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From Intention to Automaticity: Examining the Relationship Between Meditation Session Duration and Habit Strength in an Online Meditation Community.

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ABSTRACT

This dissertation investigates the relationship between typical meditation session duration and habit strength among adult members of the New Leaf Meditation Project, a U.S.-based online mindfulness community. Although Mindfulness-Based Stress Reduction (MBSR) protocols prescribe sessions of twenty to forty minutes as standard practice, the behavioral mechanisms through which meditation becomes a stable, automatic habit remain underexplored. Grounded in post-positivist philosophy and contemporary habit formation theory, this cross-sectional survey study examined whether session duration predicts habit strength as measured by the 12-item Self-Report Habit Index (SRHI; Verplanken & Orbell, 2003) among 89 adult meditators. While session duration was positively associated with SRHI scores, this relationship was modest and attenuated substantially when weekly practice frequency was introduced as a predictor. Practitioners with the highest habit strength differed from the broader sample in weekly frequency, not session length. These findings challenge duration-centric assumptions in traditional mindfulness instruction and support a repetition-first model of contemplative habit formation, suggesting that practice consistency rather than session length is the primary driver of automaticity. Implications for clinicians, meditation instructors, and wellness professionals are discussed.

Keywords: mindfulness meditation, habit formation, automaticity, Self-Report Habit Index, session duration, practice frequency

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DEDICATION

This work is dedicated to the loving memory of my cousin Lily Rolander and my friend Svetlana Fuggetta. We carry your light with us and miss you terribly.

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CHAPTER I

INTRODUCTION

"How long should I meditate for?" Among wellness professionals and meditation instructors, this question is one of the most common concerns raised by novice meditators. While the Mindfulness-Based Stress Reduction (MBSR) program has long recommended twenty minutes of formal practice twice daily as the "ideal state" (Kabat-Zinn, 1990), there remains a noticeable gap between such aspirational goals and the everyday realities of habit adoption. In particular, very little empirical guidance exists to help bridge the motivational and behavioral gap between a novice's intention and a sustainable practice. As Bishop et al. (2002) argued over two decades ago, the Western clinical adaptation of mindfulness needs stronger empirical grounding in behavior change theory.

This dissertation sought to address that gap. Its core aim was to develop a psychologically-informed framework to guide helping professionals and their clients through the early stages of meditation habit formation. Specifically, it examined whether higher habit strength, as measured by the Self-Report Habit Index (SRHI), predicts longer meditation durations among practitioners. In doing so, the study hoped to support not just the teaching of mindfulness techniques, but also the cultivation of the conditions under which such techniques can take root as lasting habits.

The present chapter offers an overview of the research context and rationale. It begins by establishing the theoretical and empirical background, outlines the central problem under investigation, clarifies the study's aims and questions, and concludes by highlighting its potential contributions and anticipated limitations.

Background

Over the past two decades, mindfulness meditation has evolved from a niche contemplative practice into a subject of intense scholarly inquiry. Beginning in the early 2000s, the number of peer-reviewed studies on mindfulness increased exponentially, propelled by clinical research into its mental and physical health benefits. Early meta-analyses (e.g., Grossman et al., 2004) helped establish mindfulness as a credible intervention for stress reduction, and more recent studies have extended its potential applications to diverse fields such as opioid recovery (Killeen et al., 2024), exercise adherence (Meyer et al., 2018), and chronic pain management (Zgierska et al., 2016).

Despite this growing scientific endorsement, a critical limitation remains: mindfulness meditation is only effective when it is practiced consistently. A compelling longitudinal study by Cearns et al. (2023) analyzed over 280,000 logged meditation sessions through a digital app and found that sustained mood improvement, resilience, and emotional regulation were significantly associated with both frequency and duration of practice. The findings reinforce a central behavioral principle: meditation works best not as a one-off intervention, but as a daily, integrated habit.

Yet forming and maintaining such a habit is notoriously difficult. Habit formation, especially in behaviors requiring effortful attention, is riddled with obstacles. These include a decline in willpower over time, the unpredictability of daily routines, and the often delayed or intangible rewards of the behavior. As Birtwell et al. (2022) found in their mixed-methods study of mindfulness program participants, even those motivated to practice frequently encounter obstacles like time scarcity, negative emotional states, and a lack of environmental cues. The consequence is clear: the benefits of mindfulness are often undermined by the inability to practice it regularly.

This is not a problem unique to meditation. A broader look at behavior change confirms that most health-promoting intentions, such as exercising, saving money, or eating healthier, fail to translate into long-term action. Frey and Rogers (2014) illustrated this vividly with data on New Year's resolutions, the majority of which are abandoned within weeks. Mindfulness practitioners are not exempt from this pattern. Barcelo-Soler et al. (2023), in a systematic review of meditation adherence, found that fewer than 40% of participants reported practicing at the frequency prescribed by mindfulness-based interventions.

The challenge, then, is not only motivational but structural. As Duckworth, Milkman, and Laibson (2019) argue, behavioral failures are not primarily due to weak willpower but rather to the lack of supportive systems. Their taxonomy of behavior change strategies which range from "temptation bundling" to implementation intentions, provides promising tools for helping new meditators scaffold their practice into their routines. Importantly, these interventions are grounded in behavioral economics and psychological science, rather than relying on exhortations to simply "try harder."

From a neuroscientific perspective, habit formation is increasingly understood through the lens of automaticity and brain plasticity. The basal ganglia, particularly the striatum, have been implicated in the shift from goal-directed action to habitual behavior (Wood & Rünger, 2016). Repeated engagement in a behavior within a stable context creates a loop of cue–routine–reward that eventually requires less cognitive effort to maintain. Mindfulness meditation, although cognitively demanding at first, may similarly be routinized through this system. In fact, Kiken et al. (2021) found that frequent but brief mindfulness practices were more predictive of long-term emotional resilience than longer, inconsistent sessions. This challenges the common perception that longer meditations are necessarily more beneficial for beginners, and suggests that duration goals should be secondary to frequency in the early stages of habit acquisition.

The quality of one’s motivation significantly impacts the likelihood of habit development. Chatzisarantis and Hagger (2020) present a compelling integration of self-determination theory and habit formation research, positing that autonomous motivation, meaning behavior driven by intrinsic values or enjoyment, facilitates the internalization of the behavior and enhances the probability of long-term adherence. In the context of mindfulness, this means that practitioners who experience meditation as meaningful or emotionally rewarding are more likely to convert it into a stable habit than those motivated by guilt or obligation.

This view is echoed by Kok and Singer (2020), who examined how contemplative mental training impacts long-term motivation and well-being. Their longitudinal data suggest that affective engagement such as the emotional resonance experienced during loving-kindness meditation enhances psychological flexibility and supports sustained practice. These findings imply that successful habit formation in mindfulness may depend less on rigid adherence to protocols and more on cultivating meaningful, affect-laden experiences that “hook” the practitioner into returning.

These converging lines of research suggest that the traditional model of recommending a fixed meditation dosage (e.g., 20 minutes twice daily) may be less effective than a more adaptive approach rooted in the psychology of habit formation. While the MBSR model has been enormously influential, its emphasis on intensive daily practice may inadvertently set up new meditators for failure if not paired with strategies to reduce friction and support adherence. Indeed, as Birtwell et al. (2022) emphasize, even motivated individuals benefit from environmental supports, planning strategies, and social reinforcement.

