled with extensive data for each exhibit, which were wrangled for this study. Ethics protocols are always in place for all the recordings that were used for coding and follow the general recommendations of (Gutwill, 2003).

The final dataset consisted of 97 exhibits, for a total of 9002 visitors. Table 3.3 provides an overview of the variables measured in this study. The descriptor variables are visitor age, gender and group type, whether visitors looked at signage, took a picture or interacted with a facilitator, and the three dimensions of exhibit type. The dependent variable is the highest engagement level reached.

Data analysis

We used chi-square tests to assess whether visitor engagement levels were associated with various independent variables, where higher chi-square values indicate greater deviation from independence. Contingency tables, constructed in R Statistical Software v4.4.2 (R Core Team, 2024), visualized observed versus expected frequencies. For each test, we reported the chi-square statistic (χ^2), degrees of freedom, sample size, and p-value. Fisher’s Exact Test was applied when sample sizes were small or cell counts were uneven. To evaluate the strength of associations, we calculated Cramer’s V, where values closer to 1 indicate stronger relationships. For ordinal variables, we also calculated Kendall’s Tau-b, a non-parametric measure of association that ranges from -1 (perfect negative association) to $+1$ (perfect positive association), along with

Table 3.3: Variables selected for the Comprehensive Study

Group of variables	Variable	Description	Detail
Visitor	AGE	age group	Young Child (0-5yo); Child (6-10yo); Pre-Teen (11-13yo); Teen (14-18yo); Adult (19-64yo); Senior (65+yo)
	GND	gender	Female; Male
	GT	group type	Alone; In a group
Other behavior	LS	looking at signage	No; Yes
	TP	takes photo	No; Yes
	IF	visitor-facilitator interaction	No; Yes
Exhibit	EP	level of participation	Static; Static/Participatory; Participatory
	EV	level of virtuality	Physical; Physical/Virtual; Virtual
	EC	level of collaboration	Individual; Individual/Collaborative; Collaborative
Dependent variable	HE	highest engagement level reached	Initiation; Transition; Breakthrough

its p-value and confidence interval. This combination of tests allowed us to assess both the significance and strength of relationships (Agresti, 2018), using a .05 significance level throughout.

We employed regression models using R to evaluate the association of each descriptor (x_i , e.g: gender) with the selected response variable (HE - highest level of engagement reached; Initiation, Transition, or Breakthrough), while controlling the other variables. Given that the response variable (highest engagement level reached, HE) is ordinal, we used ordered logistic regression models via the *vglm* command from the MASS package (Venables and Ripley, 2002).

We tested the proportional odds assumption using Brant’s test, and when this assumption was violated, a partial proportional odds model was fitted using the VGAM package (Yee, 2010). We optimized the models manually by minimizing the Akaike information criterion (AIC) while ensuring that coeffi-

cients did not suffer from the Hauck-Donner effect (Agresti, 2018). Finally, we used an extension of the Hosmer-Lemeshow Test to assess the model’s goodness of fit.

Once the model was optimized, we used R to graph the predicted probabilities for the three levels of the dependent variable (Initiation, Transition, and Breakthrough) as a function of the descriptors. We used the *predict* function, with the adjusted model to calculate the predicted probabilities, then created a new dataset containing all the combinations of all the possible predictive variables, which was finally plotted using the *ggplot2* library. This allowed us to create a graph depicting the likelihood of a visitor being in each category of engagement, based on specific visitor characteristics and behaviors.

To evaluate the model’s performance, we used the *caret* package in R (Kuhn, 2008) to generate class predictions from the probability matrix, where the classes are the levels of engagement (1 = Initiation, 2 = Transition, 3 = Breakthrough). The predicted class for each observation was assigned based on the maximum probability using the *apply* function. We then computed a confusion matrix comparing these predictions to the observed class labels, obtaining overall accuracy, kappa statistics, and class-specific performance metrics including sensitivity, specificity, positive predictive value, and balanced accuracy. This approach allowed for a detailed assessment of the model’s ability to correctly classify each category of engagement and overall performance.

3.4. Extended Study

The Extended Study was designed to build upon the findings of the Comprehensive Study by incorporating more detailed and nuanced data. This allowed us to include variables that could reasonably be latent in the Comprehensive Study. We used a combination of recordings of behaviors and conducting surveys to record all the visitor attributes described in the Comprehensive Study, plus visitor’s level of education, familiarity with the center, and their motivation for visiting.

Methodology

The Extended Study builds upon the findings of the Comprehensive Study by incorporating additional data collection methods to gain a deeper understanding of visitor engagement. While the Comprehensive Study provided a

comprehensive analysis of visitor interactions using secondary data, the Extended Study expands this research by introducing surveys to gather information that cannot be captured through video or live observation alone (full text for the surveys can be found in Appendix 1). This study utilized an ordinal regression approach, drawing on observations of visitors interacting with different exhibits at different science centers. Key descriptor variables investigated are visitor gender, age, group type, level of education, familiarity with the center (how often they visit the center) and motivation, as well as interacting with a facilitator, taking a picture, looking at the signage and the type of exhibit (classified by their level of participation, virtuality and collaboration).

This approach allowed us to integrate new insights into the analysis alongside the variables from the Comprehensive Study, providing a more holistic view of visitor behavior and engagement. Through this enhanced methodology, the Extended Study aims to uncover the nuanced factors influencing visitor engagement, offering a richer and more detailed analysis.

Sample

We gathered observational data from Science North, Espacio Ciencia and Moleculario, collecting video and audio of visitors and facilitators interacting at different exhibits, over several research stays from August to October 2022. The facilitators signed consent forms and visitors gave their implicit consent, following Gutwill (2003) guidelines, as described before.

We collected data from 8 exhibits; 5 from Science North, 2 from Espacio Ciencia, and 1 from Moleculario. The exhibits that comprise this sample are described in Table 3.4.

We used DaVinci Resolve software (Blackmagic Design) to create separate video segments that showed visitors interacting with facilitators. As with the validation of the Facilitation Framework part of the study, each segment begins when a visitor walks into the space of the exhibit being recorded, and ends when they walk out of that space. In the cases where any consecutive visitor walks into the space and leaves after the first visitor, the recording ends after the last visitor leaves the space. This created a pool of hundreds of interactions (approximately 6 h of footage) which were cross-referenced with survey data.

In order to cross-reference observational and survey data, we used the following procedure. We observed visitors interacting with exhibits, making a general note of the time and a characteristic that would allow us to identify

Table 3.4: Description of sample of exhibits used for data collection in the Extended Study.

Center	Name	Description
Science North	CPR	This exhibit features two CPR training mannequins and a TV screen where visitors can watch an instructional video on how to perform hands-only CPR. After the video, 2 visitors can perform CPR on each mannequin at the same time and see how their maneuvers compare.
	Human body table	This exhibit consists of a big table with several anatomically correct models of different parts of the human body. Here visitors can learn more about how our bodies work and what we look like inside.
	Laser maze	In this table-top exhibit, visitors are challenged to use reflective, translucent and opaque blocks to create a maze with a laser beam.
	Magnet table	This exhibit features an assortment of magnets and metallic objects (like chains, screws and bolts) for visitors to explore magnetism.
	Laser harmonies	In this exhibit, visitors can play notes on two different keyboards and see a laser projection of the combined sound waves. If the notes are harmonic, the pattern is smooth.
Espacio Ciencia	Pista de carreras (“Race track”)	Visitors can race two model cars, one electric and one fuel-powered, and see how they compare in terms of energy efficiency.
	Interactive map (“Mapa interactivo”)	This exhibit features an interactive map of the country, showing rivers and high/low altitude zones. Visitors can place tokens that represent different types of energy sources (fuel, coal, solar, wind) and see on a screen how that affects the ability to cover the energy demands of the population.
Molecularario	Cambios de estado (“Changes of state”)	In this matching game, visitors are challenged to sort cards describing everyday situations (for example: “the puddle dried”) to the correct change of state that is happening.

them later (for example, "red shirt 1145"). We approached all visitors after they left the space where the exhibit was being recorded, and asked if they would be willing to participate in a survey. If they agreed, we added the identifying note to their survey response. Approximately 10 % of the visitors we approached declined filling the survey. Later, when we reviewed the video footage, we used the timestamps to be able to find the visitor, and tagged the videos with the corresponding survey responses. For this study, we limited the coding to only the visitors that had completed the survey, whose behaviors were recorded using the SOLEIL app developed for this work (see section 3.2).

The final dataset consisted of a total of 96 visitors who completed the survey (51 from Science North, 29 from Espacio Ciencia, 16 from Moleculario). The descriptive variables include visitor age, gender and group type, their education level, familiarity with the center and motivation for visiting, whether they looked at signage, took a picture or interacted with a facilitator, and the three dimensions of exhibit design. The highest engagement level reached is the response variable. Table 3.5 provides an overview of the variables measured in this Extended Study.

We employed the same data analysis methodology as described in the Comprehensive Study to ensure consistency.

Table 3.5: Variables selected for the Extended Study

Group of variables	Variable	Description	Detail
Visitor	AGE	age group	Young Child (0-5yo); Child (6-10yo); Pre-Teen (11-13yo); Teen (14-18yo); Young Adult (19-30yo); Adult (31-64yo); Senior (65+yo)
	GND	gender	Female; Male
	GT	group type	Alone; In a group
	FA	familiarity	First time; Once a year or less; 2 - 4 times a year; 5 times a year or more
	AC	education level	No schooling; Primary school incomplete; Primary school completed; Secondary school incomplete; Secondary school completed; Tertiary school incomplete; Tertiary school completed; Postgraduate degree
	VM	visitor motivation	Facilitator; Other
Other behavior	LS	looking at signage	No; Yes
	TP	takes photo	No; Yes
	VV	visitor-visitor interaction	No; Yes
Facilitation	IF	visitor-facilitator interaction	No; Yes
	FC	uses comfort dimension	No; Yes
	FE	uses exhibit use dimension	No; Yes
	FI	uses information dimension	No; Yes
	FR	uses reflection dimension	No; Yes
Exhibit	CE	science center	Science North; Espacio Ciencia; Moleculario
	EP	level of participation	Static; Static/Participatory; Participatory
	EV	level of virtuality	Physical; Physical/Virtual; Virtual
	EC	level of collaboration	Individual; Individual/Collaborative; Collaborative
Time	DT	dwel time	Visitor's dwell time, in seconds
Dependent variable	HE	highest engagement level reached	Initiation; Transition; Breakthrough

Chapter 4

Development of research tools

The development of the SOLEIL app and the validation of the Facilitation Framework were two interconnected processes that advanced in parallel, each informing and strengthening the other. The Facilitation Framework was designed to systematically capture and categorize facilitator behaviors in science centers, providing a robust structure for analyzing their impact on visitor engagement. Simultaneously, the SOLEIL app was created to address the logistical challenges of data collection and analysis in informal learning environments, offering an efficient and scalable tool for research. As these efforts evolved, the app became instrumental in the validation of the Facilitation Framework by streamlining coding processes, enhancing the reliability of analyses, and enabling efficient collaboration between coders.

The validation of the Facilitation Framework followed a two-stage process. During the first stage, the initial version of the framework was applied to data collected at the Centro Cultural de la Ciencia, revealing areas for refinement and leading to an updated version of the framework. This revised version was then integrated into the SOLEIL app, allowing the app to serve as both a data collection and coding platform in the second stage of validation. In this second stage, data from Science North was coded using the updated framework, and the app's built-in features facilitated efficient comparisons between coders and calculation of inter-rater reliability metrics, including percentage agreement and Cohen's kappa. This iterative process ensured that both the framework and the app were optimized to support high-quality research on visitor-facilitator interactions.

The chapter is structured as follows: the next section details the develop-

ment of the SOLEIL app, including its features and functionalities designed to support efficient data collection and analysis. Following this, the two-stage validation process of the Facilitation Framework is described, highlighting the iterative improvements made to the framework and the app’s role in this refinement. Finally, the chapter concludes by discussing the broader implications of these tools for future research and practice in science centers.

4.1. Development of a Custom App

Collecting large amounts of data on visitor interactions within a science center—spanning visitor-exhibit, visitor-visitor, and visitor-facilitator dynamics—can be a significant challenge, especially in observational studies. This difficulty is compounded by the financial and human resource constraints faced by many institutions, particularly smaller centers, which often lack the budgets and expertise for extensive research. As Ash et al. (2012) point out, large-scale research models may yield generalizable data but tend to overlook the crucial “how” and “in what way” questions needed to understand learning processes in informal settings.

We successfully developed a web-based app for collecting and analyzing data in science centers and named it SOLEIL, an acronym for *Software for Observation and Logging for Exhibits in Informal Learning*. The app’s development was a multifaceted process that progressed through various stages, each addressing the specific needs of this research while considering its broader applicability for science center staff. From its initial concept to the incorporation of advanced features, the development aimed to improve functionality and reliability.

The app features an intuitive user interface, making it accessible for both novice and experienced users, and its backend consists of queryable, interconnected databases, ensuring robust data management. The app supports data collection for coding both live and recorded video, allowing researchers to record several variables, including but not limited to visitor age, gender, visitor behaviors (VBLF), facilitator gender, age, facilitator behaviors (Facilitation Framework), group size, language spoken, and general observations. Additionally, the app enables the creation of Visitor Engagement Profiles (VEP) and offers statistical analysis tools, including chi-square and Kendall’s Tau-b, to facilitate comparisons between different visitor groups.

Furthermore, we integrated functionalities for assessing inter-rater reliability, which proved to be a crucial addition to ensure we could demonstrate the reliability between coders. This feature allows users to calculate both the percentage of agreement and Cohen’s kappa (McHugh, 2012) between a pair of coders. The decision to include both metrics was informed by the limitations of Cohen’s kappa. Specifically, Cohen’s kappa cannot be calculated when either Y/Y (both coders identifying the presence of a code) or N/N (both coders agreeing on the absence of a code) is zero, because the formula for kappa relies on the observed and expected agreement between coders across all possible outcomes (Agresti, 2018). When one of these categories has a frequency of zero, the expected agreement becomes skewed, making it impossible to compute a meaningful kappa value. This limitation arises because kappa measures not just overall agreement but the extent to which agreement exceeds what would be expected by chance; without variation in coder responses, this calculation breaks down (McHugh, 2012).

The backend is structured as a series of interconnected databases, designed to capture various aspects of visitor engagement in a science center. The main database registers the type of coding (live or video), information about the day (busy or not busy), start time, extra observations, video duration, video name, and connects to the other databases: evaluator, exhibit, facilitator, visitor, and coding. Figure 4.1 shows the database architecture. The evaluator database logs the center the evaluator is associated with, along with their name and surname. The exhibit database records the exhibit’s name, its science center’s location, whether the exhibit is contextualized, the exhibition it belongs to, the exhibit’s STEM area, and its type (as per Wideström, 2020). The facilitator database includes fields to register other information about the facilitator, like their level of education, age group, the science center they belong to, their gender, their name, and their STEM background area. The visitor database holds data on the visitor’s education level, age range, gender, a brief description, familiarity with the science center, spoken language, motivation type (as categorized by Falk, 2006), and group type (alone, family group, other group). The coding database, connected to the behaviors database, logs the end time and details the behaviors of both the facilitator and the visitor. It is important to note that while the app is able to register all this data, it is not necessary to fill in every field; many entries can remain blank if not applicable.

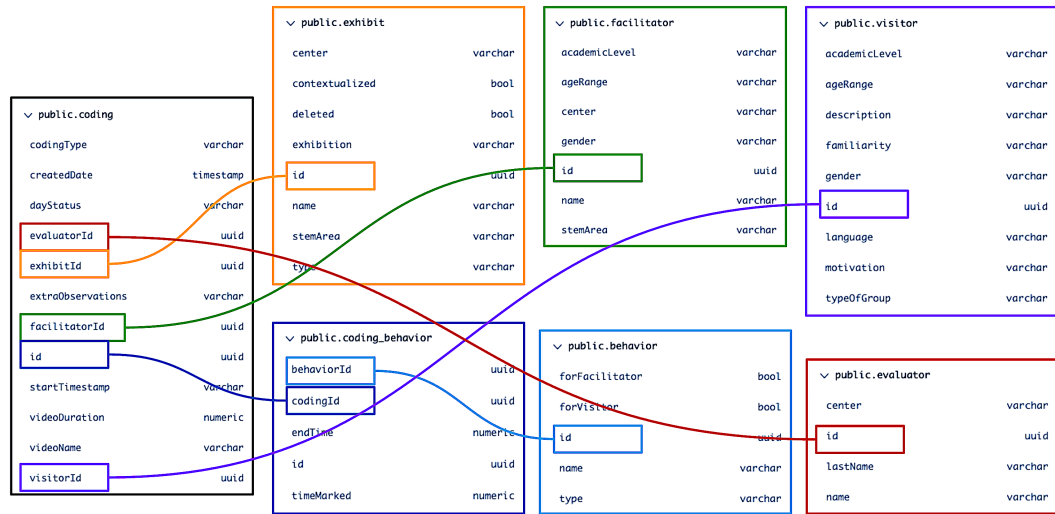


Figure 4.1: Database architecture for the SOLEIL app

4.1.1. Functional architecture

The app’s user-friendly interface, as shown in Figures 4.2 through 4.7, guides users through various tasks, from logging in to generating Visitor Engagement Profiles and inter-rater reliability reports. Data collection is flexible as users can code interactions live on the science center floor, or analyze recorded videos.

Log In

The log-in screen (Fig. 4.2) is the first point of entry for users. It includes fields for entering an email address and password, ensuring secure access to the app. This screen is straightforward, with a simple login button to complete the process, directing users to the home screen after successful authentication.

Home

The home screen (Fig. 4.3) serves as the central hub for all user activities. Upon logging in, users are greeted with options to select the exhibit they are working with. They can then choose between live or video coding, depending on their current task.

Additionally, the home screen provides access to the Visitor Engagement Profiles and Inter-Rater Reliability screens. Finally, there is an option to download all collected data, which allows users to import their data into other software, in order to perform complex data queries and detailed statistical analyses.

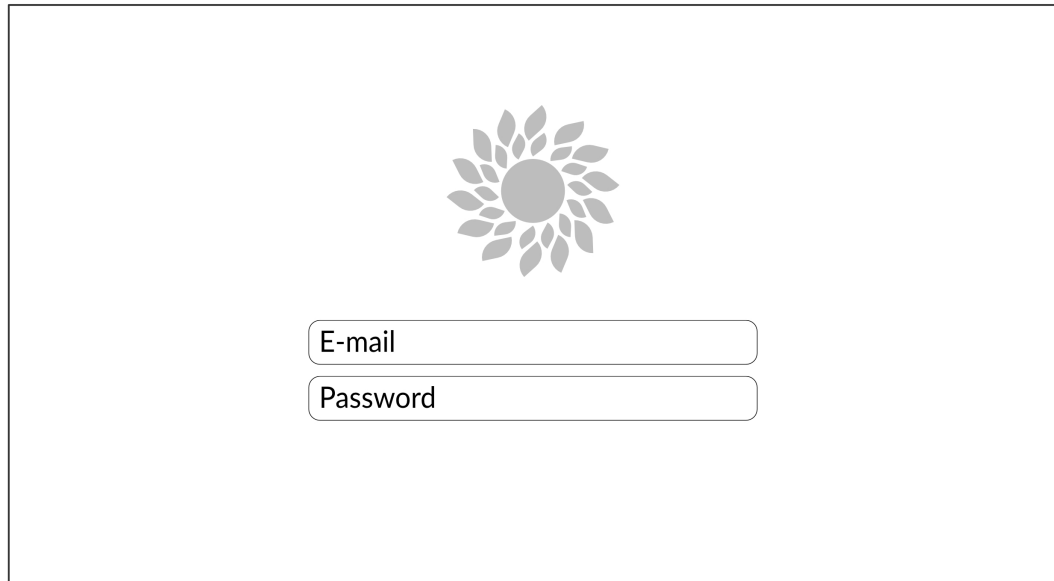


Figure 4.2: Log-in screen (simplified reproduction for clarity, not an actual screenshot)

Live Coding

The live coding screen (Fig. 4.4) is designed for real-time data collection. At the top of the screen, users will find the exhibit and coder information, which helps verify that data is being input correctly.

In the visitor section, users can record visitor behaviors using start/stop buttons that associate each behavior to a timestamp, clicking the button to mark the start of the visitor interaction and again to mark the end of the interaction. Dropdown menus allow for the selection of demographic data, such as age and gender, while a text field is available for additional visitor descriptions. The facilitator section mirrors this functionality, with start/stop buttons for recording facilitator behaviors, and dropdown menus for selecting demographic data, including age, gender, and language spoken.

An observations text field is provided for noting any general observations. Besides this, the list of recorded interactions is displayed, allowing users to review and delete any entries if necessary. Finally, the screen features buttons to start data collection for a new visitor or to end the current data collection session.

Video Coding

The video coding screen (Fig. 4.5) facilitates data collection from recorded visitor interactions. Similar to the live coding screen, it includes exhibit and

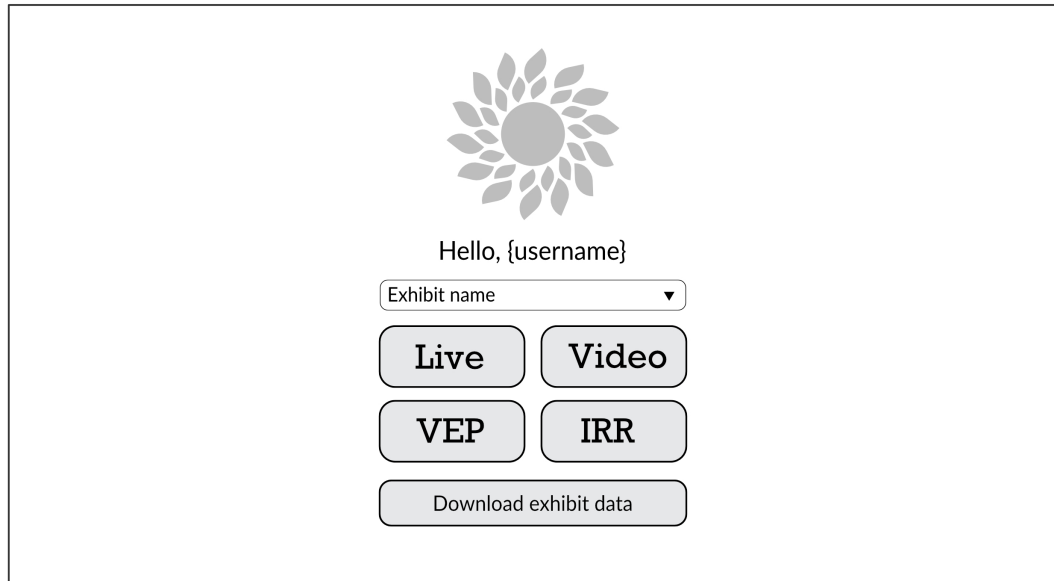


Figure 4.3: Home screen (simplified reproduction for clarity, not an actual screenshot)

coder information at the top to ensure correct data input. A video loader is available for playing recorded sessions.

In the visitor codes section, users can record behaviors using start/stop buttons. The facilitator codes section also includes start/stop buttons for recording facilitator behaviors. The dropdown menus section allows for the selection of demographic data for both visitor and facilitator, and other information, like the type of group and the research condition.

On the right side of the screen, a list of recorded interactions is displayed, with options to delete any entries if necessary. To aid in reviewing the assigned codes, users can click on any interaction from the list, and the video playhead will move to the start time of that specific interaction. This section of the screen also features text fields for visitor descriptions and general observations. A secondary dropdown menu section allows users to select the language spoken and to indicate if the day was busy or not. Finally, buttons are available to begin data collection for a new visitor (“new visitor”), or conclude the session (“end”).

Visitor Engagement Profile

The Visitor Engagement Profile (VEP) screen (Fig. 4.6) enables users to create and compare the VEP of two groups based on various criteria. Users can select the exhibit or exhibits they will create VEPs for. They can then select

Exhibit: {name}
Coder: {coder}

TIMER

Gender ▾ Age ▾ Group ▾ Busy ▾

Doing the activity Observing the activity Repeating the activity Positive emotion

Past experiences Seeking & sharing info Engaged & involved Visitor description

Visitor-visitor interaction Takes photo Reads signage

Gender ▾ Age ▾ Lang ▾

Encouraging language Welcoming Laughter, joy Focus on visitor Small talk

Show how to use Tell how to use Technical assistance Using along Reads signage

Making connections Attn to phenomena Challenge, experiment Inviting reflection

Context / Explanation How exhibit works Fun fact Tour guide / ambassador

Observations

List of interactions

Interaction 6	00:14 - 1:02	⊗
Interaction name	00:14 - 1:02	⊗
Interaction long name	00:14 - 1:02	⊗
Interaction 3	00:14 - 1:02	⊗
Interaction 2	00:14 - 1:02	⊗
Interaction 1	00:14 - 1:02	⊗

New

End

Figure 4.4: Live coding screen (simplified reproduction for clarity, not an actual screenshot)

the characteristics to compare (currently gender, age, group type, condition and facilitator presence).

Once the criteria are set, the comparison VEP is displayed, providing a detailed view of visitor engagement data. This section also offers basic statistical information, through the calculation of chi-square parameters and Kendall's Tau-b, to determine if the difference between groups is statistically significant and the strength and direction of association that exists between the two variables.

Inter-Rater Reliability

The Inter-Rater Reliability (IRR) screen (Fig. 4.7) allows for the creation of an IRR report. Users can select two coders whose data they wish to compare. There is also an option to select specific exhibits, although this is optional, and users can leave it blank to compare all videos coded by both coders.

The percentage of agreement between coders and Cohen's kappa is displayed in a grid, with color coding to highlight discrepancies. Additionally, a

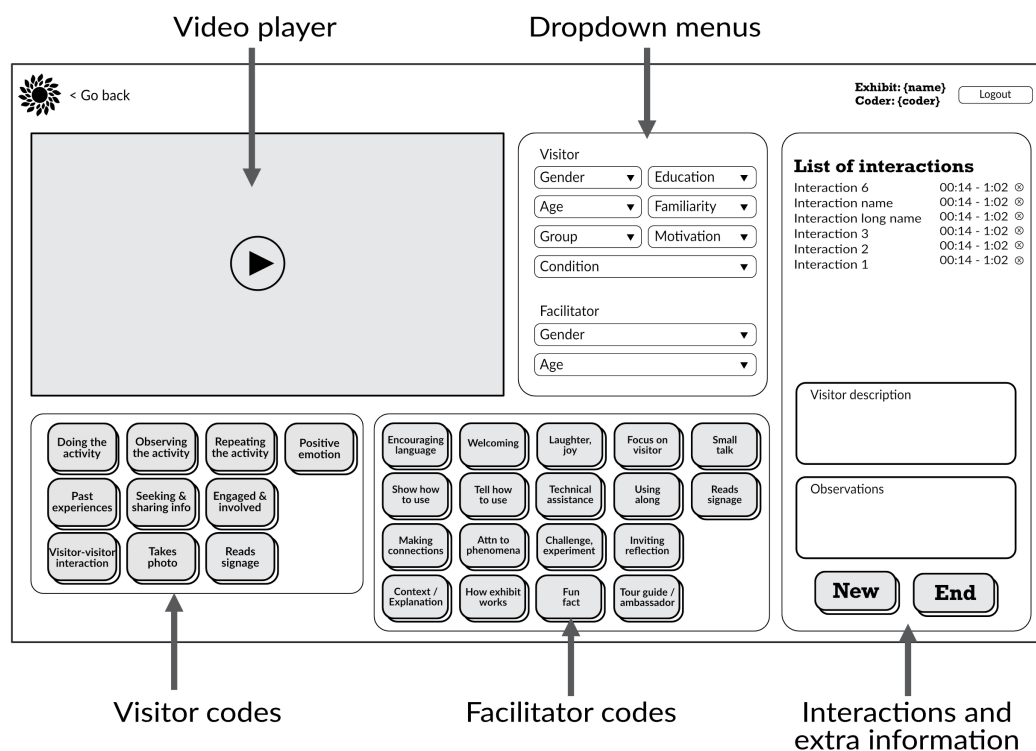


Figure 4.5: Video coding screen (simplified reproduction for clarity, not an actual screenshot)

list of unique videos coded by both coders is provided to ensure completeness and avoid double-counting.

The app proves to be an invaluable tool for science centers, offering practical solutions for capturing and analyzing visitor engagement in a way that extends beyond traditional metrics like dwell time. While early research in science centers focused on "attracting power" (whether visitors engaged with an exhibit) and "holding power" (the length of engagement) as measures of visitor interaction, these metrics primarily reflect the popularity of exhibits and fail to provide deeper insights into the nature of visitor learning (Rennie and Howitt, 2020). Our app addresses this limitation by not only automatically registering dwell time but also recording the start and end times for each specific behavior. This allows for a more nuanced view of the interaction, enabling researchers to explore the sequence, duration, and context of visitor behavior in much greater detail than with dwell time alone. By offering this level of granularity, the app facilitates a deeper understanding of how visitors engage with exhibits and how learning unfolds during these interactions, align-

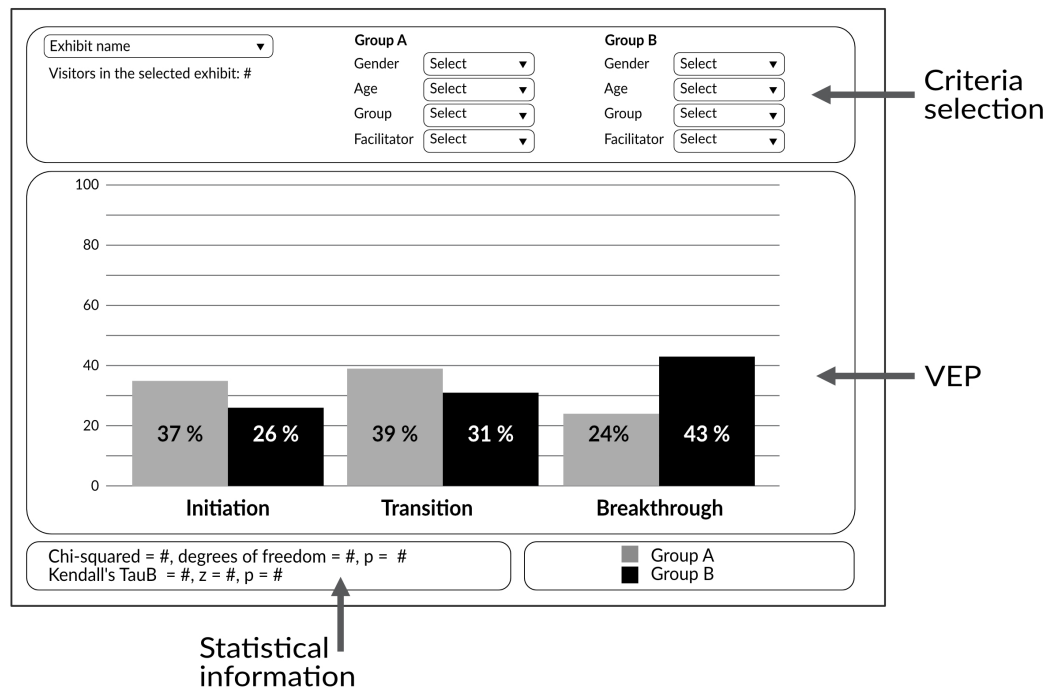


Figure 4.6: VEP screen (simplified reproduction for clarity, not an actual screenshot)

Coder 1 <input type="text"/> Coder 2 <input type="text"/> Exhibit <input type="text"/>					
<input type="button" value="Calculate"/>					
List of unique videos File 1 File 2 File 3 File 4 File 5					
Encouraging language	Welcoming	Laughter, joy	Focus on visitor	Small talk	Comfort
Agreement 78 %	Agreement 94 %	Agreement 81 %	Agreement 53 %	Agreement 94 %	Agreement 88 %
Kappa 0.537	Kappa 0.846	Kappa 0.619	Kappa 0.111	Kappa 0.632	Kappa N/A
Show how to use	Tell how to use	Technical assistance	Using along	Reads signage	Exhibit use
Agreement 88 %	Agreement 84 %	Agreement 100 %	Agreement 100 %	Agreement 97 %	Agreement 97 %
Kappa 0.710	Kappa 0.579	Kappa N/A	Kappa 1	Kappa 0.840	Kappa 0.937
Making connections	Attn to phenomena	Challenge, experiment	Inviting reflection	Reflection	
Agreement 88 %	Agreement 84 %	Agreement 94 %	Agreement 94 %	Agreement 81 %	
Kappa 0.636	Kappa 0.518	Kappa 0.717	Kappa 0.632	Kappa 0.621	
Context / Explanation	How exhibit works	Fun fact	Tour guide / Ambassador	Information	
Agreement 81 %	Agreement 94 %	Agreement 100 %	Agreement 100 %	Agreement 88 %	
Kappa 0.632	Kappa 0.632	Kappa 1	Kappa 1	Kappa 0.738	

Figure 4.7: IRR screen (simplified reproduction for clarity, not an actual screenshot)

ing with the shift toward more qualitative and comprehensive approaches to assessing learning in informal settings.

Our app directly addresses this challenge by offering an efficient balance of qualitative and quantitative data collection, minimizing the effort required and thus making research more accessible. This aims to address the shortcomings of traditional research designs, as discussed by Falk et al. (2016), which often fall short when addressing the complexities of informal learning, requiring new, cost-effective methods for data collection. By enabling staff to capture and analyze data easily through live or video recordings, the app lowers the barrier for conducting meaningful studies that might otherwise be prohibitively expensive (McCubbins, 2016). Moreover, the built-in inter-rater reliability calculator allows for consistent, reproducible results without needing extensive resources. As Andre et al. (2017) note, smaller studies often face limitations like small sample sizes and lack of instrument reliability, which the app helps mitigate by enabling larger, collaborative studies with standardized data collection methods. By providing an intuitive platform for data collection and analysis, the app empowers science centers to conduct high-quality research while keeping costs manageable, opening doors for collaboration and broader research initiatives across institutions.

4.2. Validation of the Facilitation Framework

The validation of the Facilitation Framework yielded insightful results, confirming its robustness and adaptability across different contexts. The two-stage process allowed us to validate and refine the Facilitation Framework rigorously, ensuring it was both comprehensive and reliable for analyzing facilitator-visitor interactions in science centers.

4.2.1. First stage

During the first stage, data collected from Centro Cultural de la Ciencia was meticulously coded by two coders (the principal investigator aka *Coder 1*, and *Coder 2*; both experienced facilitators) using the original Facilitation Framework (Machado Corral et al., 2021). This process revealed that while the Dimensions remained unchanged and existing codes were generally applicable, some new codes emerged and others were redundant, highlighting the

framework’s need for slight modifications. Tables 4.1 to 4.4 show the original codes, the revised codes, a description and examples.

The Comfort Facilitation Dimension describes facilitator behaviors that are welcoming and encouraging to the visitors, making the interaction with the exhibit more pleasant. For this Dimension, the “focus on visitor” code was more fully described, and the “small talk” code was added. Table 4.1 shows the updated Facilitator Behaviors for this Facilitation Dimension.

Table 4.1: Revised Facilitation Framework, Comfort Dimension. Bold text indicates changes introduced to this version.

Original code	Revised code	Description	Examples
Encouraging language	Encouraging language	Phrases or utterances that encourage the visitor to keep engaging with the exhibit.	“Yeah!!!” “Great job!” “That’s not quite right, keep trying!”
Welcoming	Welcoming	Greeting, inviting visitor to use the exhibit, general introductory questions.	“Hello, how are you today?” “Would you like to spin the wheel?” “So, are you any good at this?”
Laughter/joy	Laughter/joy	Verbal and non-verbal displays of joy, laughing, showing excitement.	Laughing out loud. Smiling.
Focus on visitor	Focus on visitor	Body language that conveys they are paying attention to the visitor. Note: this describes only the action of focusing on someone, not the general sense that a facilitator is engaged in the conversation.	Lowering body to talk to someone shorter at their eye level. Facing people without restricting access to the exhibit.
(Non-existent)	Small talk or making conversation	Sharing or discussing superficial personal information or things that do not necessarily have to do with the exhibit but aim to make the visitor comfortable.	“What’s your favorite color? Mine is... Let’s try to get that!” (in an exhibit with lights of different colors) “Do you go to school? What year are you on? What’s your favorite subject?”

The Information Facilitation Dimension includes strategies related to the science content of the exhibit and other information related to this content. For this Dimension, the “context”, “explanation” and “tell a story” codes were combined into a new code called “context and/or explanation”, which sufficiently describe the behavior (since the three original codes would often show up together), and the “tour guide, ambassador” code was added. Table 4.2 shows the updated Facilitator Behaviors for this Facilitation Dimension.

Table 4.2: Revised Facilitation Framework, Information Dimension. Bold text indicates changes introduced to this version.

Original code	Revised code	Description	Examples
Context, Explanation and Tell a Story	Context and/or explanation	Information that provides context and/or explanation for the visitor, about the exhibit or the science or topic the exhibit covers. This includes general statements and stories or anecdotes.	“There are electrical charges on the ground, often in something like a tower or a tall building, or something like that, like the CN tower... the charges build up on that and they go up trying to find an opposite charge and it finds it inside the cloud.”
How the exhibit works	How the exhibit works	Explaining the science of how the exhibit works, NOT the science or topic the exhibit covers or is about.	”There is an infrared camera there, which allows us to see the heat, things that are cold are blue, things that are hot are red and white.” (exhibit is about how reptiles see)
Fun facts	Fun facts	Short, quick bits of memorable information.	”An elephant trunk has up to 40,000 muscles!”
(Non existent)	Tour guide, ambassador	Providing information that’s not about science, but about the science centre itself or the area it’s located in.	“There’s a show about gravitational waves starting at 3 pm” Suggesting a restaurant or tourist spot that first-time visitors might enjoy.

The Exhibit Use Facilitation Dimension includes all strategies and behaviors related to exhibit use, including instructions on how to use the exhibit and technical assistance. For this Dimension, the “tip or hint” code was deleted because it could be included in several of the other codes, which more accurately describe the intention of the tip or hint, and the “reading signage for

visitor” code was added. Table 4.3 shows the updated Facilitator Behaviors for this Facilitation Dimension.

The Reflection Facilitation Dimension encompasses the strategies and techniques used by facilitators to help visitors fully engage with the exhibit, through reflection and making connections. For this Dimension, the “ask for a guess or hypothesis” and “challenge or experiment” codes were combined into a new code called “challenge, experiment or hypothesis”, which sufficiently describe the behavior (since the original codes would often show up together and there wasn’t enough frequency for either code to maintain the separation), and no other codes were removed or added. Table 4.4 shows the updated Facilitator Behaviors for this Facilitation Dimension.

4.2.2. Second stage

In the second stage, the principal investigator and an independent coder (Coders 1 and 3) applied the updated framework, which was incorporated into the SOLEIL app, to a different set of videos from Science North. The coders’ consistent and accurate application of the revised Facilitation Framework demonstrated its reliability and comprehensiveness. Table 4.5 shows the agreement percentages and Cohen’s kappa, with its confidence interval, for all codes and Dimensions of the revised framework.

The inter-rater agreement results indicate that the Facilitation Framework was applied consistently across most categories, with generally high levels of agreement between coders. The Exhibit Use and Information Dimensions showed the strongest consistency, with total agreement scores of 96.88 % and 87.50 %, respectively, and kappa values indicating substantial to almost perfect agreement (0.937 and 0.738, respectively). In the Exhibit Use category, “using along” had perfect agreement (100 %) and a kappa of 1, meaning both coders identified this behavior in the same instances. Similarly, “reading signage for visitor” had very high agreement (96.88 %) and a strong kappa (0.840), suggesting that this behavior was easy to recognize and categorize. The only category with a kappa of “N/A” in this Dimension was “technical assistance,” as it was not observed in the selected videos, therefore making Cohen’s kappa impossible to calculate. However, we determined that this was still a valid category to retain in the framework, as its absence in this dataset does not mean it would not be relevant in future studies. The Information Dimension also

Table 4.3: Revised Facilitation Framework, Exhibit Use Dimension. Bold text indicates changes introduced to this version.

Original code	Revised code	Description	Examples
Showing how to use	Showing how to use	Physically showing how to use the exhibit this includes providing tips, hints, or different ways to engage with the exhibit.	<p>"You can also try this (facilitator demonstrates), it's fun!"</p> <p>Facilitator uses the exhibit first to show visitor how to do it.</p>
Telling how to use	Telling how to use	Giving verbal instructions of how to use the exhibit, this includes providing tips, hints, or different ways to engage with the exhibit.	<p>"All you do is... you squeeze the lever and see how strong you are."</p> <p>"For one of them, I'll give you a hint, you have to step back from the table"</p>
Using along	Using along	Using the exhibit alongside the visitor.	Facilitator uses the exhibit as Player 2 on a two-player exhibit.
Technical assistance	Technical assistance	Providing assistance with the use of exhibits, either by fixing issues or malfunctioning exhibits, or by providing aids that make the visitor more comfortable.	<p>Rebooting the system for an exhibit that has a projector and computer system.</p> <p>Bringing up a stool where a smaller kid can stand and use the exhibit more comfortably.</p>
Tip or hint	Removed	-	-
(Non existent)	Reading signage	Reading signage out loud for visitors.	<p>Reading signage out loud for a young child who's learning to read.</p> <p>Reading signage out loud for a senior with poor eyesight.</p> <p>Reading and pointing at a specific section of the signage that gives a clue as to how to engage with the exhibit.</p>

Table 4.4: Revised Facilitation Framework, Reflection Dimension. Bold text indicates changes introduced to this version.

Original code	Revised code	Description	Examples
Making connections	Making connections	Giving clues, hints or context that help the visitor make connections with other topics and science concepts.	<p>“Do you guys want to see why you’re not quite as strong as an orangutan? Follow me!” (takes them to another exhibit)</p> <p>At an exhibit which shows real-time thermal imaging of the visitor, the facilitator brings out a snake and says “that this is how they see their prey”.</p>
Attention to phenomena	Attention to phenomena	Calling attention to something that’s happening and it’s relevant to the exhibit topic.	“The marbles near the center go faster.”
Ask for a guess or hypothesis, Challenge or experiment	Challenge, experiment, or hypothesis	Asking the visitor for a guess or a possible explanation for a phenomenon, inviting the visitor to try something.	<p>“You can try and build something.”</p> <p>(Visitor 1 interacts with the exhibit, then visitor 2 interacts with the exhibit) “How about together?”</p> <p>“So, how many eggs do you think she laid.”</p> <p>“If I were to take an egg from a robin and give it to either a tomtit, a dunnock, or a starling, which one do you think would make the best adoptive parents? Why?”</p>
Inviting reflection	Inviting reflection	Asking questions or making comments that invite the visitor to think deeper about a topic or idea.	<p>Why do you think we take eggs from robins’ nests?</p> <p>(To a girl looking into a microscope) “Do you know what you’re looking at in there?”</p>

Table 4.5: Agreement percentages, Cohen’s kappa and its confidence interval (CI) for the Facilitation Framework

Code	Agreement (%)	Cohen’s kappa	CI
Encouraging language	78.13	0.537	[0.234, 0.840]
Laughter, joy	81.25	0.619	[0.344, 0.894]
Focus on visitor	53.13	0.111	[-0.217, 0.439]
Small talk	93.75	0.632	[0.138, 1.13]
Welcoming	93.75	0.846	[0.640, 1.052]
Comfort Dimension	87.5	N/A	N/A
Using along	100	1.00	[1.00, 1.00]
Technical assistance	100	N/A	N/A
Telling how to use	84.38	0.579	[0.240, 0.918]
Showing how to use	87.5	0.710	[0.445, 0.975]
Reading signage for visitor	96.88	0.840	[0.531, 1.15]
Exhibit use Dimension	96.88	0.937	[0.815, 1.06]
Making connections	87.5	0.636	[0.303, 0.969]
Challenge or experiment	93.75	0.717	[0.337, 1.097]
Inviting reflection	93.75	0.632	[0.138, 1.13]
Attention to phenomena	84.38	0.518	[0.130, 0.906]
Reflection Dimension	81.25	0.621	[0.347, 0.895]
How the exhibit works	93.75	0.632	[0.138, 1.126]
Tour guide or ambassador	100	1.00	[1.00, 1.00]
Context and/or explanation	81.25	0.632	[0.367, 0.897]
Fun facts	100	1.00	[1.00, 1.00]
Information Dimension	87.5	0.738	[0.498, 0.978]

showed high reliability, with ”tour guide, ambassador” and ”fun facts” reaching perfect agreement (100 %) and a kappa of 1. Meanwhile, ”context and/or explanation” had slightly lower agreement (81.25 %) but still demonstrated a solid kappa of 0.632, indicating a strong level of consistency.

The Reflection Dimension also demonstrated substantial agreement, with total agreement at 81.25 % and a kappa of 0.621. This suggests that the coders generally aligned well in identifying reflective behaviors, although there was slightly more variation compared to Exhibit Use and Information. ”Challenge or experiment” and ”inviting reflection” both had high agreement (93.75 %) and moderate kappa values (0.717 and 0.632, respectively), meaning these behaviors were relatively easy to recognize. ”Attention to phenomena,” on the other hand, had a lower kappa (0.518) despite having an agreement of 84.38 %, indicating that while coders mostly agreed, there were some inconsistencies in how this behavior was identified. The variability in kappa values within this Dimension highlights the complexity of coding reflective engagement, which often involves interpreting subtle visitor behaviors and facilitator prompts.

The Comfort Dimension presented more variability across its categories, with an overall agreement of 87.50 %, though the kappa value was not calculated for the total due to the lack of instances where Comfort strategies were completely absent. Most individual behaviors within this Dimension had strong agreement, with "small talk" and "welcoming" both reaching 93.75 % agreement and kappa values of 0.632 and 0.846, respectively, suggesting that these behaviors were clear and easy to code. "Laughter, joy" also had high agreement (81.25 %) and a moderate kappa (0.619), reinforcing that facilitators' use of humor and expressions of enjoyment were consistently recognized. However, "focus on the visitor" stood out with the lowest agreement (53.13 %) and a very low kappa (0.111), indicating that coders had different interpretations of what this behavior entailed. Rather than being a drawback, this disagreement led to a critical realization—the coders were working with different implicit definitions of "focus on the visitor," prompting a refinement of the coding framework to better standardize this concept. The refined framework explicitly notes that code describes only the action of focusing on someone, not the general sense that a facilitator is engaged in the conversation (Table 4.1). Additionally, Cohen's kappa for the total Comfort Dimension was "N/A", because there were no instances where neither coder identified a Comfort behavior, which makes the statistic impossible to calculate. However, it is important to note that this does not mean there were no disagreements. There were instances where one coder identified a Comfort behavior and the other did not, particularly within "focus on the visitor," which explains why the agreement percentage was not 100 % for the Dimension as a whole. These results underscore the importance of refining coding definitions through iterative reliability testing.

Overall, these results indicate a strong level of agreement between coders, with most categories achieving substantial kappa values and high agreement percentages. The discrepancies that did arise were largely productive, leading to refinements in coding definitions rather than indicating fundamental flaws in the framework. The ability to achieve high inter-rater reliability across multiple Dimensions of facilitation suggests that this framework can serve as a useful and reliable tool for studying facilitator-visitor interactions in informal learning settings. Taken as a whole, these results affirm that the improved Facilitation Framework effectively captures the nuances of facilitator-visitor interactions,

providing a solid foundation for further research and practical application in science centers.

4.2.3. Alignment with existing facilitation models

The development of facilitation frameworks in science centers and museums has been explored before, with several studies proposing different models of facilitation practices. Many of these frameworks share key elements with the Facilitation Framework, reinforcing the idea that certain aspects of effective facilitation are consistently recognized. The four Dimensions in the Facilitation Framework (Comfort, Information, Reflection, and Exhibit Use) align with existing models, highlighting common factors that contribute to successful visitor engagement. In addition to providing a structured approach to facilitation, this framework serves as a practical tool for assessing and improving facilitation practices, in line with previous research. Its distinct contribution lies in its foundation in direct observations of facilitators and its inclusion of perspectives from three science centers of varying sizes and cultural contexts.

Pattison, Rubin, and Wright (2017) highlight five facilitation strategies—orienting, challenging, providing explanations, showing appreciation, and establishing visitor ownership—which align closely with our Dimensions. For example, the "orienting" strategy, which helps visitors understand how to interact with an exhibit, maps directly to the "Exhibit Use" Dimension. This is essential for ensuring that visitors are not only engaged but also able to use the exhibits effectively. The "challenging" strategy, which encourages deeper thinking, corresponds to the "Reflection" Dimension, where facilitators promote cognitive engagement and critical thinking. The strategy of "providing explanations" ties directly to the "Information" Dimension, as it emphasizes the role of facilitators in conveying content. Lastly, the strategies of "showing appreciation" and "establishing visitor ownership" could be captured by the "Comfort" Dimension, which focuses on fostering a supportive and encouraging environment that enhances the visitor's experience.

Andanen et al. (2016) discuss the importance of balancing educational content with visitor needs through a responsive facilitation cycle. This approach involves facilitators observing and adjusting their strategies based on visitor interactions with exhibits. This aligns with all four Dimensions of our framework, as it emphasizes the importance of considering visitor comfort (ensuring

a positive experience), providing effective information, guiding how exhibits are used, and encouraging reflection during interactions. The study highlights how facilitators need to continuously adapt their approaches, ensuring that they are responsive to the needs of visitors and the goals of the exhibit. In this sense, the Facilitator Framework provides a structured way to approach this adaptive practice, helping facilitators engage visitors effectively and enhance the learning experience.

Harlow (2019) introduce a framework that focuses on visitor engagement through the use of STEM practices, with the P*IX*EL matrix linking visitor engagement levels to facilitation pathways. This framework closely connects with the "Reflection" and "Exhibit Use" Dimensions of our Facilitation Framework. The Reflection Dimension is particularly relevant in this context, as facilitators encourage visitors to deepen their understanding of STEM concepts through guided engagement. The "Exhibit Use" Dimension is also key, as facilitators help visitors interact with exhibits in ways that maximize learning. By emphasizing the need to optimize practice and engagement pathways, this framework complements our Dimensions, underscoring the need for facilitators to guide visitors through progressively more engaged and reflective interactions with exhibits.

Chien et al. (2024) examine the role of facilitators in museum settings and how their support impacts learning. The study finds that while facilitators help visitors engage with exhibits, they may not always emphasize deepening conceptual understanding. This observation points to the importance of the "Comfort," "Information," and "Reflection" Dimensions. Facilitators who use positive language, ask questions, and employ scientific terminology can increase visitor engagement and help them recall prior knowledge, especially when encouraging reflection on the exhibit experience. However, the study suggests that facilitators may need to place more emphasis on reflective practices to foster deeper learning outcomes. This supports the need for a balanced approach, where the "Reflection" Dimension becomes critical in enhancing the learning experience. Thus, the study underscores how the Dimensions in our framework can be used to guide facilitators in creating more impactful learning environments.

4.3. Conclusion

The parallel development of the SOLEIL app and the validation of the Facilitation Framework exemplifies the power of combining technological innovation with theoretical rigor. The iterative validation process not only strengthened the framework, making it a more precise and adaptable tool for analyzing facilitator behaviors, but also showcased the app's capabilities in streamlining data collection and analysis. By incorporating the revised version of the Facilitation Framework into the app after the first stage of validation, the second stage benefited from faster and more accurate coding, facilitated by the app's ability to compare coder outputs and calculate inter-rater reliability metrics with ease.

The SOLEIL app's impact on the validation process was significant, reducing the time and effort required for coding and analysis while increasing the reliability of the results. Features like automated contingency tables, agreement calculations, and kappa statistics allowed for clear and systematic evaluation of the framework's application across different contexts. This collaborative and iterative approach not only validated the framework but also demonstrated how digital tools can advance educational research by enabling more efficient and scalable methodologies.

As this chapter illustrates, the integration of the Facilitation Framework into the SOLEIL app represents a step forward in the study of informal learning environments, providing a model for how technological and theoretical advancements can complement each other. The following sections will delve into the findings from the two-stage validation process and the broader implications for exhibit design, visitor engagement, and facilitation practices in science centers.

The next chapters present the results and discussion of the Comprehensive and Extended Studies, delving into the findings, examining how they contribute to understanding the factors influencing visitor behavior and engagement in science centers.

Chapter 5

Comprehensive Study

Understanding the factors that influence visitor engagement in informal science learning spaces, such as science centers, is crucial for enhancing educational outcomes. This chapter discusses the Comprehensive Study, which analyzes secondary data from an extensive database, exploring visitor demographics and assessing how factors such as gender, age, group type, reading signage, taking pictures, facilitator presence, and exhibit type influence engagement.

The Comprehensive Study forms the foundation of our research, utilizing an extensive dataset to analyze visitor engagement at science centers. This very extensive dataset provided a unique opportunity to explore the factors influencing visitor engagement, enabling us to identify patterns and predictors with a high degree of statistical significance. The results from this large-scale study provide critical insights and set the stage for further exploration in the subsequent Extended Study.

5.1. Visitor sample description

The distribution of visitors by gender and age in our sample (shown in Table 5.1) shows some interesting patterns. The most common visitor types are adults (43.6 %) and children (28.8 %), who together account for the majority of observations. Adults are the largest group, followed by children, while seniors (3.0 %) represent the smallest category. As for gender, female visitors represent 54.1 % of the sample, and they outnumber male visitors in all age categories except for children (16.1 % male, 12.7 % female). Keeping with

this trend, male seniors are the smallest category of visitors (1.2 %). These findings align with previous research on museum visitation patterns. Chang (2006) noted that museum attendance is not evenly distributed across age groups, with adults between 25 and 44 and children between 5 and 9 being the most frequent visitors. Their work with demographic surveys from the Smithsonian museums showed that half of their visitors were between 20 and 44 years old, with children comprising 30 % of attendees and seniors making up a small fraction. This pattern is consistent with findings from science centers and other informal science settings, where families constitute the predominant visitor group. For example, Barriault (2014) found that 61.5 % of adult visitors to an aquarium during peak summer tourism were accompanied by children under 18, and family groups nearly always included both male and female members. Furthermore, data from Kocaeli Science Center also show a strong presence of children and young people, particularly those aged 6-15 (Laçın-Şimşek and Öztürk, 2022). In our study, the predominance of adults and children, with relatively few seniors, is in line with these broader trends in science center and museum attendance.

Table 5.1: Distribution of visitors by age and gender in the sample ("yo" = "years old")

	Female	Male	Total	F (%)	M (%)	Total (%)
Young child (0-5yo)	392	475	867	4.4	5.3	9.7
Child (6-10yo)	1145	1450	2595	12.7	16.1	28.8
Pre-teen (11-13yo)	336	298	634	3.7	3.3	7.0
Teen (14-18yo)	433	280	713	4.8	3.1	7.9
Adult (19-64yo)	2402	1521	3923	26.7	16.9	43.6
Senior (65+yo)	164	106	270	1.8	1.2	3.0
Total	4872	4130	9002	54.1	45.9	100.0

When analyzing the data considering the other variables (group type, taking pictures, looking at signage, and interacting with a facilitator) in relation to age and gender, several patterns emerge and provide a more nuanced overview of the sample. Tables 5.2 through 5.5 show the percentage of visitors by age and gender for each variable. Tables detailing the number of visitors for each variable are provided in Appendix 2.

Table 5.2 presents the percentage of visitors who engage with the exhibit as part of a group. As would be expected, the youngest visitors are almost never alone, as 95.0 % of young children and 93.1 % of children interact with

Table 5.2: Percentage of visitors who engage with the exhibit as part of a group

	Female (%)	Male (%)	Total (%)
Young child (0-5yo)	96.4	93.9	95.0
Child (6-10yo)	92.7	93.4	93.1
Pre-teen (11-13yo)	87.8	88.9	88.3
Teen (14-18yo)	92.1	85.4	89.5
Adult (19-64yo)	91.8	86.4	89.7
Senior (65+yo)	89.0	84.0	87.0
Total	92.1	89.8	91.0

exhibits as part of a group. And even though being in a group is less common in the other age groups, it's still a considerable percentage (between 87 and 89 %). Although in total, more females than males engage with exhibits as part of a group (92.1 % vs 89.8 %), there is no distinct gender trend among the age categories. This is consistent with what other researchers have found. Barriault (2014) states that 81.5 % of visitors appeared to be in a family group, while Allen and Gutwill (2004) note a large majority of visitors come in groups. Massarani, Norberto Rocha, et al. (2021) and Bobbe (2022) also state that museums and science centers are highly social spaces where visitors mostly visit in social groups consisting of families or friends.

Table 5.3: Percentage of visitors who take pictures, by age and gender

	Female (%)	Male (%)	Total (%)
Young child (0-5yo)	2.0	2.5	2.3
Child (6-10yo)	2.9	2.1	2.5
Pre-teen (11-13yo)	1.5	0.7	1.1
Teen (14-18yo)	3.2	1.8	2.7
Adult (19-64yo)	4.0	2.2	3.3
Senior (65+yo)	1.8	0.9	1.5
Total	3.3	2.1	2.7

In general terms, taking pictures (Table 5.3) is very uncommon in the sample (2.7 % of total visitors), and it is primarily an adult activity (3.3 % of adults take a picture). When considering gender, more females than males take pictures in all cases, except for young children, where slightly more males do (2.0 % vs 2.5 %). Adult females take the most pictures (4.0 %) and male pre-teens take the least (0.7 %). There is relatively little research on pictures at science centers, therefore it is hard to determine if these trends follow what

other researchers have observed. One study by Massarani, Norberto Rocha, et al. (2021), found that 27 % of total time spent at exhibits involved “conversation about the exhibit,” a category that includes photo-taking, discussions about topics that caught the visitors’ attention, and checking what the exhibit was about. Unfortunately, the study does not specify the frequency of photo-taking or provide demographic breakdowns of who engages in this activity. Barriault and Rennie (2019) included ‘taking pictures’ as a Initiation Level behaviour in zoos and aquaria due to the widespread occurrence of this activity in those settings.

Table 5.4: Percentage of visitors who look at signage, by age and gender

	Female (%)	Male (%)	Total (%)
Young child (0-5yo)	7.9	7.2	7.5
Child (6-10yo)	17.3	16.1	16.6
Pre-teen (11-13yo)	20.2	16.4	18.5
Teen (14-18yo)	19.9	22.5	20.9
Adult (19-64yo)	34.1	30.1	32.5
Senior (65+yo)	40.2	30.2	36.3
Total	26.0	21.1	23.7

The percentage of visitors in our sample who look at the signage (Table 5.4) shows a trend that increases with age, and is most common among seniors (36.3 %) and adults (32.5 %). In terms of gender, more females than males look at the signage, for all age categories. The group with most visitors who look at the signage is senior women (40.2 %) and the one with the least is male young children. This aligns with findings from other studies. For example, Rainoldi et al. (2020) found that the average fixation duration on information boards was highest within the group of older adults, followed by adults and younger adults. Chang (2006) notes that in group visits, one member usually reads segments of a text aloud for their companions and in family groups, an adult will usually read through the labels. One possible factor contributing to the gender disparity could be that females tend to outperform males in reading and writing (Longnecker et al., 2022; Rennie et al., 2007).