The goal of this dissertation was to investigate how individuals transitioning from being beginners to intermediate experience can ensure maintaining a habit while increasing length. Specifically, it sought to test whether higher scores on the Self-Report Habit Index (SRHI), an established tool for measuring behavioral automaticity, are associated with longer meditation durations among practitioners who are leaving the novice stage. This focus offered a novel empirical contribution to the literature by applying habit science to the implementation challenges faced in contemplative practice.

In doing so, the study also has practical implications for clinicians, wellness professionals, and educators who teach mindfulness. If certain psychological or contextual variables can be identified that support the transition from episodic to habitual practice, these insights can inform how meditation is taught, prescribed, and supported. Ultimately, the success of mindfulness-based interventions depends not only on what is taught, but on how regularly it is practiced. Helping new meditators install daily habits may thus be one of the most crucial steps in unlocking the full healing and growth potential of mindfulness.

The Research Problem

Mindfulness-Based Stress Reduction (MBSR) stands as the most widely studied meditation form, validated by over two decades of rigorous inquiry as the gold standard for deriving meditation-related health benefits. Typically, the MBSR protocol instructs practitioners to engage in 20 minutes of meditation twice daily or 30 minutes once daily (Ludwig, 2008;

Grecco, 2008). However, behavioral psychologists observe that this duration may impose considerable initiation friction for novice meditators (Havranek, 2017).

Friction, defined as resistance or barriers to effortful action, significantly undermines adherence to initial behavior routines. Wood (2024) has consistently shown that even minor frictions, such as extra travel distance or time costs, can dramatically reduce habit execution. This insight raises questions about whether typical MBSR durations are misaligned with the early stages of habit formation.

The significance of friction is magnified by established habit formation timelines. Wood and colleagues report a median of 66 days (range: 18 to 254 days) required to form a new habit, including meditation. A 2024 health-behavior meta-analysis reaffirmed this median timeframe (approximately 59 to 66 days), indicating robust consistency across behavioral domains (Singh, 2024).

This understanding intersects with behavioral persuasion frameworks. Fogg’s Tiny Habits model emphasizes starting with minimal, context-anchored practices that leverage existing routines to reduce initiation friction and enhance frequency (Akash & Chowdhury, 2025). For example, integrating a one-minute breath exercise after brushing one’s teeth capitalizes on existing cues, reducing motivational declines (Fogg, 2021). Even meditation apps with timed reminders over eight weeks, framed around incremental practices, saw limited long-term adherence, suggesting that frequency and cue alignment, rather than duration, may be the critical levers (Kermavnar, 2023).

Neuroscience corroborates this friction-frequency dynamic. Wyatt (2024) demonstrates that stability in repetition and environment fosters dopaminergic reinforcement of habit circuitry, embedding practices in neural pathways. Reinforcing this, Stojanovic et al. (2022) found that stable contexts (consistent time and place) significantly increase automaticity and goal attainment, with automaticity mediating the effect of contextual stability on behavior performance.

Yet, while there is extensive literature on habit science, explicit guidance integrating these insights into meditation practice remains limited. Li et al. (2024) highlight that experienced meditators rely on brief, personalized routines, social structures, and controlled use of technology to sustain practice. This indicates that flexible, context-aligned, low-friction strategies may be most effective.

Consequently, meditators face unanswered questions: Should they strive for extended daily sessions as per MBSR, or could shorter, more frequent practices anchored in stable contexts be more viable for habit formation? This research sought to address this tension by interrogating the relationship between session length, habit strength, and associated variables.

Research Aims, Objectives & Questions

This study aimed to examine the relationship between meditation duration and habit strength among adult members of the New Leaf Meditation Project, an online mindfulness community. Specifically, the primary objective was to determine whether the typical length of daily meditation practice predicts the strength of meditation as a behavioral habit, as operationalized by the Self-Report Habit Index (SRHI; Verplanken & Orbell, 2003). The SRHI is a validated 12-item measure that captures key dimensions of habit automaticity, identity integration, and behavioral frequency.

This investigation was grounded in contemporary habit theory (Fogg, 2019; Wood & Neal, 2007), which suggests that both repetition and contextual stability contribute to habit formation. Within this framework, the duration and frequency of a behavior, such as meditation, are expected to influence the degree to which it becomes automatic and embedded in daily routines. By analyzing self-reported data on typical meditation duration, frequency, and total experience meditating (in years), the study sought to generate practical insights into the behavioral determinants of sustainable mindfulness practice. The central research question guiding this study was as follows.

Primary Research Question: To what extent does the typical duration of daily meditation practice predict overall habit strength, as measured by the SRHI?

To deepen the investigation and explore potential interaction effects and additional predictors, the following sub-questions were also posed:

Q1a: What is the relationship between daily session duration and SRHI for first year meditators?

RQ1b: Does meditation frequency predict SRHI after accounting for daily session duration?

RQ1c: How do the highest-habit-strength meditators differ from the rest of the sample in their duration and frequency?

Together, these questions provided a structured and theory-informed approach to understanding how meditation behaviors translate into habit strength. The findings were intended to inform meditation instructors and wellness professionals about optimal practice parameters that support the development of enduring meditation habits in novice and intermediate practitioners.

Theoretical and Empirical Framework

MBSR's duration prescription is anchored in clinical outcome efficacy and assumes novice practitioners can accommodate the time investment. However, contemporary habit-research challenges this by indicating that early habit stages may benefit from shorter, frequent, contextual routines that reduce initiation friction (Wood, 2024; Akash & Chowdhury, 2025).

Evidence that simple meditative routines reach automaticity within three weeks (Lewis et al., 2021) suggests that session duration may be less pivotal than repetition and context stability. Wyatt's neural model supports this, demonstrating that repetition in consistent environments yields significant neuroplastic changes that underpin habit formation. Stojanovic et al. (2022) empirically demonstrate that stable contexts enhance both automaticity and behavioral consistency, and that automaticity mediates goal attainment.

Further, Li et al. (2024) show that experienced meditators utilize brief practices, personalized cues, and moderated technological aids to maintain their meditation routines long-term. The convergence of these lines of evidence suggests that novices could benefit from a paradigm shift away from MBSR's duration metrics toward a frequency-and-context-centric approach that is neurobehaviorally supportive and pragmatically manageable.

This study aimed to fill a critical gap: applying rigorous habit-formation science directly to meditation duration prescriptions. Identifying duration thresholds that balance habit strength gains with feasible effort constraints could lead to empirically grounded guidelines, improving adherence while preserving therapeutic outcomes.

By bridging clinical mindfulness practice with habit-formation research from psychology and neuroscience, this research aspired to deliver actionable guidance for meditation training. Rather than prescribing substantial initial durations, habit-first strategies might encourage sustainable engagement through accessible entry points. This work advanced theoretical understanding and offers practical recommendations, enriching intervention design across mindfulness-based modalities.