Finally, interacting with a facilitator is relatively uncommon in our sample across all age groups, as it represents only 5.4 % of all visitors (Table 5.5). In general, interacting with a facilitator is most common for children (6.2 %), followed by adults (5.7 %) and seniors (5.2 %). The group that showed the smallest percentage of visitors interacting with a facilitator is young children,

Table 5.5: Percentage of visitors who interact with a facilitator, by age and gender

	Female (%)	Male (%)	Total (%)
Young child (0-5yo)	3.1	3.4	3.2
Child (6-10yo)	6.4	6.0	6.2
Pre-teen (11-13yo)	5.1	4.7	4.9
Teen (14-18yo)	4.8	4.3	4.6
Adult (19-64yo)	5.2	6.4	5.7
Senior (65+yo)	3.7	7.5	5.2
Total	5.2	5.7	5.4

for both genders (3.1 % females, 3.4 % males). Even though in total, more males than females interact with a facilitator (5.7 % vs 5.2 %), and the percentage of male seniors doubles that of females (7.5 % male, 3.7 % female), there is no distinct gender trend among the age categories. Interestingly, these distributions perfectly align with estimates from the research staff at Science North, that facilitators engage with fewer than 5 % of visitors when exhibits are being recorded, possibly to avoid disrupting the exhibit’s operation during the recording process (A. Henson, personal communication, June 24, 2020). Previous research found that adult family members often act as ”gatekeepers” when staff members attempt to engage with families in a museum setting, controlling whether or not museum staff can interact with the family (Pattison and Dierking, 2012). That study also noted that staff members found it hard to connect with families or meaningfully facilitate learning without the support of adult family members.

5.2. Exhibit sample description

The 97 exhibits in this study were classified using Widerström’s framework 2020. As discussed in the Literature Review chapter, Widerström proposes a classification framework for interaction with exhibits based on the level of Participation (Static vs. Participatory content), the level of Virtuality (Physical vs. Virtual space), and the level of Collaboration (Individual vs. Collaborative interaction). Table 5.6 shows the distribution of exhibits by each level, and full list of the exhibits, including their classification can be found in Appendix 3.

Table 5.6: Distribution of exhibits by dimension (Participation, Virtuality, and Collaboration)

Dimension		n	%
Participation	Static	65	67.0
	Static- Participatory	22	22.7
	Participatory	10	10.3
Virtuality	Physical	51	52.6
	Physical/Virtual	20	20.6
	Virtual	26	26.8
Collaboration	Individual	38	39.2
	Individual/Collaborative	52	53.6
	Collaborative	7	7.2

In terms of Participation, Static exhibits are the most common (65 exhibits, 67.0 %), followed by Static/Participatory (22 exhibits, 22.7 %) and Participatory (10 exhibits, 10.3 %). The fact that only a minority of exhibits are fully Participatory is not surprising, given the types of exhibit typically found in a science center exhibition. Even in centers that emphasize constructivist approaches, not all exhibits can focus on co-creation and active visitor involvement; some must present predetermined content for visitors to explore, reducing cognitive load and museum fatigue (Bitgood, 2002; Davey, 2005). Regarding Virtuality, Physical exhibits are the most common (51 exhibits, 52.6 %), while Physical/Virtual accounts for 20 exhibits (20.6 %), and 26 exhibits (26.8 %) are purely Virtual. This distribution is also understandable, as Virtual interfaces, such as computer screens, have become more accessible and ubiquitous, but it could be argued that a key appeal of science centers remains the hands-on experience of interacting with Physical exhibits. In the Collaboration dimension, Individual/Collaborative exhibits are the most prevalent (52 exhibits, 53.6 %), followed by Individual exhibits (38 exhibits, 39.2 %), whereas fully Collaborative exhibits are the least represented (7 exhibits, 7.2 %). Even though it is rare for visitors to approach exhibits or visit the science center alone, they are present, and it would make sense that most exhibits are designed to not require multiple people to operate or engage with them.

Each exhibit was classified using a combination of these dimensions (see Table 5.7 and Fig. 5.1), and few key patterns emerge from these classifications. The most common combination of two dimensions for exhibits is Static

Table 5.7: Distribution of exhibits by type (combined dimensions)

Participation	Virtuality	Collaboration	n	%
Static	Physical	Individual	16	16.7
		Individual/Collaborative	20	20.8
		Collaborative	0	0
	Physical/Virtual	Individual	4	4.2
		Individual/Collaborative	3	3.1
		Collaborative	0	0
	Virtual	Individual	10	10.4
		Individual/Collaborative	6	6.3
		Collaborative	6	6.3
Static/Participatory	Physical	Individual	4	4.2
		Individual/Collaborative	5	5.2
		Collaborative	0	0
	Physical/Virtual	Individual	2	2.1
		Individual/Collaborative	8	8.3
		Collaborative	0	0
	Virtual	Individual	0	0
		Individual/Collaborative	2	2.1
		Collaborative	1	1
Participatory	Physical	Individual	2	2.1
		Individual/Collaborative	4	4.2
		Collaborative	0	0
	Physical/Virtual	Individual	0	0
		Individual/Collaborative	3	3.1
		Collaborative	0	0
	Virtual	Individual	0	0
		Individual/Collaborative	1	1
		Collaborative	0	0

and Physical, with 36 exhibits (37.1 %) fitting into this combined category. This suggests that the majority of exhibits in this sample include opportunities for tangible interaction without Participatory or Virtual elements, and that content tends to be predetermined. Additionally, the most frequent combination of the three dimensions is Static, Physical, and Individual/Collaborative (20 exhibits, 20.8 %), highlighting a predominance of Physical exhibits that allow for both independent or Collaborative exploration, while their content is predetermined (as opposed to co-created by the users). Notably, none of the exhibits in this study fall into the combination of the Collaborative and Participatory categories. This absence suggests that while

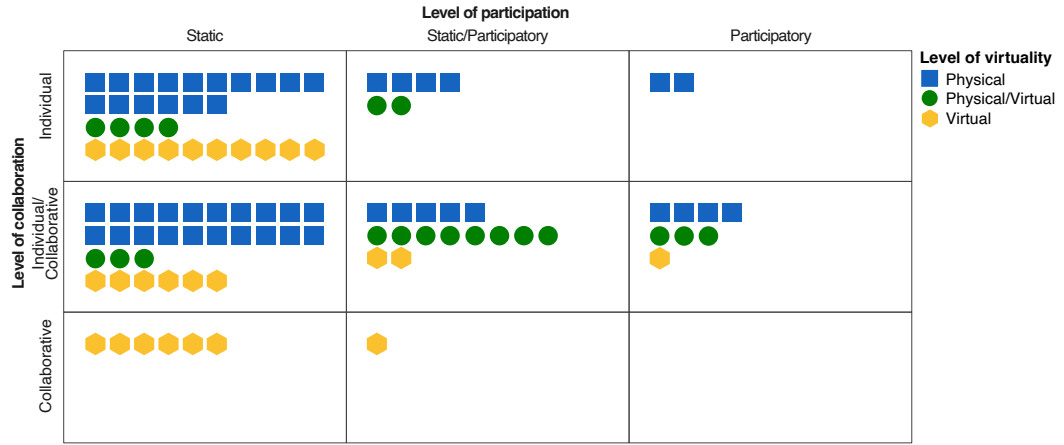


Figure 5.1: Distribution of exhibits by combined type. The quadrants represent the combinations of the levels of participation and collaboration, while the shape and color of the items represent the level of virtuality.

some exhibits require group interaction, they do not simultaneously require the visitors to contribute to the exhibit’s content and vice-versa.

The relationship between Virtuality and Collaboration reveals additional insights. Virtual exhibits show the highest proportion of fully collaborative experiences, with 27 % (7 out of 26) supporting full collaboration. In contrast, Physical exhibits tend to favor Individual/Collaborative interaction, with 59 % (30 out of 51) following this structure. Physical/Virtual exhibits, on the other hand, display a more balanced distribution between Individual and Individual/Collaborative engagement. Additionally, Static and Static/Participatory exhibits demonstrate the most versatility, appearing across all Virtuality and Collaboration types. The Static category, in particular, has the highest number of fully Individual exhibits (16 Physical, 4 Physical/Virtual, 10 Virtual), reinforcing its role as the dominant mode of engagement in this sample.

5.3. Data analysis

Association between each Individual variable and engagement

Understanding how individual visitor characteristics and exhibit features relate to engagement can provide valuable insights into exhibit design and visitor experience. This section examines the association between engagement and nine variables: age, gender, group type, taking pictures, looking at signage, interacting with a facilitator and each dimension of exhibit design. To assess

these relationships, we conducted chi-square tests and calculated Cramer’s V and Kendall’s Tau-b for each variable (Table 5.8). We used contingency tables to visualize observed versus expected engagement levels for each variable, allowing for a clearer interpretation of these associations (Figs. 5.2 through 5.10; contingency tables can be found in Appendix 2).

Table 5.8: Chi-square test results and association measures for the relationship between engagement and various predictor variables. The table reports the chi-square statistic (χ^2), degrees of freedom (df) and p-value (px), Cramer’s V for effect size, Kendall’s Tau-b (τ_b) for ordinal associations, and the p-value for Tau-b (pt).

	χ^2	df	px	Cramer’s V	τ_b	pt
Age	192.54	10	< .001	.18	.02	.019
Gender	5.27	2	.072	.16	-.02	.042
Group Type	277.75	2	< .001	.07	.11	< .001
Looking at Signage	237.73	2	< .001	.12	.11	< .001
Taking a Picture	45.24	2	< .001	.07	.01	.294
Interacting with Facility	123.19	2	< .001	.04	.11	< .001
Exh.: Participation	99.76	4	< .001	.12	.03	.001
Exh.: Virtuality	34.45	4	< .001	.10	-.01	.316
Exh.: Collaboration	238.00	4	< .001	.02	.12	< .001

These statistical tests identify whether observed patterns of engagement differ significantly from what would be expected by chance, helping to determine whether certain visitor attributes are meaningfully associated with higher or lower engagement. However, this analysis only explores the presence and strength of associations between individual variables and engagement without controlling for other factors. It is important to note that association does not imply causation; even when a predictor shows a strong association with engagement, this does not mean it directly causes changes in engagement (Agresti, 2018). The observed effect may be influenced by other predictors, whether included in the model or not, which could also drive variations in engagement. A more detailed examination of each variable’s independent influence will be presented later in the chapter through regression analysis.

As shown in Fig. 5.2, engagement levels vary across age groups. Young children exhibit a higher percentage of visitors in the Transition stage than expected, while their Breakthrough percentage is lower than anticipated. In contrast, adults and seniors show a slight trend in the opposite direction, with lower Transition levels and marginally higher Breakthrough levels than expected. The engagement distribution for children, pre-teens, and teenagers

closely aligns with the expected values. This association is statistically significant, $\chi^2(10, 9002) = 192.54$, $p < .001$, with a weak size effect (Cramer's $V = .18$) and a weak positive correlation ($\tau_b = .02$, $p = .019$). While statistically significant, the practical implications of this correlation remain limited.

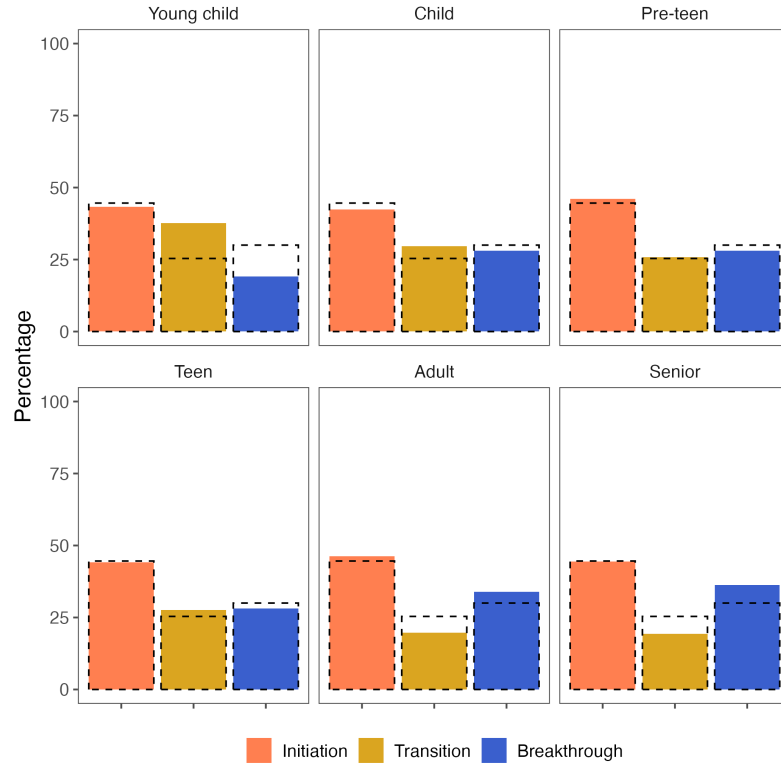


Figure 5.2: Comparison of the engagement levels for the different age groups. Filled bars represent the observed engagement, while dashed boxes indicate the expected engagement levels if the variables were not associated

For gender, Figure 5.3 illustrates that the percentage of visitors reaching each engagement level does not strongly differ between groups. The proportion of visitors at the Initiation, Transition, and Breakthrough levels remains close to expected values for both genders. The association between gender and engagement is not statistically significant, as indicated by $\chi^2(2, 9002) = 5.27$, $p = .072$, with a weak effect size (Cramer's $V = .16$). While Kendall's Tau-b test shows a statistically significant weak negative correlation ($\tau_b = -.02$, $p = .042$), its magnitude suggests no meaningful practical effect.

Engagement levels vary notably based on group type, as presented in Figure 5.4. Visitors exploring alone exhibit a significantly higher percentage of Initiation than expected, while their Transition and Breakthrough levels are both

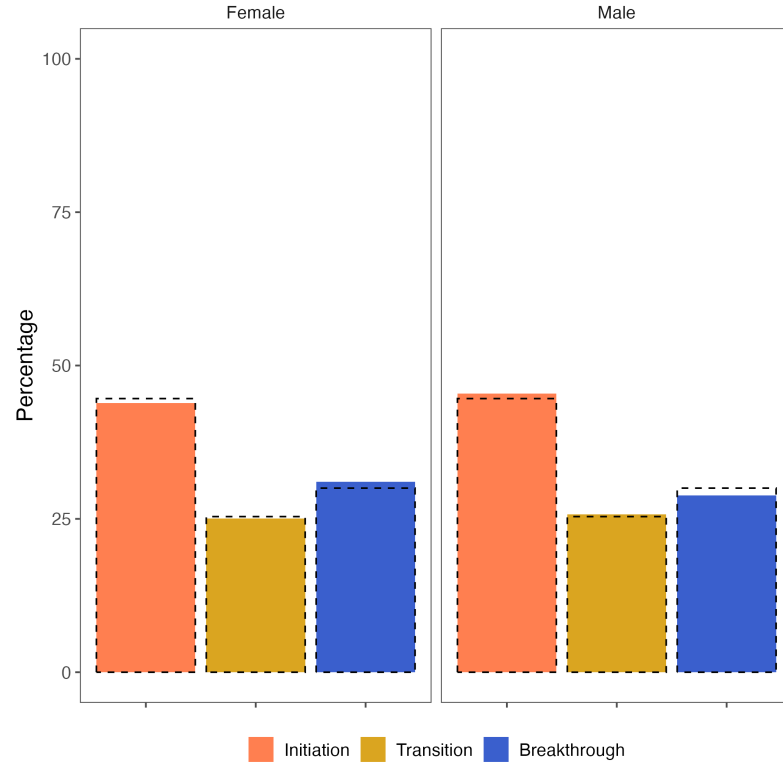


Figure 5.3: Engagement levels for gender, comparing females (left) and males (right). Filled bars represent the observed engagement, while dashed boxes indicate the expected engagement levels if the variables were not associated

lower. Conversely, visitors in groups display a slightly lower-than-expected Initiation percentage, while both Transition and Breakthrough levels are slightly higher. This association is statistically significant, $\chi^2(2, 9002) = 277.75$, $p < .001$, with a weak effect size (Cramer's $V = .07$). The positive correlation ($\tau_b = .11$, $p < .001$) further supports the finding that being in a group is linked to a higher likelihood of reaching higher engagement levels.

Examining the effect of looking at the signage, Figure 5.5 reveals a clear difference in engagement levels between visitors who read signage and those who do not. Visitors who read the signage exhibit lower Initiation and Transition percentages than expected and a higher proportion at the Breakthrough level. This association is statistically significant, $\chi^2(2, 9002) = 237.73$, $p < .001$, with a moderate effect size (Cramer's $V = .12$). Additionally, there is a positive correlation ($\tau_b = .11$, $p < .001$), indicating that reading signage is linked to higher engagement.

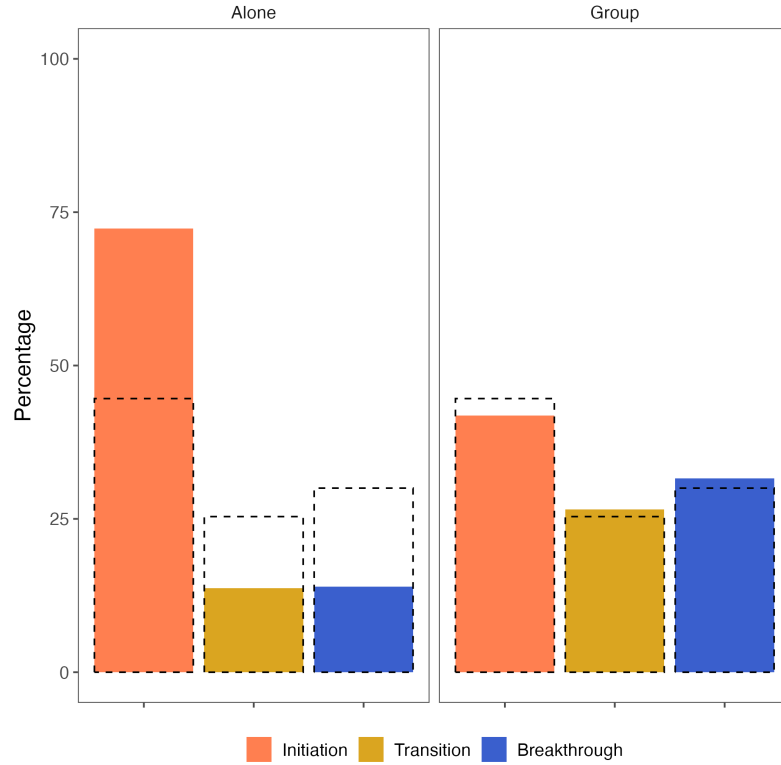


Figure 5.4: Engagement levels for each group type, comparing visitors alone (left) and visitors in a group (right). Filled bars represent the observed engagement, while dashed boxes indicate the expected engagement levels if the variables were not associated

Visitors who did not take pictures exhibit engagement levels that closely match the expected values when there is no association. Those who did take pictures, however, show nearly double the expected Transition percentage, while their Initiation and Breakthrough percentages are both lower (Fig. 5.6). Although the association is statistically significant, $\chi^2(2, 9002) = 45.24$, $p < .001$, the effect size is weak (Cramer’s $V = .07$). In this case, Tau-b is not an appropriate measurement of association, because the effect is not increasing towards either Initiation or Breakthrough, but instead is “concentrated” in Transition (Agresti, 2018).

Facilitator interaction significantly influences engagement levels, as illustrated in Figure 5.7. Visitors who interact with a facilitator show lower Initiation level, while their Transition is consistent with expected values, and their Breakthrough is notably higher. In contrast, engagement levels for visitors who did not interact with a facilitator closely match the expected distribution

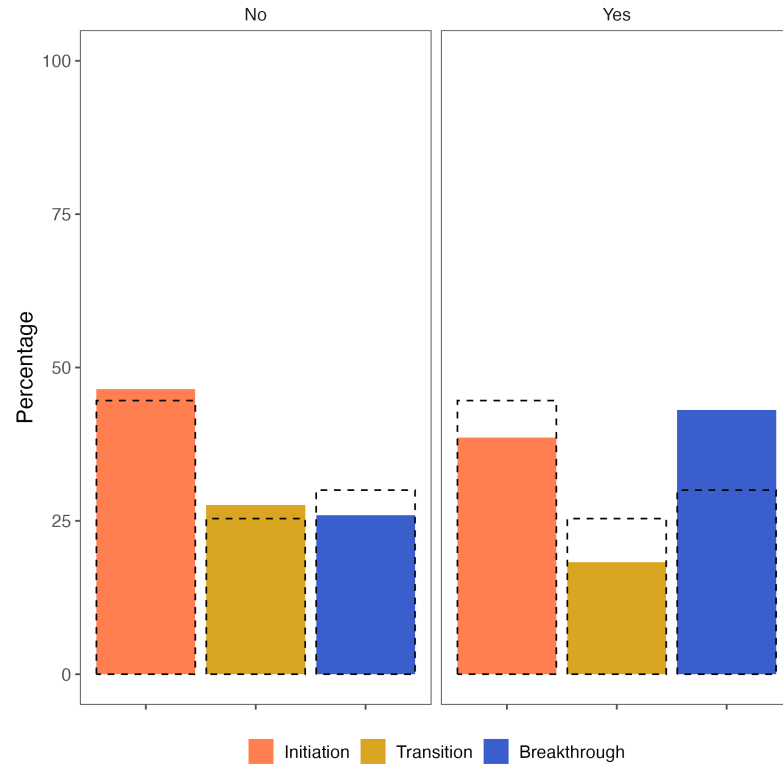


Figure 5.5: Engagement levels comparing visitors who do not look at the signage (left) and visitors who do (right). Filled bars represent the observed engagement, while dashed boxes indicate the expected engagement levels if the variables were not associated

by chance. This association is statistically significant, $\chi^2(2, 9002) = 123.19$, $p < .001$, with a moderate effect size (Cramer's $V = .11$). The positive correlation ($\tau_b = .11$, $p < .001$) suggests that facilitator interaction is associated with a higher likelihood of reaching higher engagement levels.

The relationship between engagement and the level of Participation of the exhibit shows notable variations, as seen in Figure 5.8. Static/Participatory exhibits display engagement levels close to expectations, while Participatory exhibits have the highest Transition percentage among the three types. Static exhibits display slightly higher Initiation and slightly lower Transition percentages than expected, while Breakthrough remains consistent across exhibit types. The association between engagement and Participation is statistically significant, $\chi^2(4, 9002) = 99.76$, $p < .001$, with a weak effect size (Cramer's $V = .12$). This suggests that for more Participatory exhibits, visitors are more likely to reach Transition.

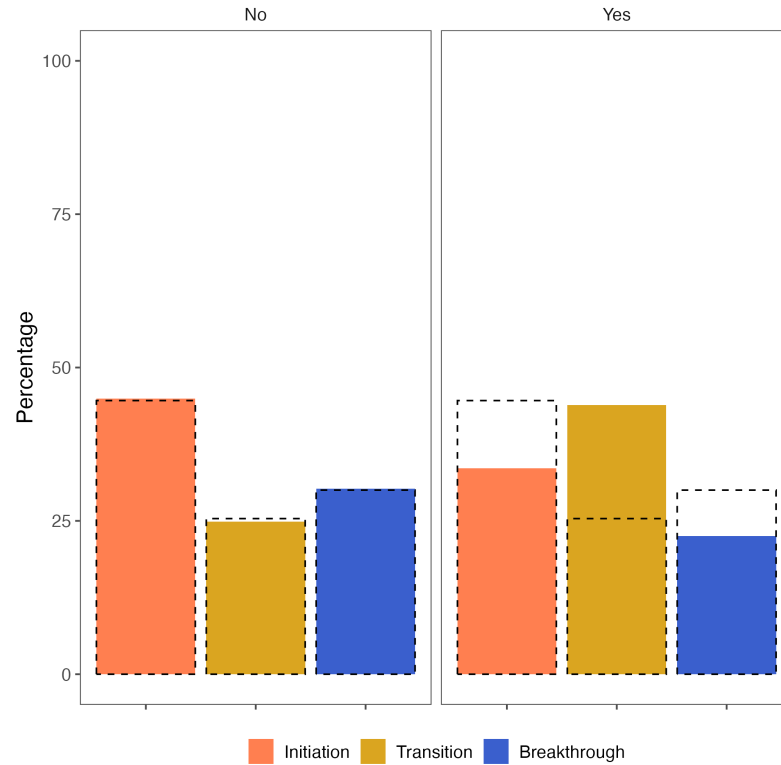


Figure 5.6: Engagement levels comparing visitors who do not take pictures (left) and visitors who do (right). Filled bars represent the observed engagement, while dashed boxes indicate the expected engagement levels if the variables were not associated

The level of Virtuality does not appear to have a strong influence on engagement levels, as presented in Figure 5.9. The observed engagement levels align closely with expected values by chance across different exhibit types. While the association is statistically significant, $\chi^2(4, 9002) = 34.45$, $p < .001$, the effect size is weak (Cramer's $V = .10$). This suggests that the degree to which an exhibit has more physical or more virtual elements has little practical impact on engagement.

Finally, an exhibit's level of Collaboration strongly correlates with engagement, as illustrated in Figure 5.10. Individual exhibits have slightly higher Initiation and slightly lower Breakthrough percentages than expected, while Interactive/Collaborative exhibits follow the expected distribution. Collaborative exhibits show the most significant variation, with much lower Initiation and the highest Breakthrough levels. This association is statistically significant, $\chi^2(4, 9002) = 238$, $p < .001$, with a negligible effect size (Cramer's V

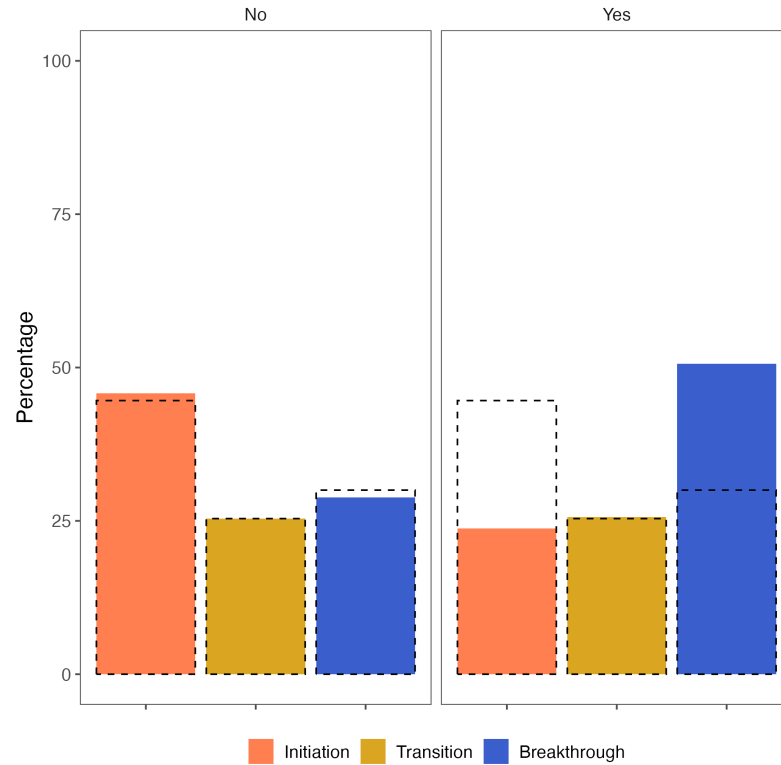


Figure 5.7: Engagement levels comparing visitors who do not interact with a facilitator (left) and visitors who do (right). Filled bars represent the observed engagement, while dashed boxes indicate the expected engagement levels if the variables were not associated

= .02). The positive correlation ($\tau_b = .12$, $p < .001$) further suggests that more collaborative exhibits are associated with a higher engagement level of engagement.

Overall, while multiple variables show statistically significant associations with engagement levels, their practical implications vary. Group type, signage reading, facilitator interaction, and exhibit interaction type show an association with engagement, while variables like gender and level of virtuality do not. These findings highlight the multifaceted nature of visitor engagement and the importance of considering multiple factors when designing science center exhibits and experiences. However, this analysis focuses solely on the presence and strength of associations between individual variables and engagement, without accounting for other latent variables. A deeper exploration of each variable's independent effect will follow in the regression analysis section.

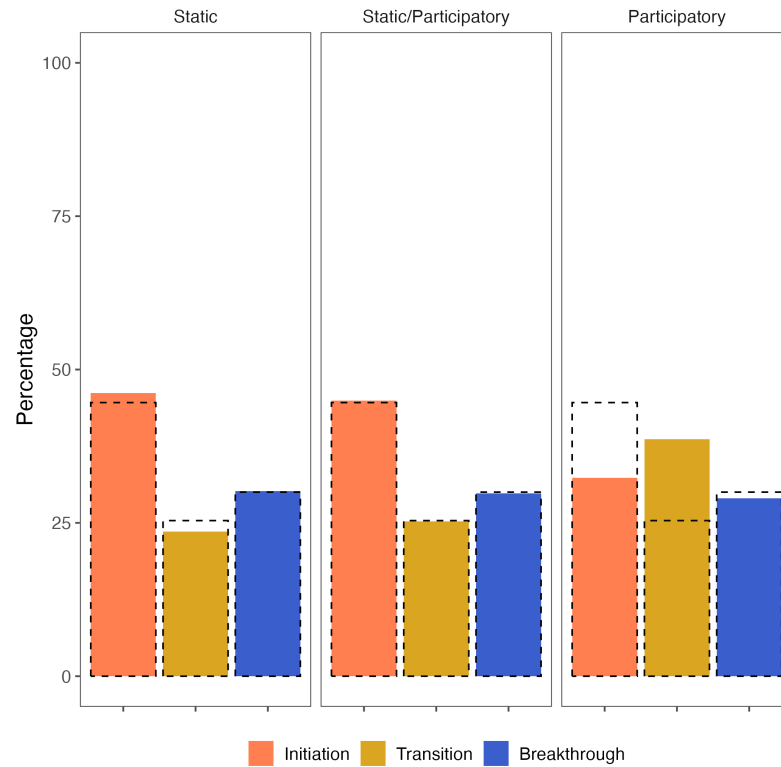


Figure 5.8: Comparison of the engagement levels for the three different levels of Participation. Static is on the left, Static/Participatory is in the center, and Participatory is on the right. Filled bars represent the observed engagement, while dashed boxes indicate the expected engagement levels if the variables were not associated.

Regression analysis

We used an ordinal regression model with the highest engagement level reached by each visitor as the dependent variable, categorized into Initiation, Transition, and Breakthrough. Predictor variables included age, gender, group type, interacting with a facilitator, taking a photograph, looking at signage, and the three dimensions of exhibit design. This allowed us to evaluate the Individual impact of each descriptor while holding all other variables constant.