Significance of the Study

As anecdotal evidence of the medicinal qualities of meditation turned into an inescapable mountain of peer reviewed research, the helping professions have been turning more and more frequently to mindfulness and meditation as central tools for helping individuals improve their mental health. Any counseling student or clinician in the field will tell you about how often meditation is used as an intervention. In fact, mindfulness and meditation are the foundational interventions of what is arguably the most important therapeutic technique of our time; Dialectical Behavior Therapy. (Linehan, 1993) There is an appetite for direction from clinicians for more guidance in how to offer the best protocols for their patients and clients.

By dissecting the relationship of meditation duration and habit strength, this study sought to contribute actionable insights to the fields of psychology, mindfulness, and therapeutic practice, ultimately enhancing the efficacy and accessibility of meditation as a transformative habit.

CHAPTER II

LITERATURE REVIEW

This chapter provides a comprehensive review of the interdisciplinary scholarship informing the present study's exploration of mindfulness meditation and habit formation. As the empirical literature on mindfulness continues to expand, so too has interest in understanding how individuals initiate, maintain, and deepen their meditation practices over time. While substantial research has documented the psychological and physiological benefits of mindfulness which range from reduced stress and improved emotional regulation to enhanced immune functioning, far less is known about the behavioral mechanisms that enable sustained practice, particularly as novices transition from brief sessions to longer, more integrated habits. This chapter situates the current research within that emerging gap, examining how behavioral science, neuroscience, motivation theory, and habit psychology converge to explain the conditions under which mindfulness becomes an enduring part of daily life.

The chapter unfolds in a thematic progression. It begins by tracing the rise of mindfulness in clinical and behavioral research, establishing its efficacy and the importance of consistent practice. The next sections explore foundational and contemporary theories of habit formation, emphasizing the roles of automaticity, cue-dependence, and identity integration. These psychological insights are further enriched by neuroscientific findings on the brain structures and processes involved in habit consolidation. Additional sections examine how motivation and behavioral economics inform adherence strategies, including the role of nudges, incentives, and environmental design. Finally, the chapter introduces the Self-Report Habit Index (SRHI), a validated instrument central to the present study's methodology, offering a multidimensional framework for measuring habit strength. Taken together, this literature review lays the conceptual and empirical foundation for investigating how and why meditation habits deepen over time, providing the theoretical scaffolding for the research questions that follow.

Introduction

Since the 1980s, academic interest in mindfulness meditation has expanded considerably, with a marked acceleration in the early 2000s. For example, a PubMed search in January 2004 for the term “meditation” yielded 972 results (Haynes, 2004), while a more recent search of Marywood University’s library returns over 69,000 peer-reviewed articles that include the term. The growing body of literature highlights a range of documented benefits, including reduced occupational stress (Slemp, 2019), decreased opioid use and improved pain management (Zgierska, 2016), and the ability to sustain exercise regimens through seasonal changes (Meyer, 2018).

However, these benefits are contingent upon consistent practice. The advantages of mindfulness meditation do not accrue passively; they require regular engagement. As a result, meditation instructors and wellness professionals must do more than transmit techniques. They must also provide reliable frameworks for cultivating and maintaining daily meditation habits. The difficulty of forming new habits is well established. In a foundational longitudinal study, Norcross and Vangarelli (1988) found that 23 percent of participants who made New Year’s resolutions had abandoned them within the first week, and 81 percent had failed within two months. Subsequent research across diverse populations and goals has confirmed this pattern. Individuals often blame themselves for their inability to follow through, rather than recognizing the structural and psychological challenges inherent in behavior change (Rogers, 2014).

Supporting this perspective, contemporary research in neuroscience, psychology, and behavioral economics has provided insights into how automatic behaviors are formed and maintained. Wyatt (2024) emphasizes that habit formation depends on a complex interplay between neuroplasticity, cultural context, and lifestyle. He argues that effective strategies for habit formation must be tailored to the individual's environment and psychological makeup. While much is known about how habits begin, far less is understood about how they deepen or expand over time. Meditation offers a particularly promising domain for investigating these mechanisms.

For new meditators, it is widely recommended to begin with small, manageable commitments. Fogg (2019) and Lally and Gardner (2022) endorse a "start small and anchor to existing routines" approach. Typically, this means meditating for three to five minutes per day and linking the practice to already established behaviors, such as brushing one's teeth or making morning coffee. Yet this raises an important question: what facilitates the shift from these foundational practices to longer, more substantive sessions? In the case of mindfulness meditation, that might mean progressing from five to 40 minutes per day. Here, the literature becomes sparse. The concept of "friction" is the psychological and environmental resistance that interferes with increased engagement and has not been adequately addressed in relation to the deepening of meditation habits.

Emerging research on digital meditation adherence offers valuable insight. Cearns and Clark (2023), analyzing over 280,000 sessions, found that consistent practice, establishing a morning routine, and balancing attention between internal and external focal points were better predictors of long-term adherence than session length alone. Their work suggests that how meditation is structured within a daily routine is more influential than how long each session lasts. Similarly, Flanders-Machinek and Cooper (2023) introduce the Sussex Mindfulness Meditation (SuMMed) model, which reframes meditation as healthy behavior. The model outlines the phases of habit development from initial engagement to long-term maintenance and identifies supports, such as environmental cues and contextual planning, as critical mechanisms for successful progression.

The question of optimal meditation duration also deserves reexamination. Smith and Lee (2023) conducted a randomized controlled trial comparing ten-minute and twenty-minute sessions. They found only modest differences in immediate outcomes: both durations significantly increased state mindfulness, and only individuals with high levels of trait mindfulness reported greater anxiety relief from the longer sessions. These findings challenge the assumption that longer meditation is always better and suggest that the optimal duration may vary based on an individual’s baseline characteristics and current phase of habit development.

Wyatt (2024) underscores that repetition alone does not guarantee habit formation. Neural circuits that support automatic behaviors are most effectively reinforced in environments that offer both predictability and relevance. For mindfulness meditation, this may mean aligning practice with daily routines in a way that respects the meditator’s cognitive and emotional bandwidth. In this context, Fowers et al. (2025) contribute important findings from their analysis of app-based meditation patterns. Their study shows that both temporal consistency such as practicing at the same time every day and contextual responsiveness, such as meditating in response to stress cues, can contribute to long-term engagement. Their work supports a more flexible and personalized understanding of what sustains and strengthens meditation habits over time.

Taken together, these studies highlight a notable imbalance in the literature. There is substantial guidance for initiating mindfulness habits, especially for total beginners. Yet there is little empirical insight into the mechanisms that support the expansion of meditation duration once a baseline routine has been established. Instructors may confidently recommend short, daily practices anchored to existing behaviors. But what should they suggest after the initial habit has taken root? How can practitioners navigate the tension between psychological friction and the aspirational goal of meditating for 30 to 40 minutes per day?

This literature review serves to examine the mechanisms that support both the maintenance and expansion of mindfulness meditation habits among novice practitioners. It focused on several key lines of inquiry: how practice consistency and the embedding of cues into daily routines contribute to long-term adherence (Cearns & Clark, 2023; Flanders-Machinek & Cooper, 2023); the moderating role of trait mindfulness in determining how individuals respond to different meditation durations (Smith & Lee, 2023); whether temporal regularity or context-sensitive timing more effectively promotes the deepening of practice (Fowers et al., 2025); and the neurobiological processes that underlie gradual increases in meditation duration (Wyatt, 2024). By integrating these diverse perspectives, this dissertation aimed to advance the growing body of research on habit formation and behavioral maintenance. In doing so, it offers practical guidance for helping new meditators move beyond initial routines toward longer, more sustainable mindfulness practices.