To examine the relationships between the predictor variables, we constructed a correlation matrix (shown in Fig. 5.11). This matrix provides an overview of the associations between the variables, which helps in identifying potential multicollinearity issues that could affect the ordinal regression analysis. The results indicate that there is no substantial correlation between the variables included in the study, suggesting that multicollinearity is not a concern.

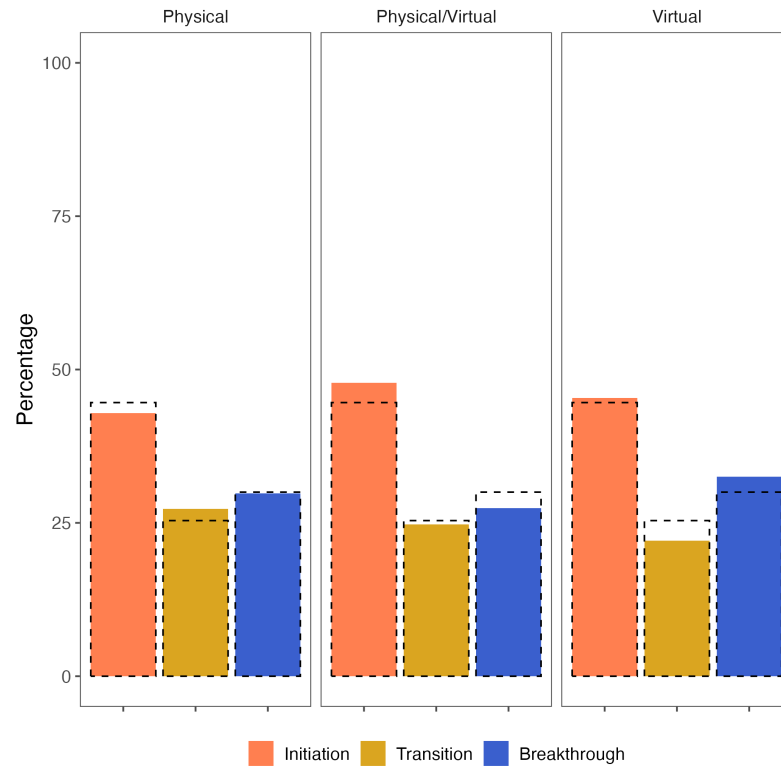


Figure 5.9: Comparison of the engagement levels for the three different levels of Virtuality. Physical is on the left, Physical/Virtual is in the center, and Virtual is on the right. Filled bars represent the observed engagement, while dashed boxes indicate the expected engagement levels if the variables were not associated

To appropriately build the regression model, we first considered that the ordinal regression model assumes the coefficients describing the relationship between, for example, the lowest versus all higher categories of the response variable are the same as those describing the relationship between the next lowest category and all higher categories, and so on. This is known as the *proportional odds assumption*. Because the relationship between all pairs of groups is the same, there is only one coefficient in the model for each predictor. If this assumption is violated for some predictors, separate coefficients related to each pair of outcome groups must be calculated for them, which is called the *Partial Proportional Odds Model*.

We tested the proportional odds assumption using the Brant test. The results, shown in Table 5.9, indicate the parallel regression assumption holds for interacting with a facilitator, gender, group type and the level of collaboration ($p > .05$). This means that looking at signage, taking pictures, age, the level

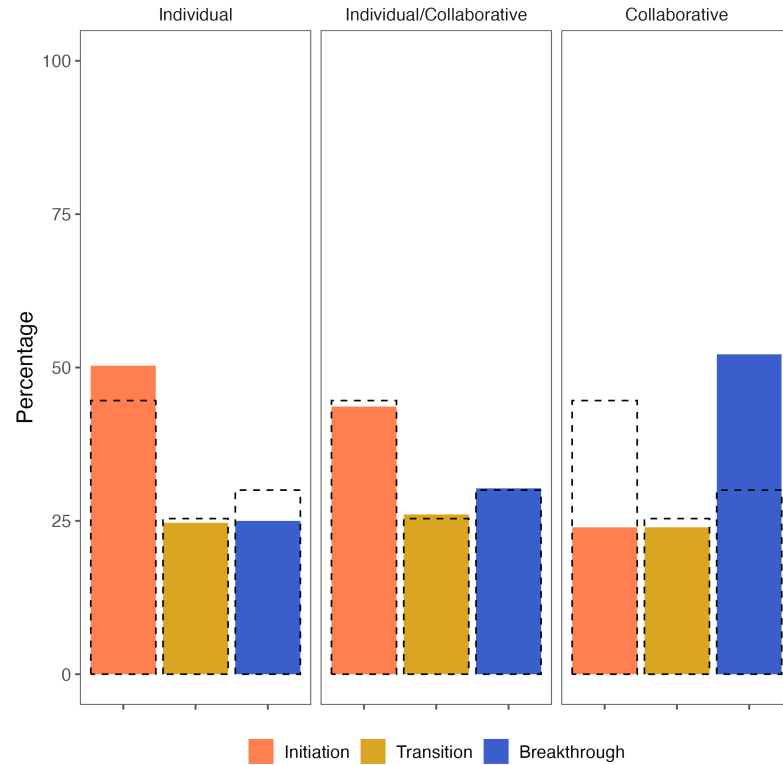


Figure 5.10: Comparison of the engagement levels for the three different levels of Collaboration. Individual is on the left, Individual/Collaborative is in the center, and Collaborative is on the right. Filled bars represent the observed engagement, while dashed boxes indicate the expected engagement levels if the variables were not associated

of collaboration and the level of virtuality have non-proportional effects ($p < .05$). Therefore, these descriptors require separate coefficients for each pair of outcome groups (Initiation-Transition and Transition-Breakthrough).

In light of this, we fitted the data using a Partial Proportional Odds Model. The optimal model is summarized in Table 5.10. Significant predictors of higher engagement levels ($p < .05$, indicated with one or more asterisks) include looking at signage (LS), taking a picture (TP), interacting with a facilitator (IF), age, group type (GT), and all three exhibit dimensions: Participation (EP), Virtuality (EV) and Collaboration (EC). The model has an AIC value of 18246.7, indicating its relative fit, and none of the estimates showed signs of the Hauck-Donner effect, suggesting stable and reliable coefficient estimates.

We used an extension of the Hosmer-Lemeshow test that can be applied to an ordinal logistic regression to determine the model's goodness-of-fit. The null hypothesis (H_0) of the test is that there is no lack of fit, meaning the model

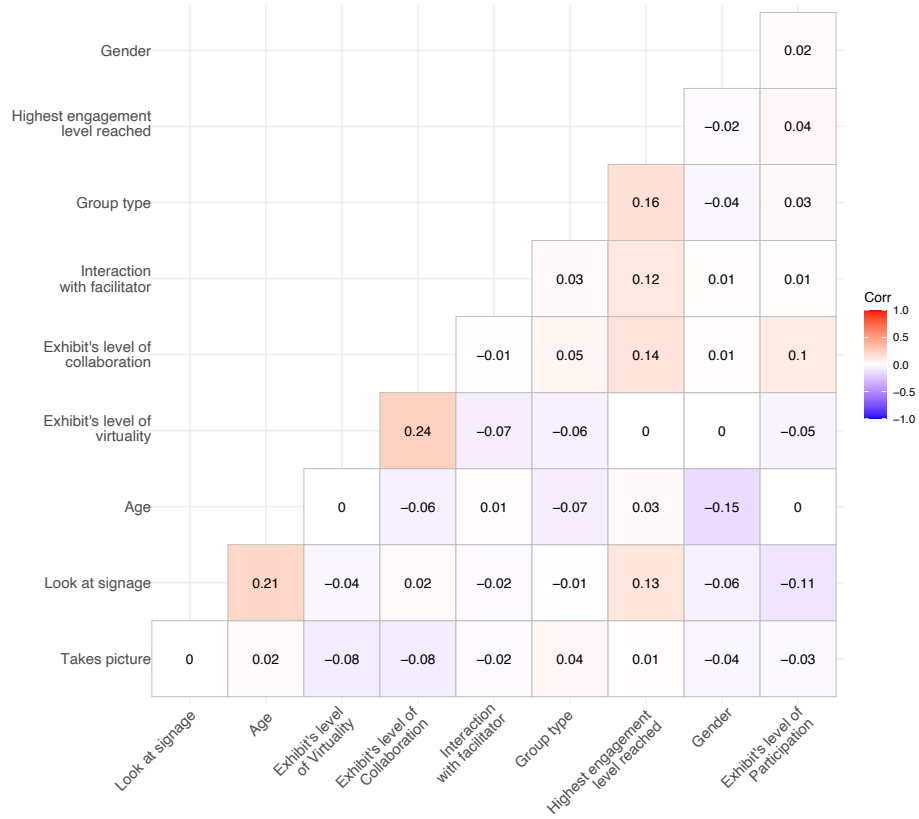


Figure 5.11: Correlation matrix between the descriptor variables and the dependent variable (highest level of engagement reached)

fits the data adequately. Our analysis revealed a lack of fit in the model ($p < .001$), likely due to the presence of latent variables that were not accounted for. This finding supports the rationale for conducting the Extended Study, as it highlights the need for additional data to fully understand the complexities of visitor engagement.

The model's performance, as reflected in the confusion matrix and associated statistics (Tables 5.11, 5.12, and 5.13), reveals some challenges in accurately classifying the three levels of engagement. The overall accuracy of 50.08 % (% 95 % CI: 49.04 %, 51.12 %), is slightly higher than the no-information rate (NIR) of 44.61 %, which indicates that while the model performs better than random guessing, its predictive power remains limited. This is further supported by the kappa value of .1665, suggesting weak agreement between the model's predictions and the actual class labels. McNemar's test yielded a highly significant p-value ($< .001$), which points to systematic mis-

Table 5.9: Brant test results assessing the proportional odds assumption, including degrees of freedom (df) and p-value.

	χ^2	df	p
Looking at Signage (LS)	45.75	1	< .001
Taking a Picture (TP)	28.78	1	< .001
Interacting with a Facilitator (IF)	0.06	1	.810
Age	118.27	1	< .001
Gender	0.56	1	.454
Group Type (GT)	3.05	1	.081
Level of Participation (EP)	40.15	1	< .001
Level of Virtuality (EV)	10.05	1	.002
Level of Collaboration (EC)	2.36	1	.124

classification errors, with some classes being mispredicted far more frequently than others.

The classification model performs well in predicting Initiation, with high sensitivity (82.02 %) but lower specificity (36.44 %), indicating it captures most true cases but also misclassifies many non-Initiation cases. Transition has the highest specificity (93.48 %) but very low sensitivity (13.79 %), suggesting the model struggles to identify true Transition cases while effectively rejecting non-Transition cases. Breakthrough shows moderate performance, with balanced sensitivity (33.27 %) and specificity (85.92 %). Precision varies across categories, with Initiation (50.97 %) and Breakthrough (50.34 %) having relatively higher values compared to Transition (41.83 %). Balanced accuracy remains around 53-60 %, suggesting overall moderate model performance, with particular difficulty in correctly identifying Transition cases.

These results reflect clear imbalances in the model’s ability to detect different classes (Initiation, Transition, Breakthrough), with Transition being particularly underrepresented in predictions. This suggests few and/or insufficiently distinctive features for class separation. However, the model’s strong performance in correctly predicting Initiation has practical implications. By accurately identifying visitors in the Initiation phase, the model can be used to assess whether a given set of visitors is likely to remain in Initiation or progress to higher engagement levels, such as Transition or Breakthrough. This information is valuable for tailoring interventions and designing exhibits that aim to enhance overall visitor engagement.

Table 5.10: Results of the ordinal regression analysis, including coefficients, estimates, standard errors (SE), z-values, and p-values for each predictor in the model. For predictors with two coefficients, these are indicated with (1) and (2). The z-values represent the test statistic for each coefficient, while the p-values indicate the statistical significance of the predictors in the model. Significant codes are indicated with asterisks.

Coefficient	Estimate	SE	z	p
(Intercept) 1	-1.730	0.125	-13.838	< .001
(Intercept) 2	-3.322	0.133	-25.039	< .001
Looking at Signage 1 (LS1)	0.403	0.053	7.553	< .001
Looking at Signage 2 (LS2)	0.704	0.054	12.963	< .001
Taking a Picture 1 (TP1)	0.582	0.140	4.145	< .001
Taking a Picture 2 (TP2)	-0.368	0.159	-2.309	.021
Interacting with a Facilitator (IF)	0.994	0.090	10.993	< .001
Age 1	-0.048	0.014	-3.353	.001
Age 2	0.116	0.016	7.402	< .001
Group Type (GT)	1.176	0.081	14.485	< .001
Level of Participation 1 (EP1)	0.211	0.034	6.194	< .001
Level of Participation 2 (EP2)	-0.006	0.036	-0.171	.865
Level of Virtuality 1 (EV1)	-0.076	0.027	-2.854	.004
Level of Virtuality 2 (EV2)	-0.003	0.029	-0.117	.907
Level of Collaboration (EC)	0.426	0.035	12.137	< .001

Table 5.11: Confusion matrix for the model

Prediction	Reference		
	Initiation	Transition	Breakthrough
Initiation	3294	1592	1577
Transition	212	315	226
Breakthrough	510	377	899

Odds ratio

Table 5.14 presents the odds ratios derived from the ordinal regression analysis, with their respective confidence intervals (with 95 % confidence). This highlights the relationship between each predictor and the outcome variable (level of engagement), which are discussed next. For the predictors with non proportional effects, we report the odds ratio for the Initiation-to-Transition and the Transition-to-Breakthrough shifts.

Visitors who read the signage present significantly higher odds of reaching higher engagement levels, reinforcing the importance of textual information in science centers. The odds of moving from Initiation to Transition are 1.50

Table 5.12: Overall model performance

Metric	Value
Accuracy	50.08 %
95 % CI	(49.04 %, 51.12 %)
No Information Rate (NIR)	44.61 %
P-Value (Acc > NIR)	<2.2e-16
Kappa Score	0.1665
McNemar's Test	<2.2e-16

Table 5.13: Model's Performance per class

Metric	Initiation	Transition	Breakthrough
Sensitivity (Recall)	82.02 %	13.79 %	33.27 %
Specificity	36.44 %	93.48 %	85.92 %
Precision (PPV)	50.97 %	41.83 %	50.34 %
Balanced Accuracy	59.23 %	53.64 %	59.60 %

Table 5.14: Odds ratio for the significant predictors, with confidence intervals. The statistically significant associations are highlighted with an asterisk.

	Initiation - Transition	Transition - Breakthrough
Looking at signage (LS)	1.50 [1.35, 1.66]*	2.02 [1.82, 2.25]*
Takes picture (TP)	1.79 [1.36, 2.35]*	0.69 [0.51, 0.94]*
Age (Age)	0.95 [0.93, 0.98]*	1.12 [1.09, 1.16]*
Exhibit's Participation (EP)	1.24 [1.16, 1.32]*	0.99 [0.93, 1.07]
Exhibit's Virtuality (EV)	0.93 [0.88, 0.98]*	1.00 [0.94, 1.05]
Exhibit's Collaboration (EC)		1.53 [1.43, 1.64]*
Interacts with facilitator (IF)		2.70 [2.27, 3.22]*
Group type (GT)		3.24 [2.77, 3.80]*

times higher for those who read signs, and the odds of progressing from Transition to Breakthrough are 2.02 times higher. These findings align with existing literature highlighting signage as a key mediator of visitor learning (Barriault, 1999; Falk and Storksdieck, 2005). Interpretive materials, including labels and text panels, support cognitive engagement by providing visitors with necessary context and scientific explanations (Hein, 2004; Massarani, Scalfi, et al., 2021). Additionally, reading signage fosters discussion among groups, reinforcing knowledge through social interaction (Chang, 2006; Davidsson and Jakobsson, 2012). Longnecker et al. (2022) suggest integrating interactive text elements such as quizzes to further enhance engagement. While this study did not differentiate between signage types, future research could explore whether open-ended question labels or introductory panels have distinct impacts on engagement levels. Photography appears to have a complex relationship with engagement, as visitors who take photos are 1.79 times more likely to move from Initiation to Transition but 1.45 times less likely to reach Breakthrough from Transition. This dual effect suggests that while taking pictures may encourage initial engagement, it could also divert attention away from deeper interaction. Prior research supports the idea that photography can enhance memorability and personal connection to exhibits (Shaby, Ben-Zvi Assaraf, and Tal, 2019a), with visitors often choosing to document aesthetically or interactively appealing moments (Laçin-Şimşek and Öztürk, 2022). The role of photography in museums extends beyond the immediate visit—photos serve as memory anchors and can spark post-visit reflection (Rauterberg, 2021; Runnel, 2014). Future studies could investigate whether designing exhibits to accommodate photography—such as including designated photo spots or interactive elements—could optimize both documentation and engagement.

Age also plays a role in engagement trajectories, as older visitors are 1.05 times less likely to move from Initiation to Transition but 1.12 times more likely to reach Breakthrough from Transition. This suggests that older visitors are more likely to fall into one of two categories: either they remain in Initiation, engaging with exhibits at a surface level, or they reach Breakthrough, fully immersing themselves in the experience. A plausible explanation is that older visitors might be less likely to transition quickly from initiation to transition, which could explain the negative coefficient for the Initiation-to-Transition change. For example, they may need more time to explore or process the information, and that could lead to older visitors not going beyond initiation.

But, when they do reach Transition, they may engage with exhibits in a more reflective or deliberate manner, leading them to Breakthrough. Another possible explanation is that older visitors often take on the role of facilitators themselves, particularly in family groups, where they provide context and explanations for younger members. This aligns with studies on family learning in museums, which highlight the role of adult visitors in guiding children’s experiences (Pattison, Rubin, and Wright, 2017; Sanford, 2010). (Massarani, Scalfi, et al., 2021) reinforces the idea that parents play a significant role as mediators of learning for their children in science museums. They mediate between the exhibit discourse and their children, answering questions and establishing conversations, and often reinforce reading of panels and text by children.

The odds ratio analysis for the level of Participation of the exhibit (EP) suggests that the Participatory characteristics of exhibits play a modest role in fostering engagement. The odds ratio of 1.24 for the Initiation-to-Transition change indicates that exhibits where content is more Participatory slightly increase the likelihood of visitors moving beyond initial engagement. This is in line with Falk and Gillespie (2009) notes that content is rarely the single most important factor influencing a museum visit, as visitors divide their attention between exhibits and other aspects, like conversations. Furthermore, when visitors co-create the content through Participatory elements of the exhibits, they can “become (too) immersed” in the activity, as described by Lykke et al. (2021), which could consume their time or cognitive resources to engage with the science aspects of the exhibit.

The level of Virtuality of an exhibit (EV) appears to have a negligible effect on engagement, with odds ratios of 0.93 for Initiation-to-Transition. This suggests that introducing virtual elements to the exhibit design does not significantly impact visitors’ likelihood of progressing through higher engagement levels. Shaby et al. (2017) found that interaction is encouraged by exhibits that are familiar, easy to activate, and facilitate social interaction. Given the ubiquity of technology today, virtual elements can be just as intuitive as Physical affordances, which may help explain these results.

The level of Collaboration (EC), on the other hand, emerges as a more powerful predictor of engagement, with an odds ratio of 1.53. This suggests that exhibits with more collaborative elements significantly increase the likelihood of visitors reaching higher levels of engagement. Mulvey et al. (2020) support that learning is enhanced when there’s an opportunity for social in-

teraction. And Shaby et al. (2017) found that exhibits which encourage social interaction tend to enhance engagement, particularly when they are harder to activate. They also found that the exhibits with the highest engagement levels were those designed to accommodate large groups, whereas the exhibits with the lowest engagement levels were the ones that did not support group Participation. The impact of group interactivity opportunities on learning behaviors was recognized early in visitor studies, with research by Boisvert and Slez (1994) and Borun and Dritsas (1997) also highlighting the role of social interaction in enhancing engagement and learning. In this context, incorporating opportunities for group interactivity should be a key priority for exhibit developers seeking to maximize visitor engagement. However, it is also important to consider that some visitors explore science centers alone. To accommodate diverse visitor experiences, exhibits should be designed with multiple modes of interaction, allowing for both Individual and social engagement.

Interaction with facilitators emerges as one of the strongest predictors of engagement, with visitors who engage with a facilitator being 2.70 times more likely to reach higher levels of engagement. This finding aligns with previous work (Machado Corral et al., 2021) and with studies suggesting that visitors prefer learning from a live person rather than static text (Mony and Heimlich, 2008). Facilitation provides dynamic, responsive interactions that adapt to visitor interests, making scientific concepts more accessible and engaging (Hauan and Kolstø, 2014). Furthermore, Pattison et al. (2018) found that staff facilitation had a positive impact on engagement time, mathematical reasoning, and satisfaction. Unlike signage, which offers passive learning, facilitators can tailor explanations, ask questions, and encourage hands-on Participation. Being in a group significantly enhances engagement, with visitors in groups being 3.24 times more likely to reach higher engagement levels. Social interactions serve as a key mechanism for engagement, reinforcing knowledge through discussion and shared experiences (Davidsson and Jakobsson, 2012). This aligns with findings by Longnecker et al. (2022), who emphasize that togetherness, Collaboration, and shared Physical activities are key motivations for visiting exhibitions. Similarly, Mulvey et al. (2020) suggest that learning is enhanced when learners have the opportunity for social interaction, and Shaby, Ben-Zvi Assaraf, and Tal (2019b) argue that conversations serve as tools for learning, helping visitors position themselves as experts within their groups. However, the relationship between group size and engagement is not entirely straightfor-

ward. Block et al. (2015) found that while groups of two interacted significantly longer at interactive exhibits than solo visitors, groups of three did not show a significant increase in engagement time, suggesting that social dynamics beyond dyads may be more complex. Additionally, Block et al. (2015) found that increased simultaneous interaction in larger groups sometimes led to conflict, which could hinder engagement. Therefore, this is definitely a variable that should be further explored in future works.

Predicted probabilities

To evaluate the impact of different combinations of predictors on visitors' levels of engagement, we calculated the predicted probabilities of reaching each engagement level for various scenarios, based on the best-fitting model.

Influence of the visitor status and behavior

To enhance clarity and interpretability, we first included key predictors related to visitor status and behavior—age, interacting with a facilitator (IF), group type (GT), looking at signage (LS), and taking a picture (TP)—and calculated the probability of falling into each engagement category (Fig. 5.12). This visualization captures all possible combinations of these significant descriptors while averaging the outcomes for the remaining predictors (the exhibit's level of Participation, EP; level of virtuality, EV; and the level of collaboration, EC) from the optimal ordinal regression model.

The analysis of probabilities reveals several key patterns that highlight how different behaviors (like reading signage, taking a picture and interacting with a facilitator) and conditions (like being alone or in a group) influence the likelihood of reaching higher levels of engagement. These patterns will be explored by examining how the probabilities for the three levels of engagement change when comparing different combinations of variables. For ease of reference, the combinations will be referred to by the letter in their respective quadrants. For example, quadrant C depicts the predicted probabilities for visitors who do not take pictures ($TP = 0$), look at the signage ($LS = 1$), do not come as part of a group ($GT = 0$) and do not interact with a facilitator ($IF = 0$, top row).

Social interaction plays a crucial role in fostering deeper engagement with exhibits, both through interactions with facilitators and among visitors themselves. In all cases, the probability of reaching Initiation is lower and the probability of reaching Breakthrough is higher for visitors in groups compared

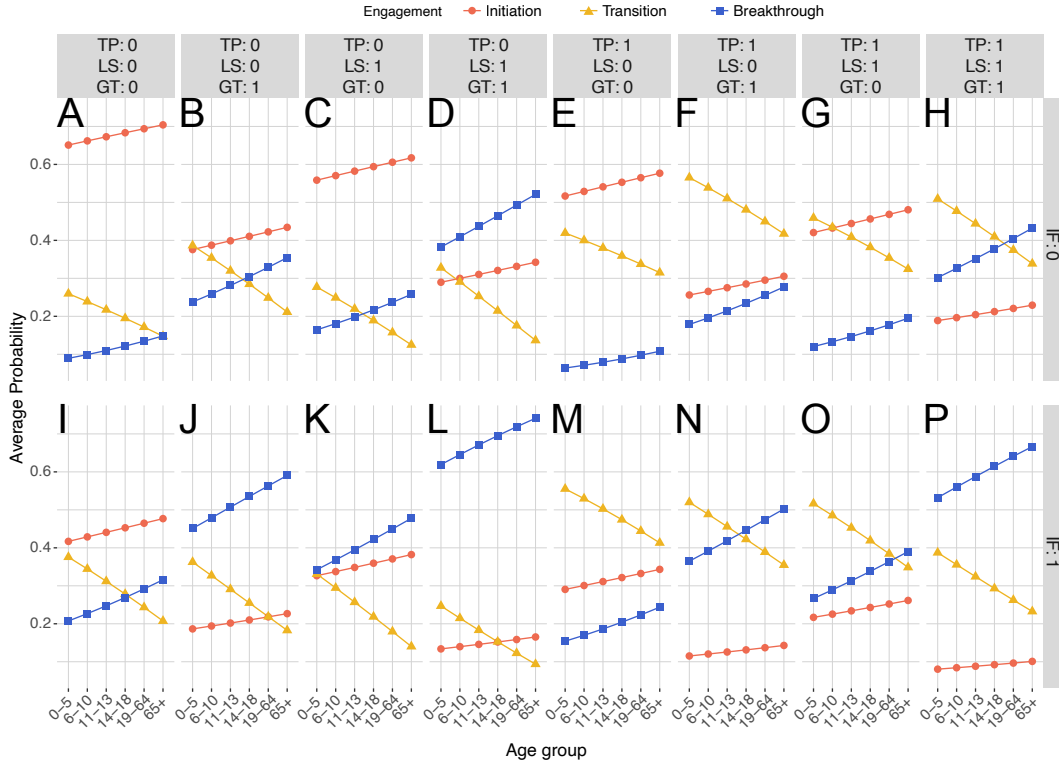


Figure 5.12: Predicted probabilities for the three levels of engagement (Initiation, plotted as red circles; Transition, plotted as yellow triangles; and Breakthrough, plotted as blue squares) as a function of interacting with a facilitator (IF), group type (GT), looking at signage (LS), and taking a picture (TP). The results represent averages across the rest of the predictors, the exhibit’s level of Participation (EP), its level of virtuality (EV), and its level of collaboration (EC). Letters A through P indicate the combinations of predictors, for ease of reference in the discussion.

to those exploring alone (A *vs* B, C *vs* D, E *vs* F, G *vs* H, I *vs* J, K *vs* L, M *vs* N, and O *vs* P). This reinforces the idea that discussion and shared meaning-making enhance engagement. Facilitators also play a key role in this process, as interactions with them are associated with a decrease in Initiation probabilities and an increase in probabilities of Breakthrough across the board (A *vs* I, B *vs* J, C *vs* K, D *vs* L, E *vs* M, F *vs* N, G *vs* O, H *vs* P). This aligns with McGuire et al. (2022), who found that visitors with lower initial interest in an exhibit reported greater learning when engaging with educators. This suggests that facilitators can serve as important scaffolds, particularly for those who might otherwise engage at a surface level. Additionally, different age groups may interact with facilitators in distinct ways, with developmental level influencing both the nature of these interactions and the extent to which

they enhance engagement. Beyond facilitation, visitor-visitor interactions are also key drivers of engagement, as conversation has been shown to stimulate thinking, contribute to knowledge acquisition, and provide a means of expressing emotions related to the exhibit (Longnecker et al., 2022). Visitors bring their prior experiences and knowledge into these interactions, shaping and reinforcing their engagement with the content. Thus, social interaction—whether with facilitators or fellow visitors—plays a fundamental role in moving visitors toward more immersive and reflective engagement with exhibits.

Visitors who neither take pictures, read signage, arrive in a group, nor interact with a facilitator (Fig. 5.12-A) are most likely to remain in Initiation. This probability increases with age, suggesting that solitary and physically passive engagement is more common among older visitors when external stimuli are not present. Conversely, the opposite type of visitor; one that looks at the signage, interacts with a facilitator, takes a picture, and comes in a group (Fig. 5.12-P) is significantly more likely to reach Breakthrough. This could be due to visitors in groups being more likely to read signage aloud, engage in conversations about exhibit content, and take turns interacting with an exhibit (Chang, 2006). Moreover, photography in group settings can promote engagement by sparking discussions and reflections on shared experiences (Runnel, 2014). These findings support the idea that engagement is a cumulative process, where multiple reinforcing factors contribute to deeper involvement with exhibits.

A particularly interesting trend emerges when comparing the engagement of visitors who are not part of a group and do not interact with a facilitator (A, C, E, G), when they take pictures (E and G) versus when they do not (A and C). For these visitors, taking a picture significantly lowers the probability of Initiation, increases the probability of Transition, and somewhat lowers the probability of reaching Breakthrough. This provides further evidence to support that photography might serve as a mid-level engagement activity, nudging solitary visitors beyond passive observation but not necessarily driving them to the highest level of engagement. Transition is associated with repetition and emotional response (Barriault and Rennie, 2019; Barriault and Pearson, 2010), as the act of taking a photo may indicate an emotional reaction to the exhibit, suggesting that the visitor is experiencing some level of enjoyment or appreciation. Interestingly, this trend shift also happens when a facilitator is introduced into this scenario (I, K, M, O). When comparing visitors who are

not part of a group, interact with a facilitator and take pictures (M and O) with those who do not (I and K) Initiation and Breakthrough decrease, while Transition increases for the visitors who took pictures. This suggests that facilitators can encourage alone visitors to process information more deeply, but the interaction may not always lead to Breakthrough, perhaps because the act of taking pictures could take visitors away from the facilitation process.

The effect of taking pictures follows the same trend for visitors who engage in social interaction, either by just being part of a group (B, D, F, H) or by being part of a group that also interacts with a facilitator (J, L, N, P). Even though, as discussed previously, the probability of Breakthrough is higher overall for these “social” visitors, when comparing the visitors who take pictures with those who do not, the probabilities of Initiation and Breakthrough lower and the probability of Transition increases for all combinations (B *vs* F, D *vs* H, J *vs* N and L *vs* P).

Reading signage emerges as one of the most consistently influential factors in engagement. Visitors who read exhibit signs (C, D, K, L, G, H, O, P) have higher probabilities of reaching Breakthrough than those who do not (A, B, E, F, I, J, M, N). The trends for Initiation and Transition are less evident. Initiation and Transition either lower or remain virtually the same for all cases. The one exception to the Transition trend is for visitors who are completely alone and do not take pictures (A *vs* C), where looking at the signage increases the probability of reaching Transition. These trends can be explained because reading signage requires active cognitive processing, which may help visitors construct more complex narratives around the exhibit. This is further supported by research showing that interpretive talk is a key factor in museum learning (Sanford, 2010). Signage provides visitors with structured information that can stimulate discussion, especially in family groups where adults often take on an explanatory role (Pattison, Randol, et al., 2017). This effect is particularly pronounced in group visitors (B *vs* D, F *vs* L, H *vs* J, N *vs* P), suggesting that reading signage often serves as a catalyst for discussion and shared meaning-making, reinforcing previous findings on intergenerational communication in museums (Pattison, Randol, et al., 2017). The presence of signage not only provides direct information but also serves as a conversational prompt, helping visitors connect exhibit content with prior knowledge and personal experiences. This also aligns with research on scaffolding, which emphasizes the importance of structured learning aids in guiding visitors to-

ward deeper understanding (Wells, 1999; Ash, 2004). Additionally, National Research Council (2009) found that interpretive labels are particularly effective for adult learners, while Davidsson and Jakobsson (2012) note that older visitors often engage through text-based interactions. Furthermore, Rainoldi et al. (2020) found that the average fixation duration on exhibition information boards was highest within the group of older adults, followed by adults and then younger adults. This follows the age-trend of the Breakthrough curve, and suggests that older adults might value information boards more than younger adults, who may prefer other media.

This predicted probabilities analysis of visitor status (group or no group) and behavior (reading signage, taking photo and interacting with a facilitator) contextualizes one of the most striking findings of this work: the highest probability of Breakthrough occurs for visitors who are in a group, read signage, and interact with a facilitator but do not take pictures (Fig. 5.12-L). This aligns with the idea that deep engagement often requires sustained attention and active Participation, which might be disrupted by pausing to take photos. This pattern could be explained considering the Zone of Proximal Development: facilitators scaffold visitor experiences, adjusting their approach based on the group's engagement level (Ash et al., 2012; Pattison, Randol, et al., 2017). When visitors are already highly engaged—discussing exhibits, reading signage, and benefiting from facilitator interactions—pausing to take a picture might momentarily interrupt their cognitive flow, pulling them out of the "learning zone". However, it may also be posited that for some visitors, it is "enough" to engage emotionally, and they do not feel the need for further interaction or deeper engagement. As mentioned earlier, photo-taking is related to emotion and moments of pleasure (Barriault and Rennie, 2019; Barriault and Pearson, 2010), and therefore, capturing something they find enjoyable or meaningful might be the extent of the engagement the visitor desires.

Overall, these findings reinforce the importance of social and interpretive elements in fostering deeper visitor engagement. The interaction of different factors—group dynamics, facilitator presence, signage reading, and photography—suggests that engagement is a multifaceted process shaped by both Individual behaviors and social contexts. Future research could explore how these variables interact over time and whether certain types of facilitation strategies are more effective in promoting long-term learning beyond the museum visit.

Influence of the exhibit's features

To better understand the influence of exhibit characteristics on visitor engagement, we visualized the predicted probabilities of being in each engagement category while varying age, facilitation interaction and the explanatory variables associated with the kind of exhibit.

We started by including the level of Participation: Static (EP = 1), Static/Participatory (EP = 2), and Participatory (EP = 3). Figure 5.13 presents these results, with outcomes averaged across the remaining predictors (group type, looking at signage, taking pictures, level of virtuality, and level of collaboration) for clarity. The top row represents visitors who did not interact with a facilitator (IF=0) and the bottom row represents those who did (IF=1).

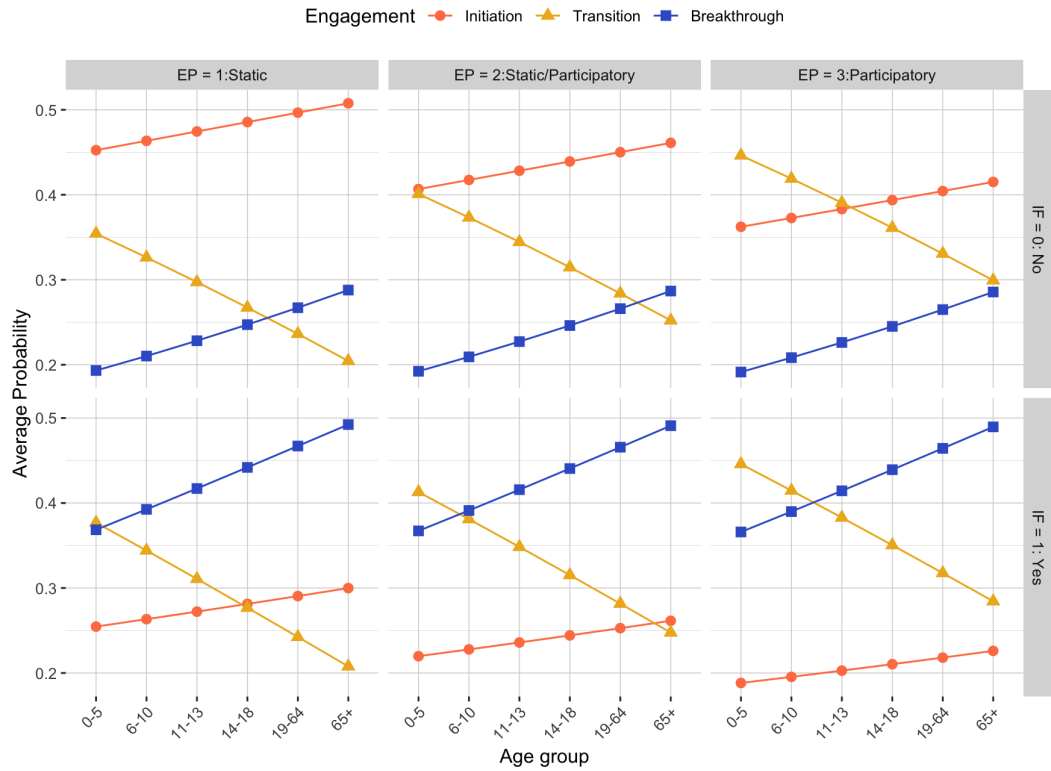


Figure 5.13: Predicted probabilities for the three levels of engagement (Initiation, Transition, and Breakthrough) as a function of the level of Participation of the exhibit (EP). The outcomes are averaged across the remaining predictors (group type, looking at signage, taking pictures, level of Virtuality and level of Collaboration).

Introducing elements of content co-creation (Participation) in the exhibit design relates to lower probability of Initiation, higher probability of Transi-

tion, while the probability of Breakthrough remains virtually the same ($EP = 1$ *vs* $EP = 2$ *vs* $EP = 3$, by row). This trend occurs both with and without interacting with a facilitator and aligns with prior research suggesting that interactive elements can foster deeper engagement (Bobbe, 2022; Ocampo-Agudelo and Maya, 2017). However, this also means that Participatory exhibits can lead to unintended uses, as visitors explore freely and sometimes playfully, a phenomenon documented by Hauan and Kolstø (2014). While such unintended interactions may seem counterproductive, they are integral to an engaging and exploratory learning experience. Notably, the presence of a facilitator significantly shifts the engagement probability distribution, leading to an inversion of Initiation and Breakthrough probabilities (top row *vs* bottom row). In fact, Barriault and Pearson (2010) suggested that this would be the case when they first proposed the Visitor-Based Learning Framework. (p.101). The facilitation process likely reinforces learning through scaffolding (Allen, 2004) and helps visitors navigate multiple interactive features without feeling overwhelmed. Taken together, these results indicate that interacting with a facilitator in exhibits where content is participative leads to lower initiation and transition, and higher breakthrough, hinting at the great potential for engagement when combining those elements. However, this could be an effect of the socio-constructivist nature of the Visitor-Based Learning Framework (VBLF), as facilitation within a Participatory setting provides more opportunities for visitors to display Breakthrough behaviors, and for those behaviors to be therefore recorded in the data, as discussed by Barriault and Pearson (2010).

Figure 5.14 illustrates the predicted probabilities for the three levels of Virtuality: Physical ($EV = 1$), Physical/Virtual ($EV = 2$), and Virtual ($EV = 3$), averaged across the remaining predictors (group type, looking at signage, taking pictures, level of collaboration, and level of interaction). The predicted probabilities of visitors remaining in Initiation for fully Physical exhibits are slightly lower than for completely Virtual exhibits, but the overall engagement curves across the different levels of Virtuality ($EV = 1$ *vs* $EV = 2$ *vs* $EV = 3$, by row) show only minor variations. This suggests that introducing virtual elements alone does not have a pronounced effect on engagement probabilities. The odds ratios confirm this, showing minimal differences between engagement levels across levels of Virtuality. This could be due to the increasing prevalence of digital interactions in everyday life, making virtual elements less of a novelty

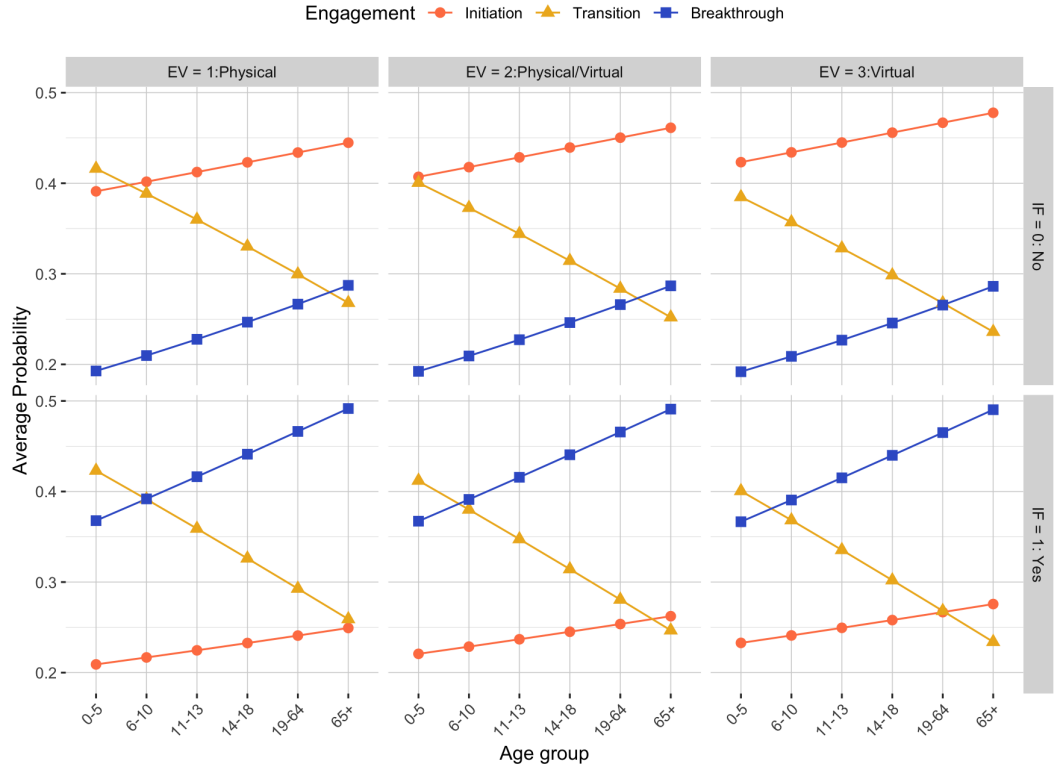


Figure 5.14: Predicted probabilities for the three levels of engagement (Initiation, Transition, and Breakthrough) as a function of the level of Virtuality of the exhibit (EV). The outcomes are averaged across the remaining predictors (group type, looking at signage, taking pictures, level of Participation and level of Collaboration).

compared to when they were first introduced in museum settings (Long et al., 2022). Additionally, factors such as the spatial arrangement of exhibits and the presence of visual competition (Schwan et al., 2014) may influence the extent to which virtual elements affect visitor engagement. As with exhibit content, the presence of a facilitator in Virtual and mixed spaces leads to an inversion of Initiation and Breakthrough probabilities (top row vs bottom row), further contributing to prior discussions on facilitation’s role in promoting engagement.

Finally, Figure 5.15 shows the predicted probabilities for the three levels of Collaboration: Individual (EC = 1), Individual/Collaborative (EC = 2), and Collaborative (EC = 3), averaged across the remaining predictors (GT, LS, TP, EC and ES). Introducing Collaborative affordances (EC = 1 vs EC = 2 vs EC = 3, by row) shows a decrease in the probability of Initiation, a small increase in the probability of Transition, and an increase in Breakthrough probabilities. In this context, visitors who interact with a facilitator (top row

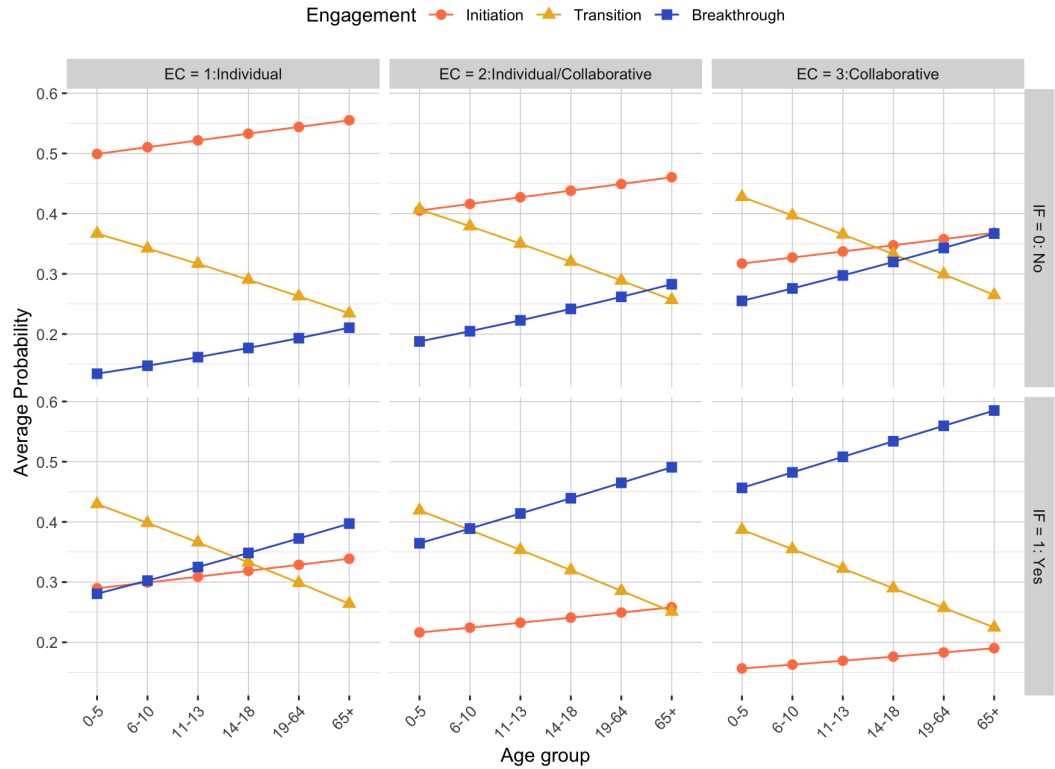


Figure 5.15: Predicted probabilities for the three levels of engagement (Initiation, Transition, and Breakthrough) as a function of the exhibit's level of Collaboration (EC). The outcomes are averaged across the remaining predictors (group type, looking at signage, taking pictures, level of Virtuality and level of Participation).

vs bottom row) show a decrease in Initiation and an increase in Breakthrough probabilities. According to previous research, successful exhibits are those that encourage meaningful communication through social interaction (Rennie et al., 2007). Allen and Gutwill (2004) highlight that exhibits designed for group use elicit more self-generated exploration, while Borun et al. (2010) further suggests that multi-sided, multi-user, and multi-outcome designs are essential for group learning. However, not all forms of interactivity lead to better outcomes; adding more interactive features does not always enhance learning, as excessive interactivity can lead to disruption (Allen and Gutwill, 2004). Furthermore, exhibits encouraging social interaction, such as those that allow for group Collaboration or competition, tend to increase engagement, though the complexity of the exhibit also plays a role in visitor Participation (Macias et al., 2020; Shaby et al., 2017). Lykke et al. (2021) found that whole-body activities and group Collaboration were strong motivators for Participation, although

they sometimes limited in-depth scientific discussions. Tscholl and Lindgren (2016) caution that highly interactive exhibits may inhibit social interaction, suggesting a balance is needed to optimize visitor engagement. Interestingly, the probability distributions for visitors at Collaborative exhibits who do not interact with a facilitator ($EC = 3$, $IF = 0$) are remarkably similar to those of visitors at Individual exhibits who interact with a facilitator ($EC = 1$, $IF = 1$). This pattern could point to the significant role of social interaction in shaping visitor behavior, suggesting that the presence or absence of facilitator interaction may influence engagement in a similar way to the collaborative nature of exhibits themselves.

These findings on exhibit characteristics highlight the importance of designing exhibits that encourage social and Participatory engagement. As Ocampo-Agudelo and Maya (2017) emphasize, exhibit design is a complex and subjective process that must balance interactivity, social engagement, and learning goals. Designers should consider the role of facilitators in structuring engagement and ensure that interactivity is purposeful rather than overwhelming (Allen and Gutwill, 2004). Additionally, attention should be paid to exhibit placement and visibility, as spatial design and line-of-sight factors influence visitor behavior (Schwan et al., 2014). Ultimately, effective exhibit design should support visitors' innate learning processes, creating meaningful opportunities for exploration, discussion, and discovery (Dudzinska-Przesmitzki and Grenier, 2008).

Chapter 6

Extended Study

This chapter explores the Extended Study, which broadens the scope of investigation into visitor engagement by incorporating a wider array of variables, including visitor familiarity with the science center, level of education, and motivation for visiting, as well as the impact of visitor-visitor interaction, facilitation strategies, and dwell time. This study provides a more detailed examination of factors influencing engagement across three science centers: Science North, Espacio Ciencia, and Moleculario. While the Comprehensive Study lays a solid foundation with its extensive dataset and statistically significant results, the Extended Study seeks to enrich these findings by exploring other variables that could impact visitor engagement in science centers beyond Science North.

6.1. Sample description

In terms of age and gender (Table 6.1), adults are the most common visitor type in the sample ($N = 96$), accounting for 59.4 % of the total (19.8 % are male and 39.6 % are female). In terms of gender, females outnumber males in the total (37.5 % are male and 62.5 % are female) and in all age categories, except young adults, where 12.5 % are males, while 8.3 % are females. A table presenting distribution of visitors by age and gender per center can be found in Appendix 2.

Several patterns emerged when analyzing the data considering the other variables in relation to each center. Tables 6.2 through 6.9 show the percentage of visitors for each center, for each variable. A table presenting the number

Table 6.1: Percentage of visitors by gender and age, by center and in total

	Female	Male	Center	Fem	Male
Child	1.0	0	Science North	0	0
			Espacio Ciencia	0	0
			Moleculario	6.3	0
Teen	4.2	1.0	Science North	3.9	0
			Espacio Ciencia	3.4	3.4
			Moleculario	6.3	0
Young adult	8.3	12.5	Science North	3.9	13.7
			Espacio Ciencia	0	3.4
			Moleculario	37.5	25.0
Adult	39.6	19.8	Science North	39.2	21.6
			Espacio Ciencia	58.6	17.2
			Moleculario	6.3	18.8
Senior	9.4	4.2	Science North	11.8	5.9
			Espacio Ciencia	10.3	3.4
			Moleculario	0	0
Total	62.5	37.5	Science North	41.2	58.8
			Espacio Ciencia	27.6	72.4
			Moleculario	43.8	56.3

of visitors in the sample by type of group, level of education, familiarity with the center, motivation, visitor-facilitator interaction, average dwell time, and engagement levels, for each center and for the total can be found in Appendix 2.

Group composition across the three science centers (Table 6.2) shows a high prevalence of visitors attending in groups, consistent with the results of the Comprehensive Study. Espacio Ciencia has the highest percentage of group visitors at 96.6 %, followed closely by Science North at 92.2 % and by Moleculario at 87.5 %. This pattern aligns with expectations for informal learning environments, where group visits are common.

When it comes to visitors taking pictures (Table 6.3), the numbers are

Table 6.2: Visitors who engage with the exhibit alone or as part of a group, by science center

	Science North		Espacio Ciencia		Moleculario		Total	
	n	%	n	%	n	%	n	%
Alone	4	7.8	1	3.4	2	12.5	7	7.3
In group	47	92.2	28	96.6	14	87.5	89	92.7

Table 6.3: Visitors who take pictures and visitors who do not, by science center

	Science North		Espacio Ciencia		Moleculario		Total	
	n	%	n	%	n	%	n	%
No	50	98,0	25	86,2	15	93,8	90	93,8
Yes	1	2,0	4	13,8	1	6,3	6	6,3

generally low, but there is notable variation across the centers. Science North and Moleculario show similarly low percentages, at 2 % and 6.3 % respectively, in line with the findings from the Comprehensive Study. In contrast, Espacio Ciencia stands out with a relatively higher percentage of 13.8 %, though it should be noted that this is still a relatively low percentage of visitors in absolute terms. The differences between the centers could stem from the unique characteristics of the exhibits chosen, or potentially to a combination of factors, including variables that were not explored in this study, suggesting that further research is necessary to fully understand these influences.

Table 6.4: Visitors who look at signage and visitors who do not, for each science center

	Science North		Espacio Ciencia		Moleculario		Total	
	n	%	n	%	n	%	n	%
No	41	80.4	11	37.9	10	62.5	62	64.6
Yes	10	19.6	18	62.1	6	37.5	34	35.4

When comparing visitors who looked at the signage with visitors who did not (Table 6.4), we find striking differences. Science North visitors read signage at rates similar to those observed in the Comprehensive Study, with 19.6 % compared to 23.7 %. Moleculario visitors show higher engagement with signage at 37.5 %, and Espacio Ciencia stands out with a very high 62.1 %, a rate that is high both relative to the other centers and in general terms. This is another instance where the difference between the centers can be attributed to multiple factors. It is possible that the disparities observed could be due to the specific features of the exhibits, or cultural differences, or perhaps other unidentified factors, highlighting the need for additional studies to explore these variables.

Interaction with facilitators (Table 6.5) presents particularly interesting results. Science North's rate of facilitator interaction (7.8 %) is comparable to the Comprehensive Study (5.4 %). Espacio Ciencia shows a considerably higher percentage at 24.1 %, while Moleculario's interaction rate is exceptionally high at 81.3 %. This likely reflects the different facilitation models in

Table 6.5: Visitors who interact with a facilitator and visitors who do not, for each science center

	Science North		Espacio Ciencia		Moleculario		Total	
	n	%	n	%	n	%	n	%
No	47	92.2	22	75.9	3	18.8	72	75.0
Yes	4	7.8	7	24.1	13	81.3	24	25.0

place, with Moleculario primarily offering guided visits where facilitators are highly engaged with visitors, unlike the more typical “free-choice” models at Science North and Espacio Ciencia, where facilitators typically walk around the exhibit floor without engaging with every visitor.

Beyond the variables already discussed, this Extended Study also includes variables not covered in the Comprehensive Study, which we will explore next. These include level of education, familiarity with the center, and visitor motivation (gathered from the survey), as well as visitor-visitor interaction, and dwell time (gathered from observations). Examining these variables will provide a deeper understanding of visitor engagement and the unique dynamics at play across the three science centers.

Table 6.6: Percentage of visitors who interact with other visitors and visitors who do not, for each science center

	Science North		Espacio Ciencia		Moleculario		Total	
	n	%	n	%	n	%	n	%
No	12	23,5	2	6.9	2	12.5	16	16,7
Yes	39	76,5	27	93.1	14	87.5	80	83,3

Visitor-visitor interaction largely aligns with group composition rates for Espacio Ciencia and Moleculario, at 93.1 % and 87.5 % respectively (Table 6.6). However, Science North’s rate of visitor-visitor interaction is surprisingly low at 45.3 %, despite more than 90 % of visitors attending in groups. This discrepancy suggests potential differences in group dynamics or exhibit design, or even cultural factors, that warrant further investigation.

Visitor motivation (as described by Falk, 2006) also varies across the centers (Table 6.7). For ease of interpretation, in this case we divided the visitors into two motivation categories: “facilitator” and “other”, which combines the “explorer”, “experience seeker”, “hobbyist/professional” and “recharger” motivations. A “facilitator” is a visitor who reports their main motivation for visiting the science center is for the people they came with to have a good

Table 6.7: Visitors who reported having a “facilitator” motivation and visitors who reported a different motivation, for each science center

	Science North		Espacio Ciencia		Moleculario		Total	
	n	%	n	%	n	%	n	%
Facilitator	38	74.5	26	89.7	4	25.0	68	70.8
Other	13	25.5	3	10.3	12	75.0	28	29.2

experience (Falk, 2006). This is the most common motivation reported by the visitors in this sample. At Science North and Espacio Ciencia, visitors who reported a “facilitator” motivation dominate, with 74.5 % and 89.7 % respectively. Moleculario, however, shows an inverse pattern, with only 25 % of visitors identifying as facilitator-type. One possible explanation for this variation in visitor motivation across the centers could be differences in the target audience, exhibit design, or the overall atmosphere of each center. For instance, Science North and Espacio Ciencia may place a stronger emphasis on family experiences, which could attract more visitors who prioritize the experience of others, aligning with the “facilitator” motivation. In contrast, Moleculario might appeal to visitors with intrinsic motivations such as curiosity or professional interest, which could explain the lower percentage of “facilitator”-type visitors. Cultural or contextual factors, such as local community dynamics or the specific types of exhibits offered, could also contribute to these patterns, indicating that visitor motivations are shaped by a variety of factors that differ across science centers.

Table 6.8: Visitors by level of education, for each science center

	Science North		Espacio Ciencia		Moleculario		Total	
	n	%	n	%	n	%	n	%
Primary incomplete	0	0	0	0	1	6.3	1	1.0
Primary complete	0	0	0	0	0	0	0	0
Secondary incomplete	3	5.9	2	6.9	2	12.5	7	7.3
Secondary complete	12	23.5	1	3.4	1	6.3	14	14.6
Tertiary incomplete	7	13.7	6	20.7	10	62.5	23	24.0
Tertiary complete	27	52.9	12	41.4	2	12.5	41	42.7
Postgraduate education	2	3.9	8	27.6	0	0	10	10.4

For this sample, the visitor’s level of education is consistently high across all three centers (Table 6.8), aligning with the established profile of science center audiences as highly educated. Previous work found that the largest group of science center visitors consists of well-educated, more affluent, white professional classes, and that individuals with higher levels of education were

significantly more likely to have visited their local science center (Black, 2015; Falk et al., 2016). The majority of visitors in this sample have, at least, completed secondary education. Anecdotally, the only visitor to not have completed primary school is under 12 years of age, and therefore their education level is what is expected for that age. Visitors who have completed tertiary education are the largest category at Science North (52.9 %) and Espacio Ciencia (41.4 %), while at Moleculario, the largest group consists of visitors with incomplete tertiary education (62.5 %). This likely reflects Moleculario’s Physical location within the School of Chemistry, attracting a high proportion of students. It’s important to note that this data reflects free-choice visitors on a specific day and excludes the more typical school group visits.

Table 6.9: Percentage of visitors by familiarity with the center, for each science center

	Science North		Espacio Ciencia		Moleculario		Total	
	n	%	n	%	n	%	n	%
First time	19	37.3	17	58.6	7	43.8	43	44.8
Once a year or less	19	37.3	10	34.5	7	43.8	36	37.5
2-4 times a year	6	11.8	2	6.9	0	0	8	8.3
5+ times a year	7	13.7	0	0	2	12.5	9	9.4

Familiarity with the center (Table 6.9) shows a consistent trend across Science North and Moleculario, with identical percentages of first-time and once-a-year visitors (37.3 % for Science North and 43.8 % for Moleculario). Espacio Ciencia, however, has a higher proportion of first-time visitors at 58.6 % and a lower percentage of occasional visitors (34.5 % visiting once a year or less), suggesting differences in audience reach and retention.

To better visualize visitor dwell time, we overlapped the density curves of the histograms for each science center, converting the original data from seconds to minutes and including the mean and median for each distribution (Fig. 6.1).

Dwell time shows distinct patterns across the centers. At Science North and Espacio Ciencia, most visitors stay around two minutes or less, with similar means and medians (Science North: mean = 2.69, median = 1.60; Espacio Ciencia: mean = 2.56, median = 1.43). Moleculario visitors, however, exhibit significantly longer dwell times, with a mean of 6.01 minutes and a median of 5.91 minutes. This extended engagement likely correlates with the higher levels of visitor-visitor and visitor-facilitator interaction observed at Moleculario.