Mindfulness Meditation and Habit Formation

Mindfulness meditation, commonly defined as the intentional directing of attention to present-moment experiences (such as the breath) with a nonjudgmental attitude, has emerged as a central practice in contemporary health and behavioral research. Although its origins lie in Buddhist contemplative traditions, early skepticism in Western scientific and medical communities, rooted in its religious associations, was assuaged by figures like Jon Kabat-Zinn. Kabat-Zinn's development of Mindfulness-Based Stress Reduction (MBSR) framed mindfulness as a secular, empirically testable intervention, paving the way for rigorous clinical and laboratory investigations (Ludwig, 2008).

Since this demarcation, the evidentiary basis for mindfulness has blossomed. As Haynes (2004) noted, disciplines such as medicine, psychology, and sociology have increasingly embraced meditation as both standalone and adjunctive therapy. Initial meta-analyses by Grossman et al. (2003) documented consistent reductions in anxiety, blood pressure, and chronic pain, while Lane (2007; 2017) extended these findings to surgery recovery and stress mitigation. The accumulation of such data catalyzed the notion that mindfulness exhibits enduring effects but only with ongoing practice.

Neuroscience, Neuroplasticity, and Habit

Evolving neuroscientific research has illuminated the biological underpinnings of meditation and habit formation. Wyatt (2024) synthesizes how basal ganglia and dopaminergic pathways respond to repeated behaviors, forming the neural architecture of habits. Crucially, lifestyle practices including mindfulness meditation remodel these circuits by enhancing neuroplasticity. Wyatt contends that meditation is not passive; rather, by shifting neural dynamics, it cultivates an organic environment that supports sustainable habit formation.

Moreover, multiple neuroimaging studies have reported structural and functional changes in brain regions implicated in emotion regulation (such as the anterior cingulate cortex and insula), memory consolidation and contextual processing (hippocampus), and stress reactivity (amygdala) following sustained mindfulness practice (e.g., Neurobiological Changes Review, 2023; Wyatt, 2024). These alterations are typically associated with increased cortical thickness or gray matter density, as well as changes in resting-state connectivity. Such findings suggest that mindfulness practice not only influences moment-to-moment psychological states but may also facilitate longer-term neuroplastic adaptations that support emotional regulation and behavioral persistence which are core components of habit formation.

SuMMed Model: Conceptualizing Mindfulness as Health Behavior

To translate research into practice, Miles et al. (2023) explicitly characterize mindfulness meditation as a “health behavior,” proposing the Sussex Mindfulness Meditation (SuMMed) model. This model delineates four stages: Pre-Intention, Intention, Action, and Maintenance. Drawing from health psychology and behavioral economics, it highlights that most individuals fail to progress beyond early stages without structured support such as habit anchoring, reminders, and follow-up reinforcement.

In an empirical validation, Bowen and Beam (2025) applied SuMMed to a representative US sample ($N = 2{,}000$), revealing that 70% were in Pre-Intention, 19% in Preparation, 2% in Action, and only 9% in Maintenance. Their analysis underscored the importance of recognizing initial experimentation through informal or app-based engagements, as distinct from structured practice. They recommended refining the SuMMed framework to incorporate this “trial phase,” which often precedes full commitment.

These insights highlight a critical tension in mindfulness practice: the wealth of evidence supporting mindfulness benefits in areas such as sleep, blood pressure, cardiovascular markers, decreasing cortisol, sleep, and immune function stands in contrast to the difficulty most individuals face maintaining consistent practice over time (Grossman et al., 2003). Thus, habit formation must be understood as a pivotal mechanism bridging efficacy with real-world adherence.

Anchoring and Incentives: Practical Habit Supports

Behavioral economics provides tools that can reinforce nascent mindfulness habits. Stecher et al. (2023) propose an RCT testing anchoring (linking meditation to existing routines), financial incentives, and self-monitoring to promote app-based adherence (≥10 minutes a day). Anchoring leverages temporal and contextual cues to embed new behaviors within pre-existing patterns, a strategy well-suited for periodized mindfulness habits (e.g., meditating immediately after morning coffee).

Importantly, incentives are timed to sustain early engagement, while self-monitoring cultivates deeper intrinsic motivation through reflection and progress awareness. Although results are pending, this design aligns with broader habit research, which suggests that incentives are most effective when paired with routine cues to foster internalized practice (Lally et al., 2010; Wyatt, 2024).

Temporal Consistency and Flexibility

Temporal consistency is a widely cited strategy for habit formation: repeatedly performing a behavior at the same time each day strengthens cue–behavior associations. A recent large-scale analysis of Calm app users ($N = 4{,}200$) categorized meditators as “Consistent” (fixed daily time), “Inconsistent,” or “Indeterminate.” While consistent users maintained practice slightly longer, over 55% of long-term users were inconsistent. They often meditated in response to internal cues such as stress or emotion rather than fixed schedules. Thus, multiple habit formation pathways exist: temporal anchoring remains effective for some individuals, while flexible or context-driven practice cam also sustain engagement over time.

Integration with Habit Theory

Fundamental habit formation models, such as Neal et al. (2006), show nearly half of daily behavior is habitual and highly context-dependent. Wyatt (2024) and Akash & Chowdhury (2025) emphasize the importance of micro-behaviors and incremental change to enable sustainable adoption. In mindfulness contexts, tiny adjustments (e.g., one-minute mindful pauses) can scaffold into full practices, consistent with the SuMMed model's progression from intention to action to maintenance.

Moreover, traditional habit theory suggests the "habit loop" (cue → behavior → reward) is neurobiologically grounded in dopaminergic learning. Meditation, by enhancing mood regulation and stress response, provides immediate psychological reward. Repetition strengthens basal ganglia circuits, consolidating practice into automated, less effortful behavior (Wyatt, 2024; Akash & Chowdhury, 2025). Mindfulness thereby functions both as the behavior and the reward, fueled by intrinsic neural change.

Daily Practice: Evidence and Implications

Consistent daily practice is a central theme in mindfulness literature. Lane et al. (2017) reported that twice-daily MBSR at Duke University Medical Center led to proportional reductions in perceived stress. This is evidence that ultimately the length and frequency matter.

Grossman's meta-analysis (2003) likewise emphasized that sustained emotional and physiological benefits depend on regular practice.

Our expanded framework integrates these findings within habit theory and intervention design. Practice must be near daily, ideally linked to life routines via anchoring strategies. Habit maintenance may benefit from temporal consistency but can be equally supported through flexible, contextual triggers. Layering initial self-monitoring, incentives, and environmental design can enhance early engagement, while neuroplastic changes produced by meditation alone reinforce the habit loop biologically.

Instructor Role and Habit Support

As helping professionals teaching meditation, our aim is to cultivate independent, self-sustaining meditators: Individuals who transition from structured classes to self-directed, habitual practice. This requires equipping learners not only with technical meditative skills but also behavioral tools: anchoring, reminders, micro-practices, reflection logs, and app-enabled support. These tactics align with SuMMed's maintenance stage and can capitalize on individuals' lifestyle and environmental contexts without compromising mindfulness's core nonjudgmental approach.