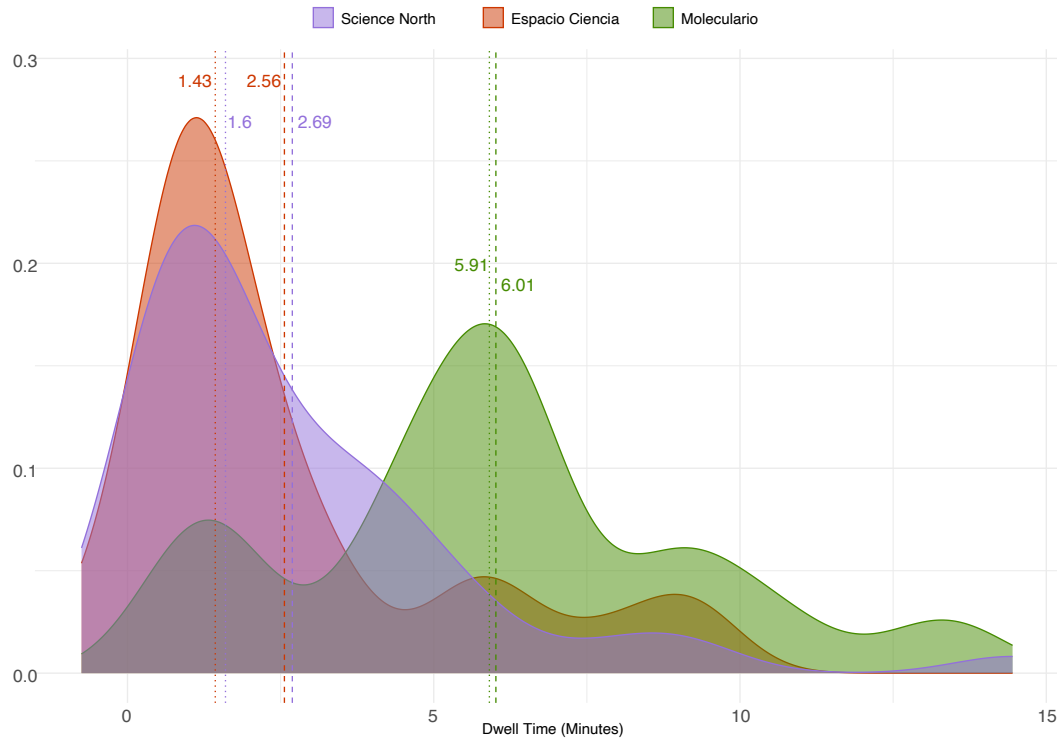


Figure 6.1: Density curves depicting dwell time, in minutes, for each center (Science North in blue, Espacio Ciencia in red, Molecularario in green). The dashed line indicates the mean and the dotted line indicates the median for each histogram (corresponding colors for each center).

Overall, the three science centers show both commonalities and important differences in visitor behavior and engagement patterns. While group composition and high educational levels are consistent across the centers and align with the Comprehensive Study, variables like signage engagement, facilitator interaction, and dwell time reveal notable variations. These differences underscore the influence of each center’s specific context, facilitation models, and visitor demographics. They also enrich the sample, enabling a more diverse representation of the population beyond Science North.

Exhibit characteristics

The 8 exhibits in this study were classified using Widerström’s framework, which considers three dimensions: Participation, Virtuality, and Collaboration. Table 6.10 shows the distribution of exhibits by each dimension.

In terms of Participation, Participatory exhibits are the most common (4 exhibits, 50 %), followed by Static (3 exhibits, 37.5 %) and Static/Participatory (1 exhibit, 12.5 %). Regarding Virtuality, Physical exhibits are the most com-

Table 6.10: Distribution of exhibits by dimension (Participation, Virtuality, and Collaboration)

Dimension		n	%
Participation	Static	3	37.5
	Static- Participatory	1	12.5
	Participatory	4	50.0
Virtuality	Physical	6	75.0
	Physical/Virtual	2	25.0
	Virtual	0	0.0
Collaboration	Individual	1	12.5
	Individual/Collaborative	7	87.5
	Collaborative	0	0.0

mon (6 exhibits, 75 %), while Physical/Virtual accounts for the other 2 exhibits (25 %), and there are no exhibits that are purely Virtual. In the Collaboration dimension, Individual/Collaborative exhibits are the most prevalent (7 exhibits, 87.5 %), followed by Individual exhibits (1 exhibit, 12.5 %), whereas there are no fully Collaborative exhibits in this sample. Even though it is rare for visitors to approach exhibits or visit the science center alone, they are present, and it would make sense that most exhibits are designed to allow but not require multiple people to operate or engage with them.

6.2. Data analysis

Association between each Individual variable and engagement

This section explores the individual association, in this three-center sample, between engagement and 13 variables: age, gender, group type, taking pictures, reading signage, interacting with a facilitator, visitor motivation, visitor-visitor interaction, academic level, familiarity with the center, and each dimension of exhibit design. To evaluate these relationships we used the same approach described in the data analysis section of the Comprehensive Study.

The statistically significant variables (see Table 6.11) include visitor motivation, looking at signage, interaction with facilitators, and visitor-visitor interaction. Despite the statistical significance of these variables, it is important to note that their effect on engagement may not be substantial enough to lead to meaningful variations in the response variable in a regression model where the rest of the predictors are controlled (see Appendix 2). This dilution

Table 6.11: Chi-square test results and association measures for the relationship between engagement and different predictor variables. The table reports the chi-square statistic (χ^2), degrees of freedom (df) and p-value (px), Cramer’s V for effect size, Kendall’s Tau-b (τ_b) for ordinal associations, and the p-value for Tau-b (pt). Asterisk (*) indicates Fisher Exact Test was applied.

	χ^2	df	px	Cramer’s V	τ_b	pt
Age	-	-	.409 *	.15	-.11	.245
Gender (GND)	0.28	2	.868	.05	.05	.602
Group Type (GT)	1.29	2	.525	.12	.09	.363
Familiarity with Center (FA)	5.24	6	.514	.17	-.04	.697
Level of Education (AC)	5.40	10	.863	.17	-.10	.284
Visitor Motivation (VM)	6.27	2	.044	.26	-.23	.018
Looking at Signage (LS)	7.15	2	.028	.27	.25	.011
Taking Pictures (TP)	1.60	2	.450	.13	.02	.814
Interacting with Facilitator (IF)	21.51	2	< .001	.47	.44	< .001
Visitor–Visitor Interaction (VV)	8.24	2	.016	.29	.28	.005
Exhibit Level of Participation (EP)	2.98	4	.560	.12	-.15	.123
Exhibit Level of Virtuality (EV)	0.25	2	.884	.05	-.01	.884
Exhibit Level of Collaboration (EC)	0.65	2	.724	.08	-.03	.742

could occur because other variables may exert a greater influence, or because some variables may act indirectly, through other factors, which diminishes their direct impact when controlling for those other variables. In future studies, increasing the sample size would be advisable to reduce uncertainty and gain a clearer understanding of the true impact of these variables.

When considering the age variable, we focused exclusively on visitors aged 18 and older, because the visitors in the younger age groups all reached Break-through, and were too few in number to provide meaningful variation. Given this limited sample and the sparse data in some categories, we opted for Fisher’s Exact Test, as it is better suited for small or unevenly distributed samples. The results showed no statistically significant association between age and engagement: Fisher’s Exact Test yielded a p-value of .409, and Kendall’s τ_b correlation indicated a weak, non-significant negative trend ($\tau_b = -.11$, $p = .245$). Although there is a slight tendency suggesting engagement might decrease with age, the evidence is insufficient to support a definitive conclusion, as illustrated in Fig. 6.2.

In contrast, visitor motivation, looking at signage, interacting with a facilitator, and visitor-visitor interaction all show significant associations. Interacting with a facilitator stands out with a high chi-square value ($\chi^2 = 21.51$, $p < .001$), a large effect size (Cramer’s V = .47), and a strong positive correlation

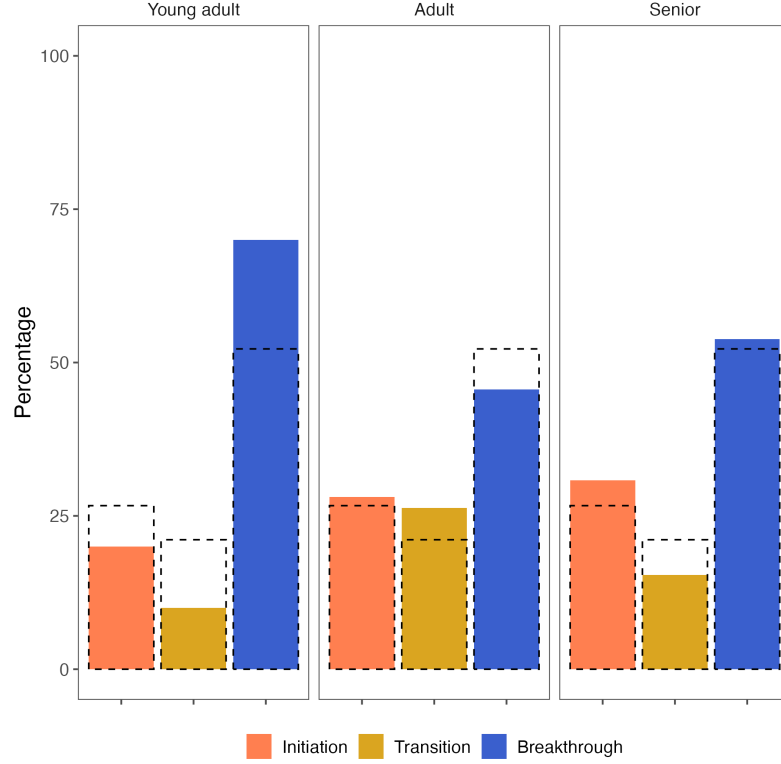


Figure 6.2: Comparison of the engagement levels for the different age groups. Filled bars represent the observed engagement, while dashed boxes indicate the expected engagement levels if the variables were not associated.

($\tau_b = 0.44$, $p < .001$), highlighting a robust association between the presence of a facilitator and higher engagement. Visitors who interacted with a facilitator show markedly higher levels of Breakthrough and an important decrease in the levels of Transition and Initiation (Fig. 6.3). On the other hand, looking at signage ($\chi^2 = 7.15$, $p = .028$; $\tau_b = .25$, $p = .011$) has a moderate positive association with engagement. Visitors who read the signage present lower Initiation and Transition, and higher Breakthrough (Fig. 6.4). These positive associations follow the trends observed in the Comprehensive Study.

Similarly, visitor motivation ($\chi^2 = 6.27$, $p = .044$; $\tau_b = -.23$, $p = .018$) shows a negative association with engagement, suggesting that facilitator-type visitors have higher levels of engagement than other visitors. This can be seen in figure 6.5, where Initiation and Transition are lower, while Breakthrough is higher, for visitors who reported that their main concern is that their companions have a good experience (they are "facilitators", as described by Falk, 2006). Although there is not much literature that explores visitor's motivation

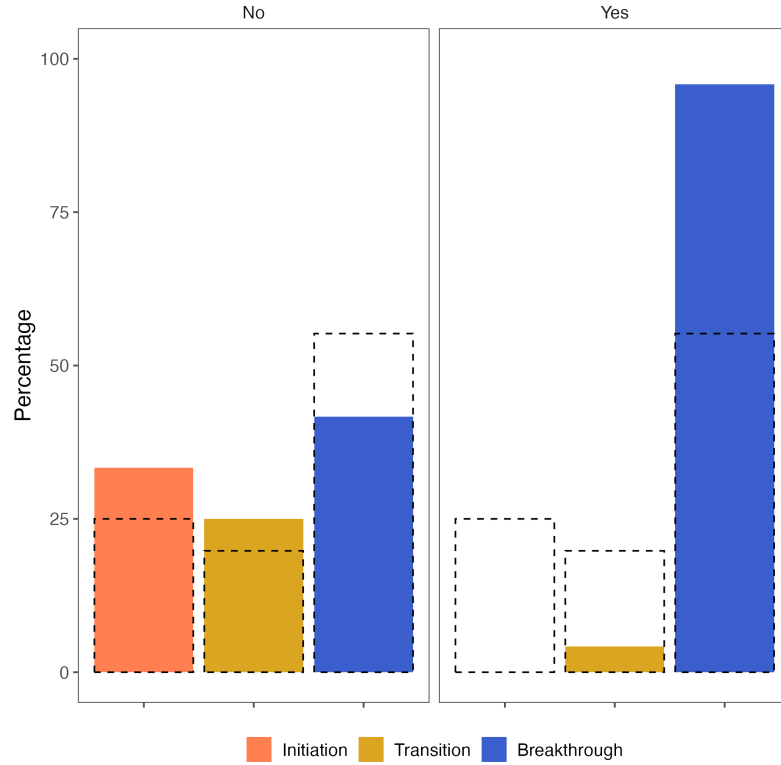


Figure 6.3: Comparison of the engagement levels for visitors who interacted with a facilitator (right) and those who did not (left). Filled bars represent the observed engagement, while dashed boxes indicate the expected engagement levels if the variables were not associated.

and engagement, Drotner et al. (2018) mention these visitors seek to enable learning and enjoyment in others. In this context, it could be posited that their motivation to help others learn leads these visitors to actively seek and share information or relate to past experiences, which are Breakthrough behaviors. For example, 28 of the 32 visitors that identified “facilitator” as their motivation did in fact engage in at least one of these activities.

Finally visitor-visitor interaction ($\chi^2 = 8.24$, $p = .016$; $\tau_b = .28$, $p = .005$) presents a moderate positive relationship with engagement. Visitors who interact with other visitors exhibit a significantly lower percentage of Initiation, a lower percentage of Transition and a higher percentage of Breakthrough. This trend occurs both when compared to visitors who did not interact with other visitors and to the expected values (Fig. 6.6). These results provide further evidence to support the role of social interaction in engagement, in line with what has been presented in the literature, and which was also discussed

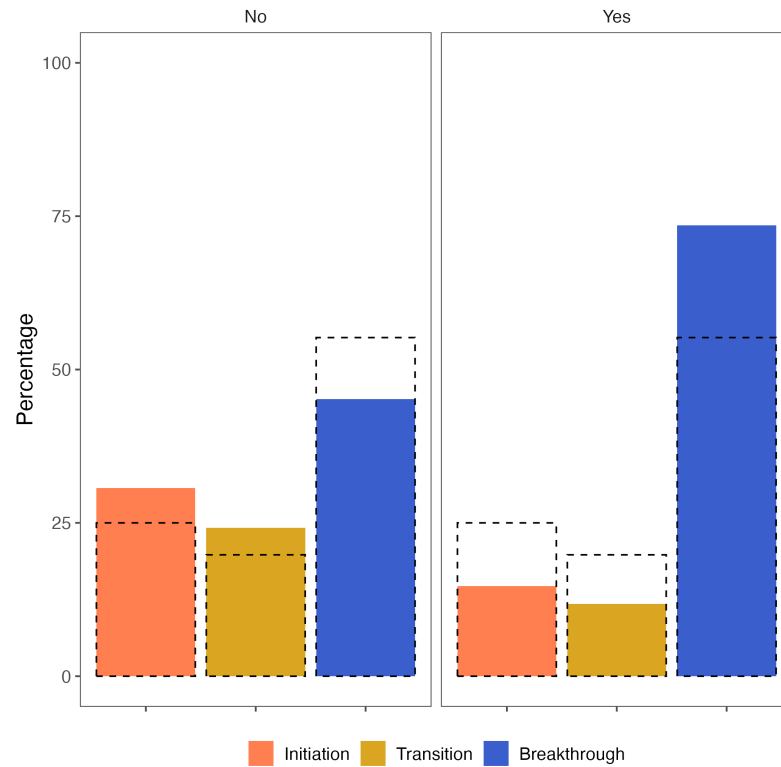


Figure 6.4: Comparison of the engagement levels for visitors who looked at the signage (right) and those who did not (left). Filled bars represent the observed engagement, while dashed boxes indicate the expected engagement levels if the variables were not associated.

in the Comprehensive Study.

Regression analysis

We applied an ordinal regression model, using the highest engagement level each visitor achieved — categorized as Initiation, Transition, and Breakthrough — as the dependent variable. The predictor variables included age, gender, group type, taking pictures, reading signage, interacting with a facilitator, using each of the four Facilitation Dimensions, visitor motivation, visitor-visitor interaction, level of education, familiarity with the center, and each dimension of exhibit design (level of participation, virtuality and collaboration). This approach enabled us to assess the individual impact of each variable while controlling for the influence of all others.

The correlation matrix (Fig. 6.7 indicates that there is substantial correlation between some of the variables included in the study. First, as would be expected, interaction with a facilitator (IF) is strongly correlated with the fa-

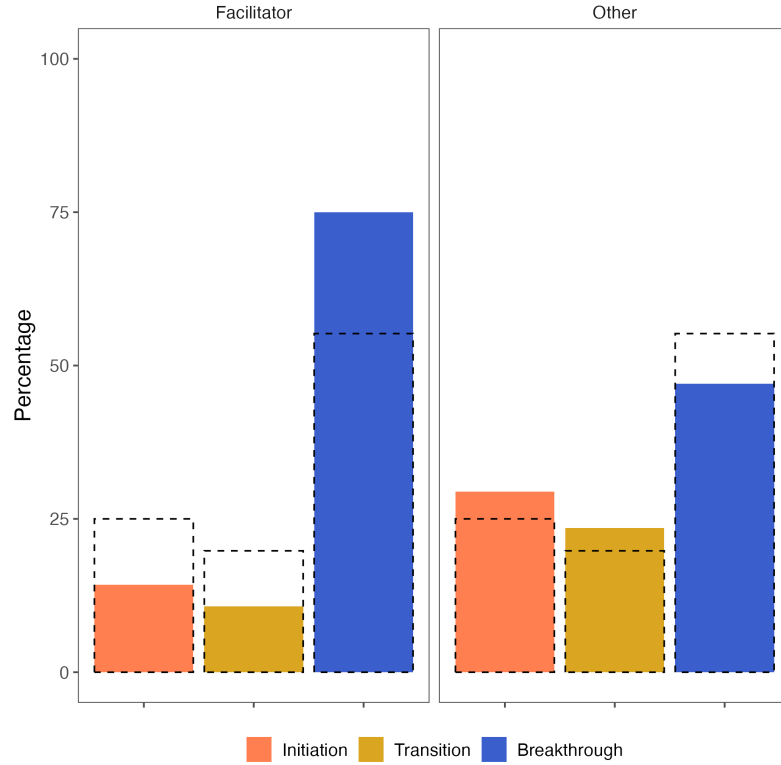


Figure 6.5: Comparison of the engagement levels for visitors who reported a “facilitation” motivation (right) and those who did not (left). Filled bars represent the observed engagement, while dashed boxes indicate the expected engagement levels if the variables were not associated.

cilitation strategies (FC: use of Comfort Dimension, FI: use of Information Dimension, FE: use of Exhibit Use Dimension, and FR: use of Reflection Dimension), because the facilitation strategies require the presence of a facilitation to occur. Second, group type (GT) is partially associated with visitor-visitor interaction (VV), since it is expected that being in a group would make it more likely that visitor-visitor interactions would happen. Finally, dwell time (DT) is partially associated with the facilitation variables (IF, FC, FI, FE, y FR), as would be expected, since the presence of a facilitator tends to encourage active participation and deeper engagement, which would result in visitors spending more time with the exhibit.

To construct our ordinal regression model, we initially excluded variables related to facilitation strategies (FC, FE, FI, and FR), due to their strong correlation with the facilitator interaction (IF). Multiple models were tested, and among those that converged without errors, the one with the lowest AIC

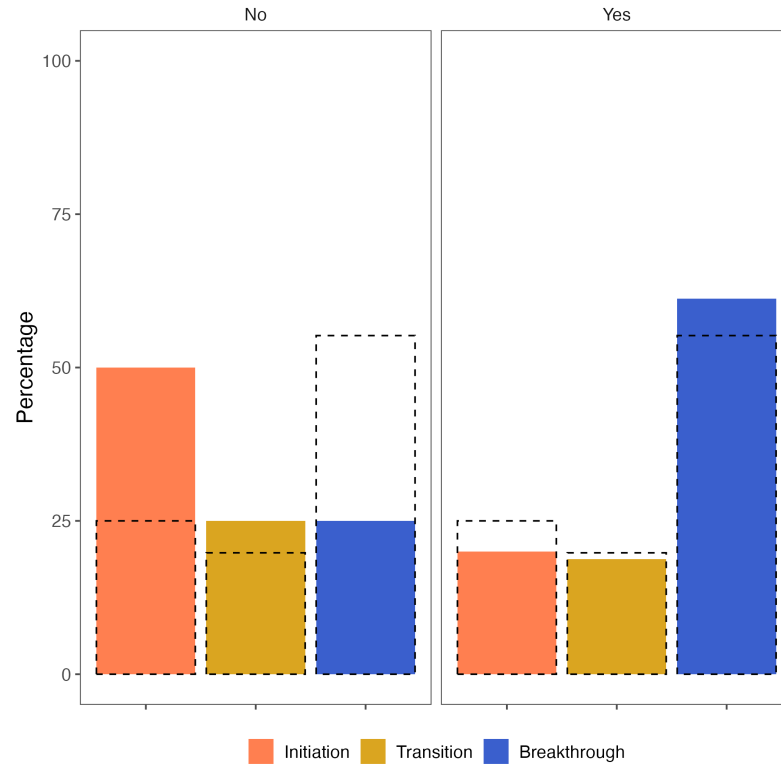


Figure 6.6: Comparison of the engagement levels for visitors who interacted with other visitors (right) and those who did not (left). Filled bars represent the observed engagement, while dashed boxes indicate the expected engagement levels if the variables were not associated.

was selected as the optimal model. A detailed description of the iterative process of refining can be found in Appendix 4.

The best fit model includes gender, visitor-visitor interaction (VV), interacting with a facilitator (IF) and dwell time in minutes (DTm) for ease of interpretation. Significant predictors of higher engagement levels included only visitor-facilitator interaction (IF) and dwell time in minutes (DTm), and the results of the ordinal regression analysis for the best fit model are summarized in Table 6.12.

The AIC for this model is 146.1736. Additionally, we found no Hauck-Donner effect in any of the estimates, ensuring stable and reliable estimates. The Hosmer-Lemeshow Test revealed a lack of fit in the model ($p = 0.002$), likely due to the presence of latent variables and the small sample size.

The model's performance, as reflected in the confusion matrix and associated statistics (Tables 6.13, 6.14 and 6.15), shows improved accuracy with

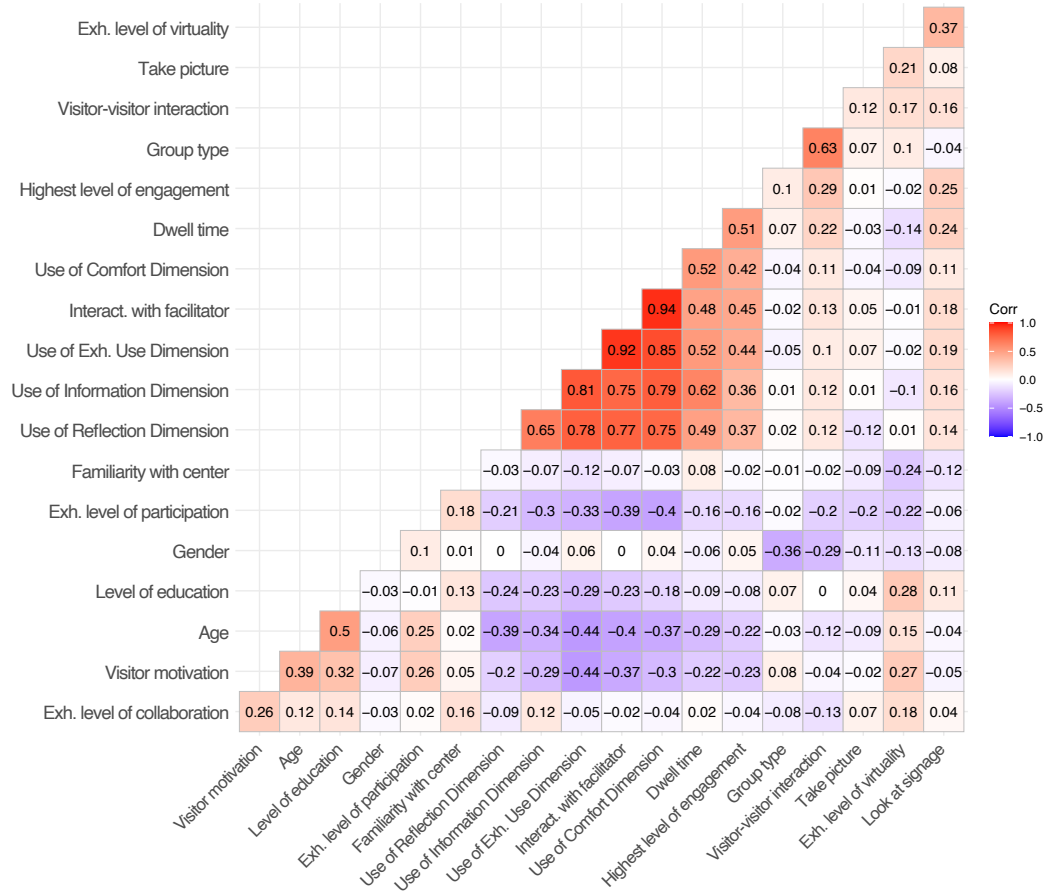


Figure 6.7: Correlation matrix between the descriptors and the dependent variable (highest level of engagement reached).

respect to the Comprehensive Study. The overall accuracy for this model is 71.88 % (95 % CI: 61.78 %, 80.58 %), which is substantially higher than the no-information rate of 55.21 %, indicating that the model performs significantly better than random classification ($p = 0.00059$). The Kappa statistic of 0.5099 points to moderate agreement between the model's predictions and the actual class labels. McNemar's test yielded a significant p-value ($p = 0.033$), suggesting that some classes are being mispredicted far more frequently than others.

The classification model shows strong performance for Initiation and Breakthrough, with high sensitivity rates of 83.33 % and 88.68 %, respectively, indicating that these classes are well detected. Specificity is also relatively high for Initiation (81.94 %) and moderate for Breakthrough (76.74 %), showing the model's ability to correctly identify the cases where the class is not present. Precision follows a similar trend, with Breakthrough achieving the highest

Table 6.12: Results of the ordinal regression analysis

	Value	Std. Error	t	p
Gender	0.882	0.528	1.671	.095
Visitor–Visitor Interaction (VV)	1.033	0.644	1.605	.109
Interacting with a Facilitator (IF)	2.787	1.119	2.490	.013
Dwell Time in Minutes (DTm)	0.012	0.003	3.645	< .001
1 / 2 Threshold	1.664	0.701	2.375	.018
2 / 3 Threshold	3.142	0.777	4.040	< .001

Table 6.13: Confusion matrix for the model

Prediction		Reference	
		Initiation	Transition Breakthrough
Initiation	20	9	4
Transition	2	2	2
Breakthrough	2	8	47

value (82.46 %) and Initiation at 60.61 %. In contrast, Transition presents significant challenges, with very low sensitivity (10.53 %) and a balanced accuracy of just 52.66 %, suggesting that the model struggles to correctly identify true Transition cases despite its high specificity (94.81 %). Overall, while the model shows promise, these discrepancies highlight the need for further refinement, particularly in enhancing the detection of Transition.

The key takeaway from these results is that this is a model that, while preliminary, demonstrates both improvements in accuracy and enhanced predictive power compared to the one presented in the Comprehensive Study. This serves as a proof of concept, showing that the inclusion of additional predictors has a positive impact on model performance. With an overall accuracy of 71.88 %, the current model suggests that future work, including the collection of a larger sample and a larger set of predictors, could further improve the model’s robustness and generalizability. In summary, these promising results set the stage for future work.

Odds ratio

To further interpret the results of our best-fitting model, we calculated the odds ratios for the included variables: gender (GND), visitor-visitor interaction (VV), interaction with a facilitator (IF), and dwell time in minutes (DTm), shown in table 6.16 with their respective confidence intervals (95 % confidence). The odds ratios provide a clearer understanding of the relationship between

Table 6.14: Overall model performance

Metric	Value
Accuracy	71.88 %
95 % CI	(61.78 %, 80.58 %)
No Information Rate (NIR)	55.21 %
P-Value (Acc >NIR)	0.00059
Kappa Score	0.5099
McNemar’s Test	0.033

Table 6.15: Model’s Performance per class

Metric	Initiation	Transition	Breakthrough
Sensitivity (Recall)	83.33 %	10.53 %	88.68 %
Specificity	81.94 %	94.81 %	76.74 %
Precision (PPV)	60.61 %	33.33 %	82.46 %
Balanced Accuracy	82.64 %	52.66 %	82.71 %

each predictor and the engagement levels, holding all other variables constant.

For visitors who interact with a facilitator, the odds of being more engaged are 16 times higher. However, it’s important to note that this result, although statistically significant, presents a considerably wide confidence interval. In contrast, for every additional minute spent at the exhibit, the odds of being more engaged double ($OR = 2.09$). The confidence interval for dwell time is much narrower, suggesting a more reliable estimate for this predictor.

Predicted probabilities

To assess how different predictor combinations influence visitors’ engagement levels, we used the best-fitting model to calculate the predicted probabilities of reaching each engagement level as a function of dwell time and interacting with a facilitator (Fig. 6.8).

The analysis of probabilities reveals interesting trends that highlight how dwell time and the presence of a facilitator influence the likelihood of reaching

Table 6.16: Odds ratio for the variables included in the best fitting model. The statistically significant associations are highlighted with an asterisk.