Critically, mindfulness practitioners should be coached to notice and reflect on bodily and emotional cues, enabling context-sensitive practice which is an evidence-based pathway to habit maintenance. Our guidance must acknowledge the diverse trajectories seen in empirical studies and emphasize autonomy: whether one chooses fixed-times or flexible emotionally triggered mindfulness, both can yield sustained practice and associated health benefits.

What Habits Are and How They Are Formed

The study of habits has a rich intellectual lineage. Early psychological theories emphasized goal-directed learning, where actions are motivated by anticipated outcomes. One foundational text in this tradition is Edward Chace Tolman's (1926) review "Habit Formation and Higher Mental Processes in Animals." Surveying over two dozen experimental studies published that year, Tolman proposed that all learning arises from goal postulation and the mental representation of desired outcomes. He noted that learning strengthens when the outcome is positive and weakens when negative. His concluding statement captures the prevailing wisdom of that era: "When these represented ends of acts are situations which when actually present lead at once to further appropriate responses, then the propensities towards the acts leading to those ends will become strengthened" (Tolman, 1926, p. 51).

While this model feels intuitive, echoing our everyday belief that behavior is guided by outcomes, it does not account for the many habitual behaviors that persist despite negative consequences or even without conscious intention. The modern understanding of habits has evolved significantly, delineating a distinction between goal-directed and habitual actions. Habits, unlike deliberative actions, are characterized by automaticity, cue-dependence, and insensitivity to outcomes (Wood & Rünger, 2021).

At its core, habit formation is a process wherein repeated behaviors in consistent contexts become automatic responses to environmental cues. As behaviors are repeated in the presence of the same stimuli, they become decoupled from goals and instead linked directly to those cues (Wood, 2020). For example, one might initially exercise to improve health, but over time, the act of putting on running shoes or seeing a gym bag becomes sufficient to initiate the behavior without further deliberation. This transition from conscious intention to automaticity is central to the psychology of habit.

Importantly, repetition alone is insufficient for habit formation. Stability in context and consistency in time, place, and environmental cues, is a crucial moderator (Lally, 2022). The more stable the cue context, the more likely the behavior will become habitual. Reinforcing mechanisms such as intrinsic rewards or social praise can also amplify this process. Orbell and Verplanken (2020) argue that strong habits exhibit three traits: high automaticity, strong cue-behavior associations, and resistance to conscious modulation. These characteristics suggest that modifying a habit requires more than just motivation; it requires disrupting the environmental structure or cue-response linkages that sustain it.

A key contribution of contemporary neuroscience is the elucidation of the dual-process framework separating habitual and goal-directed actions. Goal-directed behaviors, also termed action-outcome (AO) behaviors, rely on mental models of causality: we act because we expect a particular result (Balleine & O'Doherty, 2010; Berkman, 2018). In contrast, stimulus-response (S-R) behaviors are triggered by environmental cues regardless of expected consequences. Bornstein and Daw (2011) and Tricomi et al. (2009) underscore that habits, once formed, are largely insensitive to outcomes. This is a point demonstrated through animal studies and neuroimaging research alike.

Hardwick et al. (2019) provide empirical support for this dichotomy by showing that under time constraints, individuals default to habitual responses, while goal-directed behavior requires longer decision windows. This suggests that the neural systems for habits proved more rapid and robust under stress or distraction which are conditions where mindfulness may be especially useful.

The distinction between AO and S-R behaviors can be illustrated through a familiar scenario. Consider walking into a dark room and flipping a light switch. If the power is on, your action is goal-directed; you want to see. But if you do the same action during a blackout, you may still reach for the switch purely out of habit, triggered by the stimulus of darkness. As Yin and Knowlton (2006) observe, "goal-directed actions are controlled by their consequences, habits by antecedent stimuli" (p. 464).

Recent work by Verplanken and Sui (2019) extends this understanding by highlighting how habits may be anchored in personal identity. When behaviors align with one's self-concept (e.g., "I'm the kind of person who meditates every day"), they are more likely to be sustained. This has important implications for mindfulness practice: cultivating meditation as a habit may depend not only on repetition and context stability but also on identity reinforcement.

Intervention science has produced promising strategies to support or disrupt habits. One widely validated technique is the use of implementation intentions "if-then" plans that automate behavior initiation (Gollwitzer & Oettingen, 2020; Orbell & Verplanken, 2020). For instance, "If I brush my teeth, then I will meditate for five minutes" pairs a habitual cue with a desired action, increasing the probability of enactment. This method adds a deliberate structure to the automaticity of habit and is especially effective in early habit formation.

Environmental restructuring is another powerful intervention. By altering the cues that trigger undesired habits or introducing new cues to prompt desirable ones, behavior can be reshaped without requiring continual willpower. As Bayer et al. (2020) argue, distinguishing between habits and routines is critical in this process. Not all repeated behavior is habitual. Routines may be flexible and conscious, while habits are more rigid and unconscious. This distinction matters in both diagnosis and intervention.

In sum, habit formation is a dynamic interplay of cognitive, neural, and environmental processes. From early theories emphasizing goal-directed learning to contemporary models distinguishing automatic S-R behavior, our understanding of habits has deepened considerably. As meditation practitioners and researchers seek to cultivate mindfulness as a daily habit, these insights offer both theoretical clarity and practical guidance. Habit strength depends on more than willpower. It relies on context stability, identity congruence, neural adaptation, and the strategic use of cues and planning. Understanding these principles not only enhances individual habit change but also informs program design, instructional scaffolding, and long-term maintenance in contemplative practices.

Neuroscience Perspective on Habit Formation

The neuroscience of habit formation builds upon a legacy of psychological inquiry stretching back to foundational figures like Ivan Pavlov, William James, and B.F. Skinner. Pavlov's (1927) investigations into conditioned reflexes illuminated the influence of environmental cues on behavior, while James (1890) conceptualized habit as the brain's means of economizing effort through automatization. Skinner (1953) further refined these ideas through his operant conditioning framework, which emphasized the role of reinforcement in shaping and maintaining behavior. These early insights remain essential scaffolds for modern neuroscience, which has increasingly adopted sophisticated imaging and molecular tools to reveal the neurobiological substrates of habit formation.

Contemporary neuroscience has transformed our understanding of behavior through technologies like fMRI, PET, and optogenetics, which allow researchers to map brain activity in real time, even at the level of individual neurons. Often involving rats in mazes timed with stopwatches, the rudimentary behavioral experiments of the 20th century have evolved into complex paradigms involving genetically engineered rodents with brain implants that can selectively activate or inhibit neural pathways (Balleine & Dezfouli, 2022; Namboodiri & Stuber, 2023). These methodological advances provide a more nuanced understanding of habit formation and its neural underpinnings, particularly within the basal ganglia.

The basal ganglia, a network of subcortical nuclei embedded within the cerebrum, have emerged as central to the process of habit formation. Among its core structures is the striatum, pallidum, globus pallidus, subthalamic nucleus, and substantia nigra. For this research the striatum receives particular attention in the neuroscience literature. It serves as the primary recipient of cortical input and plays a crucial role in action selection, reinforcement learning, and the encoding of repeated behavioral routines (Graybiel, 2015; Yin, 2006; Ashby et al., 2010). The striatum's connectivity through direct and indirect pathways with the thalamus and motor cortices provides the infrastructure for modulating both motor and cognitive behaviors.

Of particular relevance is the role of dopamine in shaping the activity of the striatum. Dopamine acts as a neuromodulator that enhances synaptic plasticity, thereby reinforcing neural pathways associated with successful behavioral outcomes. Studies using real-time dopamine release monitoring have shown that temporally precise bursts of dopamine, especially during the cue and reward phases of a behavioral loop, facilitate the encoding of habitual sequences (Tang et al., 2023). This process, often referred to as “action chunking,” consolidates sequences of behavior into automated routines, reducing cognitive load and increasing efficiency.

As habits become entrenched, neural activity within the striatum becomes more temporally compressed and focused at the beginning and end of behavior sequences, a phenomenon termed “bracketing.” Early in the learning process, both the medial prefrontal cortex (mPFC) and the striatum are actively engaged throughout the behavior. Over time, however, activity in these regions shifts, with the striatum becoming dormant during the execution phase and only active during cue recognition and reward attainment (Graybiel, 2015; Namboodiri & Stuber, 2023). This neurodynamic transformation signals the transition from effortful, goal-directed behavior to effortless habitual responding.

The medial prefrontal cortex also plays a pivotal role in this process. Long understood as the seat of executive function, responsible for planning, decision-making, and simulating future scenarios, the mPFC modulates the balance between goal-directed and habitual systems. Research by Kim and Gremel (2022) demonstrates that the mPFC acts as a behavioral gatekeeper, sustaining goal-directed actions during early learning but gradually relinquishing control as behaviors are repeated and environmental contingencies become stable. Their findings underscore the flexible role of the mPFC in arbitrating between competing behavioral strategies depending on context and training.

Importantly, the prefrontal cortex does not immediately disengage when the striatum begins to chunk behavior. Evidence from rodent maze experiments shows a lag phase during which the striatum has already developed a chunked loop, but the prefrontal cortex continues to show high activity, possibly maintaining oversight or evaluative control (Graybiel, 2015; Tricomi et al., 2009). Only after this evaluative period does the mPFC itself adopt a chunked pattern, suggesting a transition from flexible oversight to full delegation of control to subcortical systems.

This transitional phase is particularly significant for behavior change interventions. During the window when the striatum has begun chunking but the mPFC remains actively engaged, there is still a viable opportunity to reverse or modify emerging habits. This is especially the case if the outcome of the behavior becomes less rewarding or contextually inappropriate. As Oh et al. (2023) show, dorsal striatal circuits encode action routines while ventral regions maintain reward sensitivity; disrupting this balance before overtraining can prevent maladaptive habits from solidifying. This offers a critical insight for clinicians and behavior change specialists: the period immediately following habit acquisition is a sensitive window for intervention.

Once both the striatum and the mPFC have fully habituated to the cue-routine-reward loop, behavioral plasticity diminishes markedly. Graybiel (2015) and Balleine and Dezfouli (2022) emphasize that in overtrained conditions, even negative outcomes fail to extinguish the habitual response. This explains, in part, the difficulty many individuals experience when attempting to unlearn deeply embedded routines such as smoking, compulsive eating, or maladaptive relational patterns. These behaviors are not merely psychological but are neurally consolidated across multiple brain systems.

In this context, the work of Namboodiri and Stuber (2023) is particularly illuminating. Using whole-brain imaging in mice, they demonstrate a progressive shift from distributed cortical activity to concentrated basal ganglia activation as behaviors become automated. This supports the hypothesis that habit formation involves a kind of neural efficiency trade-off: over time, the brain economizes effort by consolidating behavior into subcortical loops, thereby freeing up cortical resources for other tasks.

In summary, the neuroscience of habit formation presents a coherent and increasingly detailed picture of how behavioral routines are formed, consolidated, and made resistant to change. The basal ganglia, the striatum, and the medial prefrontal cortex work in dynamic concert to transition behaviors from goal-directed to automatic. Dopamine, acting as a critical modulator of synaptic plasticity, guides this transition by selectively reinforcing action sequences that are contextually successful. As technological tools become more precise, the outlines of the neural architecture underlying habit are coming into sharper focus. While we may still lack a full account of the "inner lives" of each neural structure involved, the major pathways and their functional roles are now firmly established. This growing clarity offers valuable implications for both understanding and altering human behavior in clinical and everyday contexts.

Motivation Perspective of Habit Formation

Popular discourse around motivation and change often overestimates the power of conscious intention, leading to persistent misunderstandings about the psychological mechanisms underlying habit formation. While motivation is indeed a crucial factor in initiating behavioral change, its role in sustaining long-term habits, particularly those as effortful and temporally abstract as mindfulness meditation, is limited. Empirical evidence consistently shows that explicitly held goals are weak predictors of subsequent behavioral consistency. For example, Ouellette and Wood (1998) found that past behavior, not stated intention, best predicted future habit performance. Similarly, Fogg (2017) has argued that motivation is inherently volatile and tends to decline shortly after an initial behavioral commitment, especially when the behavior requires effort or delayed gratification.

Fogg's behavior model articulates that behavior is the product of three interacting variables: motivation, ability, and prompts. As motivation diminishes over time, individuals are less likely to follow through on difficult tasks, even when intentions remain unchanged. As a result, sustainable behavior changes depend on increasing ability by reducing task complexity and solidifying external cues (triggers) that automate behavior. The implication for meditation practice is clear: only behaviors that are sufficiently easy and consistently prompted are likely to survive the inevitable decline in initial enthusiasm.

The slow trajectory of habit formation further complicates matters. A widely cited study by Lally et al. (2010) demonstrated that the median time required to form a new daily habit is approximately 66 days, though the range can vary widely based on complexity and context stability. For a cognitively effortful task such as meditation, which lacks immediate external rewards, this implies a high probability of attrition without strategic behavioral scaffolding. Lally and Gardner (2021) argue that while automaticity is the end goal of habit formation, the early phase is heavily reliant on deliberate goal pursuit. During this period, behaviors should be as frictionless as possible. Starting with small doses, such as three to five minutes of daily meditation, so that individuals can overcome the initial resistance and begin associating the behavior with a stable routine.

This strategy aligns with interventions proposed by Fogg (2017), who encourages "tiny habits" as a low-barrier entry point into complex behavioral patterns. In the same spirit, Wood and Neal (2007) contend that persuasive appeals targeting intentions or values are insufficient for shifting entrenched habits. Instead, effective interventions focus on altering environmental cues or providing new action pathways that compete with old ones. They observe that effortful inhibition of old habits can open a window for new, goal-aligned behaviors to take root particularly when cues are strategically managed.

Beyond the structuring of initial behavior, motivation can be enhanced through well-timed feedback and reframing. Koo and Fishbach (2014) provide compelling evidence that the impact of feedback on motivation depends on an individual's level of goal commitment. When individuals are highly committed, drawing attention to how much remains to be achieved can galvanize effort. Conversely, for those with lower initial commitment, focusing on past progress can enhance self-efficacy and motivate continued engagement. This dual strategy can be implemented by meditation instructors who tailor their interventions based on the student's level of engagement.