	Odds Ratio
Visitor-visitor interaction (VV)	2.81 [0.80, 9.85]
Gender (GND)	2.42 [0.86, 6.77]
Interaction with facilitator (IF)	16.24 [1.83, 144.05]*
Dwell time in minutes (DTm)	2.09 [1.41, 3.09]*

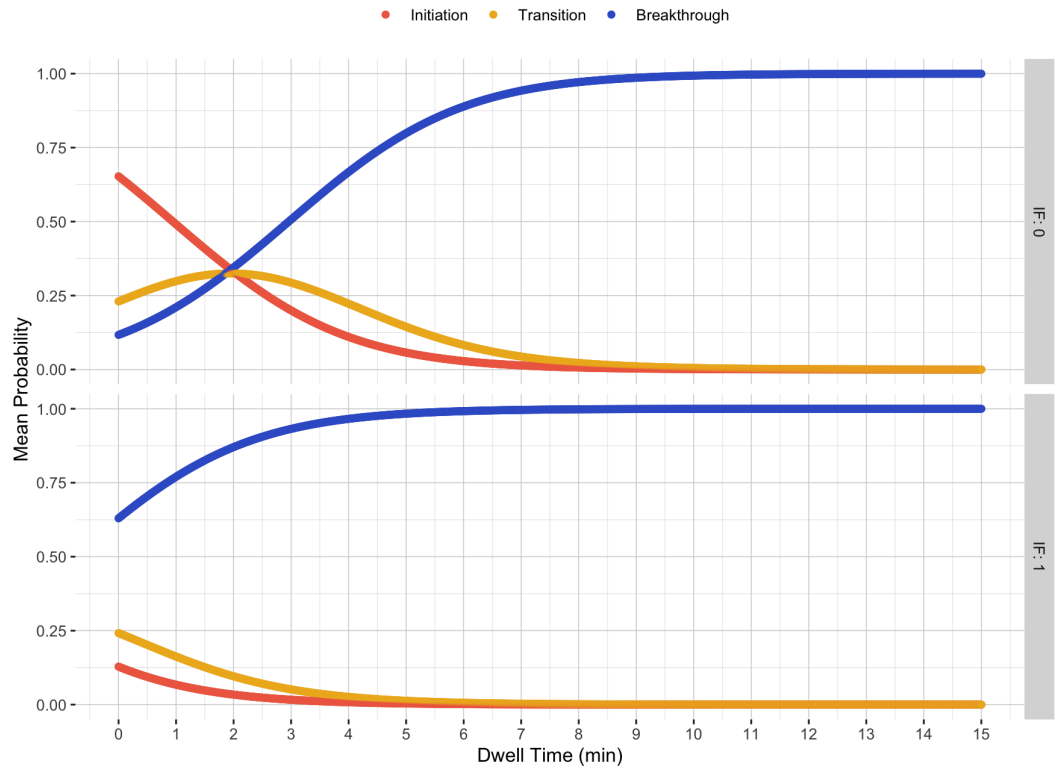


Figure 6.8: Predicted probabilities for the three levels of engagement (Initiation in red, Transition in yellow, and Breakthrough in blue) as a function of dwell time, in minutes, and interacting with a facilitator (IF). The outcomes are averaged across the remaining predictors (visitor-visitor interaction and gender).

higher levels of engagement. The most salient trend is that, as dwell time (DT) increases, the probability of reaching Breakthrough engagement tends toward 1, even when factoring in other variables like facilitator interaction (IF), gender (GND), and visitor-visitor interaction (VV). This positive influence of dwell time on engagement indicates that time spent at the exhibit plays a key role in visitor engagement. This suggests that the longer a visitor interacts with the exhibition, the more likely they are to experience higher engagement, though further research is needed to explore how facilitator interaction and dwell time together influence engagement outcomes.

One notable pattern is the distinct shift in the probability of reaching different levels of engagement for visitors who interact with a facilitator, compared to those who do not, for dwell times under 2 minutes. In that period of time, for visitors who do not interact with a facilitator, the probability of reaching Breakthrough is lower, while the probability of reaching Initiation is higher

(compared to the same probabilities for visitors who did interact with a facilitator). In contrast, for visitors who engage with a facilitator, the probability of reaching Breakthrough increases significantly, while the probability of Initiation decreases. This flip in probabilities highlights the powerful role that facilitator interaction plays in fostering deeper engagement, especially in the first minutes of the experience. This finding aligns with previous research. Lindgren-Streicher (2015), who found that participants who had at least one interaction with an educator stayed longer, tested more designs, and had more interactions overall. Similarly, Pattison et al. (2018) observed that facilitation increased dwell time, satisfaction, and mathematical reasoning, although it negatively affected intergenerational communication. These studies support the idea that both the facilitator's and the time spent interacting with exhibits are critical in fostering visitor engagement.

To close this section, we will focus on facilitation, looking at it through a more qualitative lens. Out of the 24 visitors who interacted with a facilitator, 23 reached Breakthrough engagement, and the remaining visitor reached Transition—meaning that even this one visitor progressed beyond Initiation. While this is an encouraging finding, it also makes it difficult to pinpoint which facilitation strategies are most effective in achieving Breakthrough engagement. In terms of strategies and Facilitator dimensions (Comfort, Exhibit use, Information, and Reflection), facilitators used strategies from all four dimensions with 11 of the 24 visitors. Notably, Comfort strategies were not used for just two visitors, whose dwell times were 79 seconds and 53 seconds, suggesting that applying comfort strategies may support longer engagement. McCubbins (2016) highlights that a facilitator's pedagogical approach greatly influences whether a visitor reaches breakthrough engagement. Specifically, the facilitator's teaching style—particularly when it is more constructivist—can have a significant impact on engagement outcomes. Additionally, facilitators who use positive language and scientific terminology are more likely to encourage visitors to recall previous knowledge and engage more deeply with the activities (McCubbins, 2016). Further research is needed to isolate the role specific strategies have on visitor engagement, but this result is still compelling.

Chapter 7

Conclusion

This chapter synthesizes the key findings and contributions of this research, including the results of the Comprehensive Study, the Extended Study, the validation of the Facilitation Framework (FF), and the development of the SOLEIL app. Together, these elements establish a robust methodological and theoretical foundation for examining and enhancing visitor engagement in informal science learning environments, particularly within science centers.

The Comprehensive Study serves as the cornerstone of this research. It draws on an extensive dataset of 9002 visitors at Science North and applies sophisticated ordinal regression analysis. This study systematically investigates the multifaceted factors influencing visitor engagement, including visitor demographics (gender, age, group type), visitor behaviors (reading signage, taking pictures), the presence of facilitators, and exhibit design characteristics. The results highlight the pivotal role of exhibit design and facilitator presence in promoting higher engagement levels, with participatory and collaborative exhibits showing a heightened capacity to foster Breakthrough engagement. Visitor behaviors like reading signage and taking photos also correlate positively with engagement, illustrating the importance of active visitor participation in enhancing learning experiences.

Building on these insights, the Extended Study incorporates additional variables such as visitor familiarity with the center, level of education, and motivation. It also examines the impact of visitor-visitor interaction, specific facilitation strategies, and dwell time. This study takes place across three science centers (Science North, Espacio Ciencia, and Moleculario) and reveals that dwell time significantly predicts engagement, with longer interactions con-

sistently associated with higher engagement levels. Visitor-visitor interactions and facilitation strategies also emerge as drivers of meaningful visitor experiences.

The results from both studies provide a comprehensive understanding of visitor engagement in science centers, though each has its limitations and unique contributions. The Comprehensive Study, with its extensive dataset, offered robust and statistically significant insights into various factors influencing visitor interactions with exhibits. Despite a lack of fit potentially due to latent variables, the model demonstrated satisfactory accuracy. In contrast, the Extended Study, while limited by its small sample size, provided a valuable yet tentative extension of these findings. The incorporation of other predictors, although constrained by the number of participants, added depth to our understanding of visitor motivations and behaviors. Furthermore, adding predictors increased the accuracy of the model classification. The integration of these variables into the research highlighted patterns and correlations, albeit preliminary, that aligned with and expanded upon the Comprehensive Study's results.

The Facilitation Framework underwent a meticulous two-stage validation process, ensuring its robustness, adaptability, and applicability. The revised framework retains the four Dimensions of the original (Comfort, Information, Exhibit Use, and Reflection) and updates the associated codes. High inter-rater reliability metrics confirm the framework's consistency and effectiveness, establishing it as an invaluable tool for systematically analyzing and enhancing visitor-facilitator interactions in informal learning spaces.

Finally, the development of the SOLEIL app represents a pivotal methodological innovation of this research. This web-based tool streamlines data collection and analysis for visitor engagement research. By integrating with the Facilitation Framework, the SOLEIL app facilitates efficient coding processes, enhances the reliability of observational analyses, and offers a scalable, cost-effective solution for conducting engagement research. Its ability to manage complex datasets, support live and video coding, and generate sophisticated statistical analyses underscores its transformative potential for the field.

7.1. Contributions to the Field

This research makes significant theoretical, practical, and methodological contributions to the field of informal science education, advancing both scholarly understanding and professional practice.

Theoretical Contributions

The study offers critical theoretical insights by empirically validating and expanding the Visitor-Based Learning Framework (VBLF) within diverse cultural contexts. By integrating findings from the Facilitation Framework and aligning exhibit characteristics with Wideström’s dimensions, this research provides a more responsive and comprehensive model of visitor engagement. The identification of specific visitor behaviors associated with Breakthrough deepens our understanding of engagement trajectories and highlights the role social interactions and exhibit design play in fostering sustained, meaningful engagement.

This research builds on past studies that have examined individual factors of visitor engagement, often in isolation, such as facilitation practices, exhibit characteristics, and social interaction. By bringing these elements together, this study demonstrates the interconnectedness of these factors and their combined impact on visitor behavior. It offers a more holistic understanding of engagement, bridging the gaps in previous research and providing a comprehensive model that better reflects the complexity of visitor experiences.

Furthermore, the research contributes to the ongoing discourse on socio-cultural learning theories, emphasizing the importance of social interactions, contextual learning, and reflective practices in informal science education. The validation of the Facilitation Framework offers a structured approach to understanding and enhancing the role of facilitators, shedding light on the specific strategies that promote higher engagement and more profound learning outcomes. While the full potential of the framework could not be completely exploited in this study due to the relatively small sample size, its promise for future research is substantial, offering a valuable tool for further exploration of facilitation strategies.

Practical Contributions

For science center staff and practitioners, the validated Facilitation Framework provides a systematic and evidence-based approach to professional devel-

opment, offering clear guidelines on effective facilitation strategies. The revised framework equips facilitators with the tools to create welcoming, informative, and reflective learning environments that foster deeper visitor engagement.

The research also underscores the critical role of exhibit design in shaping visitor experiences, advocating for the development of interactive exhibits that encourage active exploration and social interaction. Insights into visitor behaviors, such as the importance of reading signage and engaging with facilitators, offer practical recommendations for enhancing exhibit effectiveness and promoting meaningful visitor engagement.

Methodological Contributions

The development and deployment of the SOLEIL app represent a groundbreaking methodological advancement in visitor engagement research. By integrating digital tools for data collection and analysis, the app streamlines the research process, reduces observational bias, and enhances data accuracy and reliability. Its capabilities for coding, automated inter-rater reliability calculations, and sophisticated data visualization offer a scalable and cost-effective solution for conducting large-scale engagement studies.

The combination of quantitative and qualitative methods employed in this research further enriches our understanding of visitor engagement, demonstrating the value of mixed-methods approaches in capturing the multifaceted nature of informal learning experiences. In particular, the use of statistical methodologies such as ordinal regression and predicted probabilities represents an innovative approach for this field, allowing for a more nuanced analysis of the factors influencing visitor behavior and engagement.

7.2. Implications of the Study

For Practitioners

The findings of this research have profound implications for practitioners in informal science settings, emphasizing the need for targeted professional development and ongoing training for facilitators. By equipping staff with effective facilitation strategies, science centers can enhance visitor engagement and foster more meaningful learning experiences. The validated Facilitation Framework offers a practical tool for guiding and assessing facilitation practices, promoting consistent and high-quality visitor interactions.

For Science Centers

Science centers are encouraged to prioritize interactive and collaborative exhibit designs that foster social engagement and participatory learning. The research highlights the importance of creating engaging and impactful learning environments by focusing on developing interactive and collaborative elements for exhibits, and implementing strategies to encourage social interaction, as well as promoting opportunities for facilitation. The integration of digital assessment tools, such as the SOLEIL app, offers a scalable solution for evaluating exhibit effectiveness and refining engagement strategies.

For Researchers

This study underscores the transformative potential of digital tools in educational research, demonstrating the efficiency and reliability of the SOLEIL app for data collection and analysis. By integrating the validated Facilitation Framework (Machado Corral et al., 2021) with a more comprehensive application of the Visitor-Based Learning Framework (Barriault and Rennie, 2019) and Widenström’s framework (Widenström, 2020), this research contributes valuable tools to the researchers’ toolbox. These frameworks, when applied together, offer a more comprehensive and cohesive understanding of visitor engagement, providing a unifying theory that incorporates a wide range of influencing factors—such as social interaction, exhibit design, and visitor behavior. The ability to examine these factors holistically, rather than in isolation, opens new avenues for future research, allowing researchers to more accurately capture the complex dynamics that shape visitor experiences in science centers and museums.

7.3. Key insights and suggestions for best practices

- **Visitor Demographics:** The Comprehensive Study identifies key visitor demographics, noting that adults and children constitute the majority of visitors, with a higher representation of females overall. This aligns with findings that families are the predominant visitor group in science centers. The Extended Study reinforces this, with adults being the most common visitor type and females outnumbering males.

- **Social Interaction and Group Dynamics:** The results of both studies emphasize the importance of social interaction in the visitor experience with exhibits. The Comprehensive Study indicates that visitors in groups are more likely to reach higher engagement levels when interacting with exhibits. The Extended Study supports this, noting a high prevalence of group visits across different science centers.

Best practice suggestion: Design exhibits that accommodate and encourage group interaction, but also provide options for Individual exploration.

- **Signage:** The Comprehensive Study demonstrates that visitors who read signage exhibit higher engagement. The Extended Study reinforces this, showing that signage engagement varies across centers, with some centers having significantly higher rates of visitors reading signage.

Best practice suggestion: Prioritize clear and engaging signage to enhance cognitive engagement and facilitate discussions among visitors. Consider integrating interactive text elements like quizzes to further boost engagement.

- **Facilitator Interaction:** Both studies highlight the crucial role of facilitators in enhancing visitor engagement. The Comprehensive Study shows that interaction with facilitators significantly increases the likelihood of reaching higher engagement levels. The Extended Study supports this, with Moleculario showing exceptionally high facilitator interaction rates and longer visitor dwell times.

Best practice suggestion: Emphasize dynamic, responsive interactions by facilitators to adapt to visitor interests and make scientific concepts more accessible.

- **Photography:** The Comprehensive Study reveals a complex relationship between photography and engagement, suggesting that while taking pictures may encourage initial engagement, it could divert attention from deeper interaction.

Best practice suggestion: Providing photo opportunities can move exhibits with high Initiation into Transition. Design exhibits to accommodate photography by including designated photo spots or interactive elements.

- **Exhibit Design (Participation, Virtuality, Collaboration):** The Comprehensive Study classifies exhibits based on participation, virtuality, and collaboration, noting that Static and Physical exhibits are most common in the Science North data set. The Extended Study also uses this exhibit design classification framework, with Participatory and Physical exhibits being most prevalent in the three study sites. The level of collaboration has an impact on engagement, with exhibits that have more collaborative elements significantly increasing the likelihood of visitors achieving higher levels of engagement.

Best practice suggestion: Provide more opportunities for content co-creation to enhance meaning-making opportunities for visitors. Design exhibits that are non-linear and can be used in multiple ways by different group configurations.

- **Dwell Time:** The Extended Study identifies dwell time as a significant predictor of engagement, with longer dwell times correlating with higher engagement levels.

Best practice suggestion: Focus on strategies to extend visitor dwell time, such as encouraging visitor-visitor and visitor-facilitator interactions.

7.4. Limitations of the Study

Despite its contributions, this research acknowledges several limitations. The relatively small sample size of the Extended Study constrains the generalizability of its findings, necessitating caution in extending results to broader populations. Potential biases in observational data coding, influenced by group dynamics and visitor awareness of being observed, may have impacted visitor behavior representation and data accuracy. Additionally, the cultural specificity of the participating science centers limits the generalizability of findings to other informal learning environments.

7.5. Future Research Directions

Future research should prioritize the further validation of the Facilitation Framework across diverse cultural and institutional settings, ensuring its

adaptability and applicability. Expanding the SOLEIL app to integrate additional engagement frameworks, such as the Visitor Engagement Installation (Leister et al., 2015) or APEX (Long et al., 2022) frameworks, could enhance its utility and offer more comprehensive assessment capabilities.

A more detailed analysis of facilitator behaviors, exploring the temporal sequence and impact of specific facilitation strategies on visitor engagement, would provide valuable insights into the facilitation process. Increasing sample sizes and conducting longitudinal studies would further enrich our understanding of engagement dynamics, enabling the development of more effective and inclusive informal learning environments.

In conclusion, this research lays a solid foundation for advancing the study and practice of visitor engagement in informal science learning spaces, supporting the creation of interactive, reflective, and impactful educational experiences.

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APPENDICES

Appendix 1

Surveys

1.1. Visitor Survey, Science North, English Version

Thank you for taking the time to fill out this survey. Participating in this study is your choice (it is voluntary). You have the right to opt out, and you have the right to stop your participation at any time. If you decide to stop participating, your data will be deleted and there will be no consequences for you.

All information collected, used, or disclosed for this study is strictly confidential. Your responses to the survey will be encrypted using an identification number, and will therefore remain anonymous.

This research is conducted by María Soledad Machado Corral, from Universidad de la República, Uruguay. The title of the project is “Impact of facilitation factors and practices on the involvement of visitors in non-formal areas of science education”. We seek to better understand how staff can enrich visitors’ learning experiences in places like Science North.

You will have to complete a survey consisting of 4 questions and it will take less than 5 minutes. There are no risks to you of any kind for participating in this study, but it is possible that any question we ask you may be stressful or uncomfortable. You don’t need to answer questions that make you uncomfortable or that you don’t want to answer.

Participation does not imply a direct benefit for the participants, but a medium and long-term community benefit is expected, through a better educational experience for future visitors to science centers like this one. The

results of this research can be used to improve future exhibits, events, and workshops. In addition, the scientific community will benefit directly from your participation in this study. There is no conflict of interest with the participating institutions.

If you have further questions about this study, you can contact the researcher (smachado@fq.edu.uy) or her director Lucía Otero (lutoero@fq.edu.uy) by email.

1. I agree to participate in the study

- Yes, I agree to participate
- No, I do not agree to participate (Note: this will end the survey and no data will be collected)

2. How old are you? *

- Under 12 years old
- 12-17 years old
- 18-34 years old
- 35-64 years old
- 65 years or older

3. What is your highest level of education?

- No schooling completed
- Primary school
- Some high school, no diploma
- High school graduate, diploma or the equivalent
- Some college/university credit, no degree
- College completed
- Trade/technical/vocational training
- Undergraduate degree (like a bachelor's or a associate degree)
- Graduate degree (like a Master, PhD, or post-doc)

4. How often do you visit Science North?

- This is my first time
- Once a year or less

- 2-4 times a year
- 5 or more times a year

5. What was the reason for your visit today? (Select all that apply)

- To satisfy my own general curiosity. Science North provides me with a place where I can learn about new things.
- I came with someone else (like a child, grandchild, a relative, or a friend) and my main concern is that they have a good experience here.
- I'm here because of the experience, I wanted to visit Science North as a tourist attraction.
- I had a specific question I wanted to answer or a specific topic I wanted to learn about.
- I needed a place to relax and Science North provides a contemplative space where I feel restored.

1.2. Visitor Survey, Science North, French Version

Merci de prendre le temps de remplir ce sondage. La participation au sondage est à votre choix (volontaire). Vous avez le droit de ne pas le faire ou d'arrêter d'y participer à tout moment. Si vous vous retirez du sondage, vous le faites sans conséquence et vos données seront supprimées. Tous les renseignements recueillis, utilisés ou divulgués dans le cadre de cette étude sont confidentiels. Vos réponses seront cryptées à l'aide d'un numéro d'identification afin de protéger l'anonymat.

Cette recherche est menée par María Soledad Machado Corral, de l'Universidad de la República, Uruguay. Dans le cadre du projet intitulé "Impact of facilitation factors and practices on the involvement of visitors in non-formal areas of science education", nous cherchons à cerner davantage les façons dont le personnel peut enrichir les expériences d'apprentissage des visiteurs à des endroits comme Science Nord.

Ce sondage comprend quatre (4) questions et prendra environ 5 à 10 minutes à remplir. Bien que la participation à ce sondage ne présente aucun risque, il se peut que des questions vous causent du stress ou vous rendent mal à l'aise.

Vous pouvez passer outre ces questions et toute autre à laquelle vous ne voulez pas répondre.

La participation n'apporte aucun avantage direct aux participants, mais pourrait entraîner des bienfaits à moyen et à long terme pour la communauté, grâce à une meilleure expérience d'apprentissage des futurs visiteurs aux centres de sciences, comme celui-ci. Les résultats de cette recherche aideront à améliorer les expositions, activités et ateliers à l'avenir. De plus, la communauté scientifique profitera directement de votre participation à l'étude. Aucun conflit d'intérêts n'existe avec l'établissement participant.

Si vous avez des questions au sujet de ce projet, communiquez avec la chercheuse, smachado@fq.edu.uy, ou sa directrice, luotero@fq.edu.uy, par courriel.

1. J'accepte de participer à l'étude.*

- Oui, j'accepte d'y participer.
- Non, je ne veux pas y participer.

2. Quel âge as-tu?*

- Moins de 12 ans
- 12-17 ans
- 18-34 ans
- 35-64 ans
- 65 ans ou plus

3. Quel est le plus haut niveau de scolarité que vous avez atteint?

- Aucune scolarité
- École primaire
- Études secondaires pas complétées, aucun diplôme
- Études secondaires complétées
- Études collégiales ou universitaires pas complétées, aucun diplôme
- Études collégiales complétées
- Formation technique, professionnelle ou de métier
- Baccalauréat
- Études supérieures

4. À quelle fréquence visitez-vous Science Nord

- C'est ma première fois
- Une fois par an ou moins
- 2 à 4 fois par an
- 5 fois ou plus par an

5. Pour quelle(s) raison(s) êtes-vous venu(e) au centre aujourd'hui? (Indiquez toutes les réponses pertinentes.)

- Pour satisfaire en général ma curiosité; Science Nord me propose un endroit dans lequel faire de nouveaux apprentissages
- Pour assurer une bonne expérience à quelqu'un d'autre qui m'accompagne (enfant, petit-enfant, parenté, ou ami)
- Pour faire l'expérience de Science Nord en tant qu'attraction touristique
- Pour obtenir une réponse à une question précise ou en apprendre plus long sur un sujet particulier
- Pour me détendre, car Science Nord propose un espace de réflexion dans lequel je me sens revivifié(e)

1.3. Visitor Survey, Espacio Ciencia/Moleculario

Gracias por tomarse el tiempo para completar esta encuesta. Participar en este estudio es su elección (es voluntario). Tiene derecho a optar por no participar y tiene derecho a detener su participación en cualquier momento. Si decide dejar de participar, sus datos serán eliminados y no habrá consecuencias para usted.

Toda la información recopilada, utilizada o divulgada para este estudio es estrictamente confidencial. Sus respuestas a la encuesta se cifrarán mediante un número de identificación y, por lo tanto, permanecerán anónimas.

Esta investigación es realizada por María Soledad Machado Corral, de la Universidad de la República, Uruguay. El título del proyecto es "Impacto de los factores y prácticas de facilitación en la participación de los visitantes en áreas no formales de la educación científica". Buscamos comprender mejor cómo el personal puede enriquecer las experiencias de aprendizaje de los visitantes en lugares como el Espacio Ciencia.

Tendrá que completar una encuesta que consta de 4 preguntas y te llevará menos de 5 minutos. No existen riesgos de ningún tipo para usted por participar en este estudio, pero es posible que alguna pregunta que le hagamos le resulte estresante o incómoda. No es necesario que responda preguntas que te incomoden o que no quieras responder.

La participación no implica un beneficio directo para los participantes, pero sí se espera un beneficio comunitario a mediano y largo plazo, a través de una mejor experiencia educativa para los futuros visitantes de centros de ciencias como este. Los resultados de esta investigación se pueden utilizar para mejorar futuras exhibiciones, eventos y talleres. Además, la comunidad científica se beneficiará directamente de su participación en este estudio. No existe conflicto de intereses con las instituciones participantes.

Si tiene más preguntas sobre este estudio, puede contactar a la investigadora (smachado@fq.edu.uy) o a su directora Lucía Otero (lutoero@fq.edu.uy) por correo electrónico.

1. Acepto participar*

- Si, acepto participar
- No, no acepto participar (Nota: al elegir esta opción, no se pasará a la encuesta y no se recopilará ningún dato)

2. ¿Cuántos años tienes?*

- Menos de 12
- 12-17 años
- 18-34 años
- 35-64 años
- 65 años

3. ¿Cuál es tu nivel de estudios más alto?

- Primaria incompleta
- Primaria completa
- Secundaria incompleta
- Secundaria completa
- Terciaria incompleta
- Terciaria no universitaria completa (por ejemplo, UTU o Magisterio)

- Título de grado (por ejemplo, licenciatura)
- Título de posgrado (por ejemplo, maestría o doctorado)

4. ¿Qué tan seguido visitas el Espacio Ciencia/Moleculario?

- Es la primera vez que vengo en toda mi vida
- Una vez al año o menos
- 2-4 veces al año
- 5 o más veces al año
- Otros:

5. ¿Por qué razón visitas el Espacio Ciencia hoy? (Selecciona todas las que apliquen)

- Para satisfacer mi propia curiosidad general. El Espacio Ciencia me brinda un lugar donde puedo aprender sobre cosas nuevas.
- Vine con otra persona (como hijo, nieto, pariente o amigo) y mi principal preocupación es que tengan una buena experiencia aquí.
- Estoy aquí por la experiencia, quería visitar el Espacio Ciencia como un paseo o una atracción turística.
- Tenía una pregunta específica que quería responder o un tema específico sobre el que quería aprender.
- Necesitaba un lugar para relajarme y el Espacio Ciencia ofrece un lugar donde me siento restaurado.

Appendix 2

Visitors

2.1. Comprehensive study

Table 2.1: Number of visitors for each variable in the Comprehensive Study

Age		In a group			Looks at signage			Interacts with facilitator			Takes picture		
		Fem	Male	Total	Fem	Male	Total	Fem	Male	Total	Fem	Male	Total
Young child	No	14	29	43	361	441	802	380	459	839	384	463	847
	Yes	378	446	824	31	34	65	12	16	28	8	12	20
Child	No	84	96	180	947	1216	2163	1072	1363	2435	1112	1419	2531
	Yes	1061	1354	2415	198	234	432	73	87	160	33	31	64
Pre-teen	No	41	33	74	268	249	517	319	284	603	331	296	627
	Yes	295	265	560	68	49	117	17	14	31	5	2	7
Teen	No	34	41	75	347	217	564	412	268	680	419	275	694
	Yes	399	239	638	86	63	149	21	12	33	14	5	19
Adult	No	196	207	403	1584	1063	2647	2277	1424	3701	2306	1487	3793
	Yes	2206	1314	3520	818	458	1276	125	97	222	96	34	130
Senior	No	18	17	35	98	74	172	158	98	256	161	105	266
	Yes	146	89	235	66	32	98	6	8	14	3	1	4
Total	No	387	423	810	3605	3260	6865	4618	3896	8514	4713	4045	8758
	Yes	4485	3707	8192	1267	870	2137	254	234	488	159	85	244

Table 2.2: Contingency table and expected values for age

	Observed			Expected		
	Initiation	Transition	Breakthrough	Initiation	Transition	Breakthrough
Young child (0-5yo)	375	326	166	387	220	260
Child (6-10yo)	1099	769	727	1158	658	779
Pre-teen (11-13yo)	292	164	178	283	161	190
Teen (14-18yo)	315	197	201	318	181	214
Adult (19-64yo)	1815	776	1332	1750	995	1178
Senior (65+yo)	120	52	98	120	69	81

Table 2.3: Contingency table and expected values for gender

	Observed			Expected		
	Initiation	Transition	Breakthrough	Initiation	Transition	Breakthrough
Female	2139	1221	1512	2174	1236	1462
Male	1877	1063	1190	1842	1048	1240

Table 2.4: Contingency table and expected values for group type

	Observed			Expected		
	Initiation	Transition	Breakthrough	Initiation	Transition	Breakthrough
Alone	586	111	113	361	206	243
In a group	3430	2173	2589	3655	2078	2459

Table 2.5: Contingency table and expected values for looking at signage

	Observed			Expected		
	Initiation	Transition	Breakthrough	Initiation	Transition	Breakthrough
No	3191	1893	1781	3063	1742	2061
Yes	825	391	921	953	542	641

Table 2.6: Contingency table and expected values for taking a picture

	Observed			Expected		
	Initiation	Transition	Breakthrough	Initiation	Transition	Breakthrough
No	3934	2177	2647	3907	2222	2629
Yes	82	107	55	109	62	73

Table 2.7: Contingency table and expected values for interacting with a facilitator

	Observed			Expected		
	Initiation	Transition	Breakthrough	Initiation	Transition	Breakthrough
No	3900	2159	2455	3798	2160	2556
Yes	116	125	247	218	124	146

Table 2.8: Contingency table and expected values for exhibit's level of participation

	Observed			Expected		
	Initiation	Transition	Breakthrough	Initiation	Transition	Breakthrough
Static	2878	1470	1882	2779	1581	1870
S/P	863	485	573	857	487	577
Participatory	275	329	247	380	216	255

Table 2.9: Contingency table and expected values for exhibit’s level of virtuality

	Observed			Expected		
	Initiation	Transition	Breakthrough	Initiation	Transition	Breakthrough
Physical	2002	1274	1390	2082	1184	1401
P/V	913	473	523	852	484	573
Virtual	1101	537	789	1083	616	728

Table 2.10: Contingency table and expected values for exhibit’s level of collaboration

	Observed			Expected		
	Initiation	Transition	Breakthrough	Initiation	Transition	Breakthrough
Individual	1711	840	851	1518	863	1021
I/C	2137	1276	1485	2185	1243	1470
Collaborative	168	168	366	313	178	211

2.2. Extended study

Table 2.11: Number of visitors for each variable and each center in the Extended Study

		Science North	Espacio ciencia	Moleculario	Total
Gender	Total visitors	51	29	16	96
	Female	30	21	9	60
	Male	21	8	7	36
Age	Child	0	0	1	1
	Teen	2	2	1	5
	Young adult	9	1	10	20
	Adult	31	22	4	57
Group	Senior	9	4	0	13
	Alone	4	1	2	7
	In group	47	28	14	89
Academic lvl	Primary incomplete	0	0	1	1
	Primary complete	0	0	0	0
	Secondary incomplete	3	2	2	7
	Secondary complete	12	1	1	14
	Tertiary incomplete	7	6	10	23
	Tertiary complete	27	12	2	41
	Posgraduate degree	2	8	0	10
Familiarity	First time	19	17	7	43
	Once a year or less	19	10	7	36
	2-4 times a year	6	2	0	8
	5+ times a year	7	0	2	9
Motivation	Facilitator	38	26	4	68
	Other	13	3	12	28
Facilit interact	Yes	4	7	13	24
	No	47	22	3	72
Dwell time	Average, in seconds	161	157	361	193
Engagement	Initiation	16	8	0	24
	Transition	13	5	1	19
	Breakthrough	22	16	15	53