A longitudinal study by Van Cappellen et al. (2021) extends this motivational framework by showing that individuals who approach meditation with intrinsic motivations such as valuing mindfulness or pursuing emotional balance, are more likely to develop consistent practice habits than those driven by external rewards or social pressures. This distinction aligns with self-determination theory, which posits that autonomous motivation is more enduring and less vulnerable to disruption. Instructors, therefore, should seek to nurture these intrinsic motivations, possibly through values clarification exercises or connecting meditation to personally meaningful goals.

Additional insights emerge from behavioral economics, where strategies such as precommitment and environmental design are employed to mitigate the motivational inconsistencies that derail long-term behavior change. Morris and Konkolÿ Thege (2020) highlight how techniques like social contracts, default options, and commitment devices can reduce friction and increase accountability. These findings suggest that meditation practitioners may benefit from structured commitment strategies, such as joining a peer group or publicly declaring their meditation goals, to create external anchors that outlast initial motivational spikes.

Moreover, practical tools such as implementation intentions and self-monitoring mechanisms have demonstrated efficacy in supporting behavior change. Cook et al. (2022) report that participants who created specific “if-then” action plans (e.g., “If I brush my teeth, then I will meditate for five minutes”) and tracked their behavior via a smartphone app were significantly more successful in habit adoption. This reflects the dual role of structure and feedback in fostering behavioral consistency.

Attention must also be given to the individual’s belief system about change. Mindset research has long shown that belief in one's ability to change is a predictor of both behavioral initiation and persistence (Dweck, 2006). In a study on flossing, Judah et al. (2013) found that a positive mindset and favorable contextual cues significantly improved habit formation. Interestingly, the sequencing of behavior also mattered: individuals who flossed after brushing (aligning the new habit with an existing one) were more successful than those who attempted to do it before. This reinforces the importance of strategic cue integration in habit scaffolding.

Schwitzgebel and Ellis (2023) add a philosophical dimension to these empirical insights by investigating why people so often fail to act in accordance with their stated values. Their work reveals a “disconnection problem” in which rational endorsements fail to translate into habitual action, particularly when such action requires ongoing attention or competes with deeply ingrained patterns. The resolution, they suggest, lies in merging values clarification with structural habit interventions. This is a strategy especially resonant for meditation, which is often pursued for existential or ethical reasons.

In summary, habit formation in mindfulness meditation should not be conceptualized as a linear process driven by motivation alone. Rather, it is a complex interplay of initial motivation, contextual cueing, cognitive effort, and structured feedback. Helping professionals who teach meditation should be equipped not only with technical knowledge of contemplative practice but also with an understanding of behavioral science. By helping new meditators design micro-habits, attach those habits to existing routines, monitor progress, and commit through social and structural supports, they can facilitate a transformation from intention to automation. These evidence-based strategies, while originating in domains like behavioral economics and health psychology, are readily transferable to the domain of meditation and offer a rich toolkit for fostering sustainable inner change.

Behaviorism Theory

Philosopher Wilfrid Sellars (1963) famously described behaviorists as those who “insist on confirming hypotheses about psychological events in terms of behavioral criteria” (p. 22). This foundational commitment to empirical rigor defined behaviorism as it emerged in the early 20th century, during a period in which psychology sought to align itself more closely with the standards of the natural sciences. As behaviorists dismissed introspection in favor of observable action, their methods offered a compelling response to the epistemological challenges of studying internal mental states.

The intellectual lineage of behaviorism traces most famously to Ivan Pavlov’s work on classical conditioning in dogs. Pavlov observed that his dogs salivated at the sight of food and hypothesized that a neutral stimulus could be paired with this response. By consistently ringing a bell before delivering food, Pavlov conditioned the dogs to associate the bell with feeding. Eventually, the bell alone elicited salivation—a learned behavior that illustrated the fundamental stimulus-response mechanism. This experiment provided the template for classical conditioning and sparked widespread interest in how habitual responses could be formed through external cues.

John Watson and later B.F. Skinner expanded on Pavlov's principles. Watson championed behaviorism as a formal school of thought, while Skinner introduced operant conditioning as a complementary framework. In contrast to classical conditioning, which involves passive associations, operant conditioning emphasizes how consequences shape voluntary behavior. In Skinner's experiments with rats and pigeons housed in operant chambers or "Skinner Boxes" animals learned to press levers or peck keys in order to receive rewards or avoid punishments. This reinforcement-based model proposed that behavior could be systematically strengthened or weakened through contingent outcomes, forming the bedrock of modern behavior modification techniques.

Skinner's theory was not merely a philosophical stance; it offered an applied science of learning. Although behaviorism fell out of favor by the late 20th century amid the rise of cognitive psychology, its legacy remains influential particularly in the fields of neuroscience and behavior change. Contemporary work in behavioral neuroscience has reaffirmed many of Skinner's core claims, particularly around reinforcement. Schultz (2021) articulates how dopaminergic activity in the midbrain signals prediction errors, which are discrepancies between expected and actual rewards, which subsequently modify future behavior. This neurophysiological account closely mirrors the operant framework, where reinforcement serves as the currency of behavioral learning.

Research into the dorsal raphe nucleus has revitalized interest in learned helplessness, a phenomenon originally explored within behaviorist paradigms. Maier and Seligman (2019) revisit this concept by showing how the perception of control (or its absence) modulates neurochemical pathways linked to resilience and behavioral passivity. Their findings suggest that operant mechanisms, when coupled with cognitive appraisals, play a crucial role in determining motivational outcomes under stress.

These updates underscore that while behaviorism may no longer be the dominant theoretical framework, its mechanisms endure in the neural and behavioral sciences. The focus on observable behavior, reinforcement, and environmental manipulation persists, now integrated with insights from neuroscience, cognitive psychology, and behavioral economics.

Behavioral Economics Theory

Behavioral economics emerged as a corrective to the rational actor model of classical economics, proposing instead that human decision-making is often irrational, biased, and influenced by unconscious heuristics. As noted by Beshears and colleagues (2019), this field blends insights from cognitive psychology and economic theory to offer a more behaviorally realistic model of human action. At its core, behavioral economics shares behaviorism’s concern with environmental determinants of behavior but with a greater emphasis on the heuristics and biases that shape judgment and choice.

Daniel Kahneman and Amos Tversky's pioneering work revealed that individuals often rely on mental shortcuts that lead to systematic deviations from rationality. Their dual-process model, which distinguishes between fast, intuitive System 1 and slow, deliberative System 2 thinking, aligns with behaviorist assumptions about automaticity and stimulus-driven action. Importantly, this framework gave rise to "nudge theory," which argues that subtle modifications to choice architecture, such as placing healthier foods at eye level, can significantly alter behavior without restricting freedom (Thaler & Sunstein, 2008).

Recent applications of nudge theory have explored how to promote healthier habits through environmental structuring. Hagger and Hamilton (2020) found that habit formation in areas like physical activity and eating can be effectively nudged by changing default options, enhancing salience, and simplifying decision pathways. Their work affirms that behavioral change does not require persuasion or coercion; rather, it can be facilitated by rearranging the context in which choices are made a principle that echoes Skinner's own environmentalist leanings.