Table 2.12: Contingency table and expected values for age

	Observed			Expected		
	Initiation	Transition	Breakthrough	Initiation	Transition	Breakthrough
Child	0	0	1	0.25	0.1979167	0.5520833
Teen	0	0	5	1.25	0.9895833	2.7604167
Young adult	4	2	14	5	3.9583333	11.0416667
Adult	16	15	26	14.25	11.28125	31.46875
Senior	4	2	7	3.25	2.5729167	7.1770833

Table 2.13: Contingency table and expected values for gender

	Observed			Expected		
	Initiation	Transition	Breakthrough	Initiation	Transition	Breakthrough
Female	16	12	32	15	12	33
Male	8	7	21	9	7	20

Table 2.14: Contingency table and expected values for group type

	Observed			Expected		
	Initiation	Transition	Breakthrough	Initiation	Transition	Breakthrough
Alone	3	1	3	2	1	4
In a group	21	18	50	22	18	49

Table 2.15: Contingency table and expected values for looking at signage

	Observed			Expected		
	Initiation	Transition	Breakthrough	Initiation	Transition	Breakthrough
No	19	15	28	16	12	34
Yes	5	4	25	9	7	19

Table 2.16: Contingency table and expected values for taking a picture

	Observed			Expected		
	Initiation	Transition	Breakthrough	Initiation	Transition	Breakthrough
No	22	19	49	23	18	50
Yes	2	0	4	2	1	3

Table 2.17: Contingency table and expected values for interacting with a facilitator

	Observed			Expected		
	Initiation	Transition	Breakthrough	Initiation	Transition	Breakthrough
No	24	18	30	18	14	40
Yes	0	1	23	6	5	13

Table 2.18: Contingency table and expected values for visitor motivation

	Observed			Expected		
	Initiation	Transition	Breakthrough	Initiation	Transition	Breakthrough
Facilitator	4	3	21	7	6	15
Other	20	16	32	17	13	38

Table 2.19: Contingency table and expected values for familiarity with the center

	Observed			Expected		
	Initiation	Transition	Breakthrough	Initiation	Transition	Breakthrough
First time	11	7	25	11	9	24
Once a year or less	7	10	19	9	7	20
2-4 times a year	4	1	3	2	2	4
5+ times a year	2	1	6	2	2	5

Table 2.20: Contingency table and expected values for visitor-visitor interaction

	Observed			Expected		
	Initiation	Transition	Breakthrough	Initiation	Transition	Breakthrough
No	8	4	4	4	3	9
Yes	16	15	49	20	16	44

Table 2.21: Contingency table and expected values for level of education

	Observed			Expected		
	Initiation	Transition	Breakthrough	Initiation	Transition	Breakthrough
Up to secondary school complete	6	3	13	30	19	52
Tertiary school incomplete or complete	14	14	36	30	19	52
Postgraduate degree	4	2	4	30	19	52

Table 2.22: Contingency table and expected values for exhibit's level of participation

	Observed			Expected		
	Initiation	Transition	Breakthrough	Initiation	Transition	Breakthrough
Static	8	7	26	10	8	23
S/P	1	2	4	2	1	4
Participatory	15	10	23	12	10	27

Table 2.23: Contingency table and expected values for exhibit's level of virtuality

	Observed			Expected		
	Initiation	Transition	Breakthrough	Initiation	Transition	Breakthrough
Physical	16	14	37	17	13	37
P/V	8	5	16	7	6	16
Virtual	0	0	0	0	0	0

Table 2.24: Contingency table and expected values for exhibit's level of collaboration

	Observed			Expected		
	Initiation	Transition	Breakthrough	Initiation	Transition	Breakthrough
Individual	1	2	4	2	1	4
I/C	23	17	49	22	18	49
Collaborative	0	0	0	0	0	0

Appendix 3

Exhibits

3.1. Arctic Voices

Arctic Voices is Science North's tenth traveling exhibition, developed in partnership with the Canadian Museum of Nature. This exhibition engages visitors while they explore the Arctic through the sights, sounds, and voices of this beautiful and changing place through interactive and object-based exhibits, and multimedia experiences. They discover the wildlife, marvel at the landscapes, and meet the people who call the Arctic home.

Exhibit name	Part	Virt	Collab
Animal behaviour	St	Vi	Co
Arctic map	St	Ph	IC
Bear challenge	St	Ph	In
Feathers, fins and fur	St	Ph	In
Crawl beneath	St	Ph	In
Global connections	St	Vi	In
Hare challenge	St	Ph	In
Newcomers quiz	St	Vi	Co
On thin ice	St	PV	In
Polar bear life	St	Ph	In
Polar bear research	St	PV	In
Three bears	St	Ph	In

Table 3.1: Exhibits selected from *Arctic Voices*

3.2. Space Place, Science North

The Space Place is part of Science North's permanent exhibition, located in the fourth level of the science center. Here visitors can learn all about space and space exploration.

Exhibit name	Part	Virt	Collab
Gravity Well	St	Ph	IC
Racetrack	Pa	Ph	IC
Robotic arm	Pa	Ph	IC

Table 3.2: Exhibits selected from *Science North's Space Place*

3.3. The Science of Ripley's Believe It or Not!

Science North, in partnership with Ripley Entertainment Inc., designed a 6000 square foot traveling exhibition, The Science of Ripley's Believe It or Not!® This exhibition showcases the amazing and wonderfully unique features of our world, including animal and human biology, extreme earth events, amazing talents, unique art, and multiple illusions! Science North created this exhibition to engage visitors in discovering the science behind the weird world of Ripley's Believe It or Not!®

3.4. Wild Weather

Wild Weather was developed by Science North, in partnership with the Ontario Science Center. Through hands-on exhibits, multi-player challenges, and interactive multimedia experiences, this 6,000 square foot traveling exhibition reveals how scientists are working to better forecast severe weather events and to help mitigate the impact on communities, infrastructure and lives.

3.5. Wildlife Rescue

Wildlife Rescue is an exhibition that involves visitors in the compelling stories of animal rescue, the dedicated people taking action, and the science that supports their efforts. This 6000 square foot traveling exhibition, designed by Science North, has 30 exhibits and experiences which include mechanical

Exhibit name	Part	Virt	Collab
Age yourself	Pa	Vi	IC
Big chair	St	Ph	IC
Bio quiz	St	Vi	Co
Body modifications	St	Ph	IC
Bug bistro	St	Vi	In
Capture your moves	Pa	PV	IC
Cartoon studio	Pa	PV	IC
Cave	SP	PV	IC
Create the colours	Pa	Ph	IC
Dino marvels	St	PV	IC
Earth quiz	SP	Vi	Co
Impossible gate	St	Ph	IC
Gem illusion	St	Ph	In
How tall	SP	PV	IC
Make an impression	Pa	Ph	In
Make your skin crawl	St	Ph	IC
Mars	St	Ph	IC
McGurk	St	Vi	IC
Pay attention	SP	Vi	IC
Radio Ripley	St	Ph	In
Scavenger hunt	St	Ph	IC
Small challenge	SP	PV	IC
Vase or face	St	Ph	In
Robert Wadlow	St	Ph	In

Table 3.3: Exhibits selected from *The Science of Ripley's Believe It or Not!*

Exhibit name	Part	Virt	Collab
Body heat alert	SP	Vi	IC
Cloud wheel	St	Ph	In
Drought	St	Vi	IC
Forecasting tornadoes	St	Vi	In
How do tornadoes form	St	Vi	IC
How does lightning work	St	Vi	In
Quiz	St	Vi	Co
Report the weather	SP	PV	IC
Researcher hot zone	St	Vi	In
Slow-mo lightning	St	Vi	IC
Snowflake matching game	St	Ph	IC
Storm symphony	St	Vi	In
Study your sweat	SP	PV	IC
Survive the storm	St	Ph	IC
Tabletop tornadoes	St	Ph	IC
Thunderstorm dangers	St	Vi	In
Tornado chasers	St	Vi	In
Tornado damage	SP	PV	IC
Tornado sculpture	Pa	PV	IC
Tornadoes and climate change	St	Vi	In
Tune into the forecast	St	Vi	In

Table 3.4: Exhibits selected from *Wild Weather*

interactives, multimedia exhibits, computer interactives, large graphic panels, specimens and replicas, a video theater, and scientific tools used by rescuers.

Exhibit name	Part	Virt	Collab
Amazing Trunk	Pa	Ph	IC
Beetle	St	PV	IC
Big Globe	St	Ph	IC
Elephant Quiz	St	Vi	Co
Emergency Quiz	St	Vi	Co
Face Recognition	St	Vi	IC
Feed the Chick	SP	Ph	IC
Ferret	St	Ph	IC
Fly w Cranes	St	PV	In
Giant Panda	St	Ph	IC
Grip Strenght	St	Ph	IC
Heartbeat	St	Ph	In
Iberian Lynx	St	Ph	IC
Panamanian Frog	St	Ph	In
Panda Weight Scale	SP	Ph	In
Pets	St	Ph	IC
Puzzle	St	Ph	IC
Robin	St	Ph	IC
Seabird Rescue	St	PV	IC
Sturgeon	St	PV	In
Turtle Rehab	SP	Ph	IC
Turtle Crawl	Pa	Ph	In
X-ray	St	Ph	In

Table 3.5: Exhibits selected from *Wildlife Rescue*

3.6. Science of Guinness World Records

The Science of Guinness World Records engages visitors in real science experiences and record-breaking challenges. Visitors will learn that anyone, anywhere can be a record-breaker while using science to develop their record-breaking skills and abilities. Visitors will gain an understanding of their body and how it reacts, focuses, and endures. There will be opportunities for visitors to challenge themselves and others to officially break a world record with a formal adjudication of a record attempt. The Science of Guinness World Records was developed in partnership with Ripley Entertainment.

Exhibit name	Part	Virt	Collab
Reaction	St	Ph	In
Attempt theatre	SP	PV	IC
Hoop it up	SP	Ph	In
Hang time	St	Ph	IC
Cups attempt arena	SP	Ph	IC
Balance busters	SP	PV	In
Gigapixel	St	Vi	IC
Fast fists	SP	Ph	In
Science of endurance	St	Ph	In
Atom interactive	SP	PV	IC
Puzzle challenge	SP	Ph	IC
Science of focus	SP	Ph	In
Lego attempt arena	SP	Ph	IC
Balance challenge	SP	PV	In

Table 3.6: Exhibits selected from *Science of Guinness World Records*

Appendix 4

Iterative process of refining the model

To ensure the best possible fit for our model, we engaged in a rigorous process of manual testing and refinement, iteratively evaluating various combinations of predictors and adjusting model specifications. This process was particularly challenging due to the small sample size, making any interpretations tentative at best. The model started with the following variables: visitor's age (Age), gender (GND), group type (GT), familiarity with the center (FA), level of education (AC), visitor motivation (VM), looking at signage (LS), taking a picture (TP), visitor-visitor interaction (VV), interaction with a facilitator (IF), use of the Facilitation Comfort Dimension (FC), use of the Facilitation Exhibit Use Dimension (FE), use of the Facilitation Information Dimension (FI), use of the Facilitation Reflection Dimension (FR), the exhibit's level of participation (EP), level of virtuality (EV), and level of collaboration (EC), and dwell time (DT). The highest level of engagement reached by each visitor (HE) is the dependent variable (see Table 3.5).

Initially, we tried including all variables in the model using the `vglm` R package, but encountered errors, primarily due to TP failing the Brant test. To address this, we adjusted the model to include two coefficients for TP, yet this also resulted in errors. Recognizing that IF was strongly correlated with FC, FE, FI, and FR, we excluded these variables and retried the model, but TP continued to pose issues, even with two coefficients.

Subsequently, we removed TP and re-optimized the model using StepAIC with the `polr` R package, excluding TP, FC, FE, FI, and FR. This approach

yielded a model with significant coefficients for GND, IF, VV, and DT, representing our best model to date. Attempts to reincorporate TP or to substitute IF with FC, FE, FI, and FR resulted in further errors, often due to zero probabilities for FE and FR.

Further trials involved removing TP and DT due to their high potential for influencing engagement outcomes. Optimizing without these variables again led to errors. Even combining various subsets of variables, including and excluding TP, IF, and DT, consistently resulted in errors.

In summary, the most effective model we derived included GND, VV, IF, and DT, with only IF and DT being statistically significant. This model had an AIC of 146.1736, though the Hosmer-Lemeshow test indicated a lack of fit, likely due to latent variables and the small sample size. Despite these limitations, the model achieved a satisfactory accuracy rate of 72%, compared to the 33% accuracy of random classification. This meticulous process highlights the complexities and challenges of model optimization, particularly with a small sample size, and underscores the necessity for further research to validate these preliminary findings.

Next, the reader can find a step by step, including code snippets, of the process described before:

We start with all the variables presented in Table 3.5. We use the `polr` command from the `MASS` package to estimate an ordered logistic regression model. The command name comes from proportional odds logistic regression, highlighting the proportional odds assumption in our model.

```
data_little$HE1 <- as.factor(data_little$HE)
library(MASS)
m <- polr(HE1 ~ EP + EV + EC + Age + GND +
GT + FA + AC + VM + LS + TP + VV + IF + FC +
FE + FI + FR + DT, data = data_little, Hess=TRUE)
brant(m)
```

```
-----
Test for X2 df probability
-----
Omnibus  40.33 18 0
EP   0.82  1 0.36
EV   1.24  1 0.27
```

```

EC  0.14 1 0.71
Age  0 1 1
GND  0.07 1 0.78
GT   0 1 0.96
FA   0 1 0.97
AC   1.65 1 0.2
VM   0.8 1 0.37
LS   1.34 1 0.25
TP   8.23 1 0
VV   0.01 1 0.91
IF   0 1 1
FC   0 1 1
FE   0 1 1
FI   0 1 1
FR   0 1 1
DT   0.1 1 0.75

```

```
-----
H0: Parallel Regression Assumption holds
```

If the p-value is greater than 0.05, then the parallel regression holds. Parallel regression assumption holds for all variables except TP. We can use the Partial Proportional Odds Model for this data. This model allows the parallel regression assumption to be violated by either all variables or one of them. With package VGAM and function `vglm` in R, the result is below.

```

m_ppo <- vglm(HE1 ~ EP + EV + EC + Age + GND +
GT + FA + AC + VM + LS + TP + VV + IF + FC +
FE + FI + FR + DT, data = data_little, model=TRUE,
family=cumulative(link="logitlink", reverse=TRUE,
parallel = TRUE ~ -1 + EP + EV + EC + Age + GND + GT +
FA + AC + VM + LS + VV + IF + FC + FE + FI + FR + DT))
summary(m_ppo)

```

This model presents errors. We try optimizing without considering two coefficients for TP:

```
mopt <- stepAIC(m)
```

```
summary(mopt)
Call:
polr(formula = HE1 ~ LS + FE + FR + DT, data = data_little, Hess = TRUE)
Coefficients:
      Value Std. Error   t value
LS  0.98983  5.401e-01  1.833e+00
FE 17.03770  3.165e-09  5.383e+09
FR 16.49918  1.089e-08  1.515e+09
DT  0.01276  3.278e-03  3.891e+00
Intercepts:
      Value      Std. Error   t value
1|2 8.417000e-01 4.267000e-01 1.972500e+00
2|3 2.307100e+00 5.089000e-01 4.533400e+00
Residual Deviance: 131.0784
AIC: 143.0784
```

We use these variables and TP:

```
m <- polr(HE1 ~ LS + FE + FR + DT + TP, data = data_little, Hess=TRUE)
brant(m)
```

```
-----
Test for X2 df probability
-----
```

```
Omnibus  34.01 5 0
LS  0.84 1 0.36
FE  0 1 1
FR  0 1 1
DT  0 1 0.98
TP  25.46 1 0
-----
```

```
H0: Parallel Regression Assumption holds
```

```
m_ppo <- vglm(HE1 ~ LS + FE + FR + DT + TP, data = data_little, model=TRUE, far
summary(m_ppo)
```

This model also presents errors. We start again, removing the facilitation variables:

```
data_little$HE1 <- as.factor(data_little$HE)      # se define una variable y nuev
```

```
library(MASS)
m <- polr(HE1 ~ EP + EV + EC + Age + GND + GT +
FA + AC + VM + LS + TP + VV + IF + DT, data = data_little, Hess=TRUE)
brant(m)
```

```
-----
Test for X2 df probability
-----
```

```
Omnibus   37.6 14 0
EP    0.6 1 0.44
EV    1.09 1 0.3
EC    0.14 1 0.7
Age    0 1 0.99
GND    0.04 1 0.84
GT    0.19 1 0.67
FA    0.3 1 0.58
AC    1.59 1 0.21
VM    1.06 1 0.3
LS    0.93 1 0.33
TP    9.21 1 0
VV    0.03 1 0.87
IF    0 1 0.99
DT    0.03 1 0.87
-----
```

```
H0: Parallel Regression Assumption holds
```

Parallel regression assumption holds for all variables except TP, so we use a Partial Proportional Odds Model.

```
library(VGAM)
m_ppo <- vglm(HE1 ~ EP + EV + EC + Age + GND + GT +
FA + AC + VM + LS + TP + VV + IF + DT, data = data_little, model=TRUE, family=
parallel = TRUE ~ -1 + EP + EV + EC + Age + GND + GT +
FA + AC + VM + LS + VV + IF + DT))
summary(m_ppo)
```

This model presents many errors. We take out TP and run an ordinal regression, optimizing with StepAIC.

```
m <- polr(HE1 ~ EP + EV + EC + Age + GND + GT +
FA + AC + VM + LS + VV + IF + DT, data = data_little, Hess=TRUE)
brant(m)
```

```
-----
Test for X2 df probability
-----
```

```
Omnibus  4.97 13 0.98
```

```
EP  0.44 1 0.51
```

```
EV  1.5 1 0.22
```

```
EC  0.2 1 0.66
```

```
Age  0.02 1 0.9
```

```
GND  0.15 1 0.7
```

```
GT  0.26 1 0.61
```

```
FA  0.2 1 0.65
```

```
AC  1.24 1 0.27
```

```
VM  0.88 1 0.35
```

```
LS  0.67 1 0.41
```

```
VV  0.05 1 0.82
```

```
IF  0 1 0.99
```

```
DT  0.03 1 0.86
```

```
-----
H0: Parallel Regression Assumption holds
```

```
mopt <- stepAIC(m)
```

```
summary(mopt)
```

```
polr(formula = HE1 ~ GND + VV + IF + DT, data = data_little,
      Hess = TRUE)
```

```
Coefficients:
```

	Value	Std. Error	t value
GND	0.88238	0.528115	1.671
VV	1.03284	0.643569	1.605
IF	2.78737	1.119318	2.490
DT	0.01225	0.003362	3.645

```
Intercepts:
```

	Value	Std. Error	t value
1 2	1.6640	0.7007	2.3749
2 3	3.1416	0.7777	4.0397

```

Residual Deviance: 134.1736
AIC: 146.1736
(ctable <- coef(summary(mopt)))
p <- pnorm(abs(ctable[, "t value"]), lower.tail = FALSE) * 2
(ctable <- cbind(ctable, "p value" = p))

      Value Std. Error t value      p value
GND 0.88238410 0.528115306 1.670817 9.475780e-02
VV  1.03283756 0.643569265 1.604858 1.085250e-01
IF   2.78737099 1.119317904 2.490241 1.276566e-02
DT   0.01225452 0.003361806 3.645219 2.671643e-04
1|2 1.66397170 0.700650554 2.374895 1.755393e-02
2|3 3.14155062 0.777670127 4.039696 5.352061e-05

# Get confidence intervals for the parameter estimates.
#If the 95% CI does not include 0, the parameter estimate is statistically sig

(ci <- confint(mopt))

# default method gives profiled CIs
      2.5 %      97.5 %
GND -0.129574082 1.95607825
VV  -0.195736465 2.35461244
IF   0.935915323 5.76963948
DT   0.006283193 0.01954273
confint.default(mopt) # CIs assuming normality
      2.5 %      97.5 %
GND -0.152702879 1.91747108
VV  -0.228535020 2.29421014
IF   0.593548215 4.98119377
DT   0.005665501 0.01884354

# Calculate Odds ratio and Confidence Intervals
exp(cbind(OR = coef(mopt), ci))
      OR      2.5 %      97.5 %
GND  2.416654 0.8784695   7.071540
VV   2.809025 0.8222289  10.534045

```

```
IF  16.238273  2.5495460  320.422194
DT   1.012330  1.0063030   1.019735
```

This is the best model yet.

If we add TP with two coefficients, it throws errors.

We can repeat the procedure using the facilitation variables (FC, FE, FI y FR) instead of IF:

```
m <- polr(HE1 ~ EP + EV + EC + Age + GND + GT + FA + AC +
VM + LS + VV + FC + FE + FI + FR + DT, data = data_little, Hess=TRUE)
brant(m)
```

```
-----
Test for X2 df probability
-----
```

```
Omnibus  4.92 16 1
EP  0.67 1 0.41
EV  1.63 1 0.2
EC  0.19 1 0.66
Age  0.02 1 0.89
GND  0.2 1 0.66
GT  0.01 1 0.91
FA  0 1 0.96
AC  1.31 1 0.25
VM  0.63 1 0.43
LS  1.03 1 0.31
VV  0.03 1 0.86
FC  0 1 1
FE  0 1 1
FI  0 1 1
FR  0 1 1
DT  0.11 1 0.74
```

```
-----
H0: Parallel Regression Assumption holds
```

```
mopt <- stepAIC(m)
summary(mopt)
```

Call:

```
polr(formula = HE1 ~ LS + FE + FR + DT, data = data_little, Hess = TRUE)
```

Coefficients:

	Value	Std. Error	t value
LS	0.98983	5.401e-01	1.833e+00
FE	17.03770	3.165e-09	5.383e+09
FR	16.49918	1.089e-08	1.515e+09
DT	0.01276	3.278e-03	3.891e+00

Intercepts:

	Value	Std. Error	t value
1 2	8.417000e-01	4.267000e-01	1.972500e+00
2 3	2.307100e+00	5.089000e-01	4.533400e+00

Residual Deviance: 131.0784

AIC: 143.0784

```
(ctable <- coef(summary(mopt)))  
p <- pnorm(abs(ctable[, "t value"]), lower.tail = FALSE) * 2  
(ctable <- cbind(ctable, "p value" = p))
```

	Value	Std. Error	t value	p value
LS	0.98982797	5.401280e-01	1.832580e+00	6.686499e-02
FE	17.03770328	3.165024e-09	5.383121e+09	0.000000e+00
FR	16.49918251	1.089304e-08	1.514654e+09	0.000000e+00
DT	0.01275752	3.278475e-03	3.891296e+00	9.971026e-05
1 2	0.84166031	4.266972e-01	1.972500e+00	4.855252e-02
2 3	2.30706613	5.089015e-01	4.533424e+00	5.803523e-06


```
(ci <- confint(mopt)) # default method gives profiled CIs
```

This model fails because the p values for FE and FR are 0 (because all FR=1 and FE=1 have HE=3)

```
> table(data_little$FE,data_little$HE)
```

```

      1  2  3
0 24 19 32
1  0  0 21
```

```
> table(data_little$FR,data_little$HE)
```

```

      1  2  3
0 24 19 37
1  0  0 16
```

```
ci <- confint.default(mopt) # CIs assuming normality
```

```

          2.5 %          97.5 %
LS -0.068803414  2.04845935
FE 17.037703275 17.03770329
FR 16.499182486 16.49918253
DT  0.006331824  0.01918321
```

```
## OR and CI
```

```
exp(cbind(OR = coef(mopt), ci))
```

```

          OR          2.5 %          97.5 %
LS 2.690772e+00 9.335102e-01 7.755943e+00
FE 2.508306e+07 2.508306e+07 2.508306e+07
FR 1.463875e+07 1.463875e+07 1.463875e+07
DT 1.012839e+00 1.006352e+00 1.019368e+00
```

If we take this model and add TP with two coefficients, we get an error.

We tried using all variables except TP and the facilitation dimensions (FC, FE, FI, FR), also taking out DT, because a long dwell time can be a consequence of engagement.

```
m <- polr(HE1 ~ EP + EV + EC + Age + GND + GT +
FA + AC + VM + LS + VV + IF, data = data_little, Hess=TRUE)
brant(m)
```

```
-----  
Test for X2 df probability  
-----
```

```
Omnibus  3.67 12 0.99
```

```
EP  0.26 1 0.61
```

```
EV  0.55 1 0.46
```

```
EC  0.45 1 0.5
```

```
Age  0.01 1 0.91
```

```
GND  0.13 1 0.72
```

```
GT  0.53 1 0.47
```

```
FA  0.53 1 0.47
```

```
AC  0.37 1 0.54
```

```
VM  0.56 1 0.45
```

```
LS  0.39 1 0.53
```

```
VV  0.28 1 0.59
```

```
IF  0 1 0.99  
-----
```

```
H0: Parallel Regression Assumption holds
```

```
mopt <- stepAIC(m)
```

```
summary(mopt)
```

```
Call:
```

```
polr(formula = HE1 ~ LS + VV + IF, data = data_little, Hess = TRUE)
```

```
Coefficients:
```

	Value	Std. Error	t value
LS	0.9001	0.5012	1.796
VV	1.2077	0.5634	2.144
IF	3.3668	1.0596	3.178

```
Intercepts:
```

	Value	Std. Error	t value
1 2	0.4492	0.5115	0.8782
2 3	1.6167	0.5419	2.9832

```
Residual Deviance: 155.2179
```

```
AIC: 165.2179
```

```
(ctable <- coef(summary(mopt)))
```

```
p <- pnorm(abs(ctable[, "t value"]), lower.tail = FALSE) * 2
(ctable <- cbind(ctable, "p value" = p))
```

	Value	Std. Error	t value	p value
LS	0.9000836	0.5011680	1.7959717	0.072499019
VV	1.2076821	0.5633742	2.1436587	0.032060247
IF	3.3668057	1.0595555	3.1775642	0.001485178
1 2	0.4492240	0.5115342	0.8781895	0.379840899
2 3	1.6167026	0.5419368	2.9831938	0.002852573

```
(ci <- confint(mopt)) # default method gives profiled CIs
```

```
      2.5 %    97.5 %
```

```
LS -0.06368401 1.916322
```

```
VV  0.12362345 2.355772
```

```
IF  1.69808738 6.289467
```

```
(ci <- confint.default(mopt)) # CIs assuming normality
```

```
      2.5 %    97.5 %
```

```
LS -0.06368401 1.916322
```

```
VV  0.12362345 2.355772
```

```
IF  1.69808738 6.289467
```

```
## OR and CI
```

```
exp(cbind(OR = coef(mopt), ci))
```

```
      OR      2.5 %    97.5 %
```

```
LS  2.459809 0.9383014    6.795918
```

```
VV  3.345720 1.1315897   10.546269
```

```
IF 28.985789 5.4634878  538.86597
```

This is the second best model Taking this model and adding TP with two coefficients leads to error.

Starting with all the variables except TP, IF and DT:

```
m <- polr(HE1 ~ EP + EV + EC + Age + GND + GT +
FA + AC + VM + LS + VV + FC + FE + FI + FR,
data = data_little, Hess=TRUE)
brant(m)
```

Test for X2 df probability

Omnibus 2.78 15 1

EP 0.27 1 0.6

EV 0.37 1 0.54

EC 0.42 1 0.52

Age 0 1 1

GND 0.21 1 0.64

GT 0.29 1 0.59

FA 0.24 1 0.62

AC 0.18 1 0.67

VM 0.27 1 0.6

LS 0.42 1 0.52

VV 0.31 1 0.57

FC 0 1 1

FE 0 1 1

FI 0 1 1

FR 0 1 1

H0: Parallel Regression Assumption holds

mopt <- stepAIC(m)

summary(mopt)

Call:

polr(formula = HE1 ~ LS + VV + FE, data = data_little, Hess = TRUE)

Coefficients:

	Value	Std. Error	t value
LS	0.8512	5.052e-01	1.685e+00
VV	1.3363	5.787e-01	2.309e+00
FE	17.6042	3.513e-08	5.011e+08

Intercepts:

	Value	Std. Error	t value
1 2	4.965000e-01	5.238000e-01	9.479000e-01
2 3	1.665100e+00	5.555000e-01	2.997600e+00

Residual Deviance: 151.7228

AIC: 161.7228

```
(ctable <- coef(summary(mopt)))
p <- pnorm(abs(ctable[, "t value"]), lower.tail = FALSE) * 2
(ctable <- cbind(ctable, "p value" = p))
```

	Value	Std. Error	t value	p value
LS	0.8511594	5.051800e-01	1.684864e+00	0.092014852
VV	1.3363498	5.787361e-01	2.309083e+00	0.020938973
FE	17.6042193	3.513462e-08	5.010505e+08	0.000000000
1 2	0.4965176	5.238241e-01	9.478708e-01	0.343195223
2 3	1.6651076	5.554884e-01	2.997556e+00	0.002721539

```
(ci <- confint(mopt)) # default method gives profiled CIs
```

This model throws errors because some p-values are zero

```
(ci <- confint.default(mopt)) # CIs assuming normality
```

	2.5 %	97.5 %
LS	-0.1389751	1.841294
VV	0.2020478	2.470652
FE	17.6042192	17.604219

```
## OR and CI
```

```
exp(cbind(OR = coef(mopt), ci))
```

	OR	2.5 %	97.5 %
LS	2.342361e+00	8.702497e-01	6.304691e+00
VV	3.805129e+00	1.223907e+00	1.183016e+01
FE	4.419929e+07	4.419929e+07	4.419929e+07

ANNEXES