Further elaboration of this perspective comes from Kahneman, Sibony, and Sunstein (2021), who explore how "noise" or inconsistency in judgment undermines decision quality. By highlighting variance rather than bias alone, they suggest that stable behavior can be encouraged by reducing unnecessary complexity and variability in environments. This refinement expands the behavioral economics toolkit, suggesting that precision in context design is as important as exploiting known heuristics.

Finally, Simon, Friedman, and Kruglanski (2023) offer a unifying account of how motivation and reinforcement interact in the development of habits. Drawing from goal systems theory, they argue that behaviorist accounts of reinforcement gain predictive power when aligned with motivational constructs. For instance, the same reinforcement schedule may yield different outcomes depending on an individual's underlying goal hierarchies. This integration enhances the explanatory reach of operant conditioning by embedding it within a broader network of cognitive and motivational factors.

Together, behaviorism and behavioral economics both offer rich accounts of how human behavior is shaped by reinforcement and context. While the former emphasizes the mechanistic conditioning of actions, the latter extends this logic to the domain of judgment, choice, and policy. In contemporary research, the intersection of these traditions has become particularly fruitful, especially as neuroscientific evidence validates long-standing behavioral principles and expands their relevance to fields like mindfulness, health behavior change, and habit formation.

For scholars and practitioners interested in cultivating habits, whether through meditation or other wellness practices, this synthesis provides actionable insights. By designing environments that reward desired behaviors, minimize decision noise, and scaffold goal alignment, it becomes possible to foster long-term behavioral change in a manner that is both evidence-based and compassionate.

Evolutionary Psychology Theory

The publication of *On the Origin of Species* (Darwin, 1859) inaugurated modern biology's transformative turn, and psychology quickly fell under its paradigm-shifting influence. Daniel Dennett famously dubbed Darwin's insight a "dangerous idea" because it subverts anthropocentric assumptions and compels the reading of human cognition through the lens of adaptation and selection (Dennett, 1995).

Evolutionary psychology seeks to understand psychological traits by tracing their lineage back to the survival and reproductive challenges faced by our ancestors (Tooby & Cosmides, 1992). Within this framework, the human mind comprises a collection of functionally specialized modules, or information-processing mechanisms, shaped by natural selection to address ancient adaptive problems (Cosmides & Tooby, 1992). Each module whether tuned to digestion, threat detection, language acquisition, or mate selection, tends to operate without conscious access, running in parallel beneath awareness (Fodor, 1983).

Consistent with this view, current neuroscience rejects the notion of consciousness as a unified executive controller. Instead, the brain's architecture appears modular and massively parallel, enabling nonconscious processes to orchestrate most physiological and cognitive functions (Fodor, 1983; Ilie & Jaeggi, 2025). In fact, humans lack direct introspective access to the majority of neural computations driving decision-making and behavior (Eagleman, 2011). Kurzban (2011) further populates this schema by framing consciousness as the arbiter of intra-modular contention and the author of retrospective narratives. According to Kurzban, conscious awareness mediates conflicts, such as between a sugar-craving module and another concerned with mate attractiveness, and then constructs coherent, socially acceptable explanations for actions post hoc.

Ilie and Jaeggi (2025) extend this evolutionary modular framework into clinical psychology, showing that certain psychiatric disorders arise when modules fail to integrate smoothly under conscious coordination. Self-disorders, for instance, expose how conscious agency can falter when modular boundaries become dysregulated. Mindfulness practices, by contrast, may reinforce integration, supporting healthy self-representation through better cross-module coherence.

Robert Wright (1994) echoes these insights, asserting that evolution often conceals its own mechanisms from introspection: “we are oblivious to our deepest motivations - in ways more chronic and complete than Freud imagined” (p. 149). From this perspective, consciousness is not central, but selective. It intervenes mainly when modules collide, conserving precious neural resources otherwise occupied by automatic processes, until conscious reflection becomes advantageous.

This reorientation holds deep consequences for mindfulness instruction aimed at habit formation. The traditional model, stemming from Enlightenment assumptions (e.g., *cogito ergo sum*), envisaged consciousness as an all-powerful cartographer directing a rational voyage (Eagleman, 2011). In that view, setting intentions was sufficient to steer behavior. However, evolutionary psychology reveals that most psychological operations occur beneath this conscious overseer; thus, efficacy requires designing habits that work with unconscious machinery, not against it.

In practical terms, mindfulness serves both as conscious arbiter and unconscious tuner. Neuroplastic changes documented after mindfulness-based stress reduction show structural thickening in the prefrontal cortex and altered amygdala reactivity (Kabat-Zinn, Hölzel, & Vago, 2024), illustrating how repeated, intentional attention can recalibrate modulatory systems. These findings align with Akash and Chowdhury’s (2025) emphasis on small, frequent behavior repetition as a means of shifting neural activation patterns toward habitual automatization.

Neurologically, habitual repetition and mindfulness may integrate distinct modules such as sensory, affective, and cognitive into more coherent ensembles. Ilie and Jaeggi (2025) note that self-disorders emerge when modular coordination weakens; mindfulness, then, acts to both heighten module-restricted awareness and to smooth communication between modules.

Within evolutionary theory, modularity enhances reproductive success by economizing neural resources and enabling swift, domain-specific processing (Cosmides & Tooby, 1992). However, competition among modules, for example, survival versus social status versus self-image, necessitates arbitration. Consciousness, far from commanding, serves to adjudicate and narrativize while boosting flexibility at decision points. Thus, a meditation instructor aiming for habit formation must address both sides: structuring practice to embed within unconscious systems, and cultivating moment-to-moment conscious awareness to choose among module-driven impulses.

Kurzban's "press secretary" metaphor still resonates: consciousness spins narrative legitimacy around unconscious triggers. By developing meta-awareness, practitioners can reduce automatic reactivity, and over time, small intentional acts accumulate into new module-action linkages.

Empirical neurobiological evidence supports this. For example, experienced meditators show repeated resting-state network configurations oriented around sensory processing and reduced occupancy of frontal, deliberative states (Lakouris et al., 2025). This suggests a shift from executive dominance toward more balanced, modularly integrated resting cognition. Mindfulness thus scaffolds the underlying habit landscape by re-aligning modulatory network dynamics.

In sum, evolutionary psychology reframes mindfulness not as a mental override, but as a strategic intervention across modular and conscious domains. The instructor who wishes to foster daily meditation adherence should combine: (1) ritualized practice anchored in daily routines, (2) scaffolding reflective habits through mobile prompts or group accountability, and (3) continuous cultivation of meta-awareness to observe and regulate module-driven tendencies.

The Self-Report Habit Index (SRHI)

Understanding the nature and measurement of habit is essential for any research examining the mechanisms of behavioral change and maintenance, especially in areas such as health behavior, environmental decision-making, and mindfulness practices. Among the most influential tools developed for this purpose is the Self-Report Habit Index (SRHI), introduced by Verplanken and Orbell (2003), which operationalizes habit strength as a multidimensional psychological construct. The SRHI is grounded in the view that habits are not solely repetitive behaviors but also include elements of automaticity, identity relevance, and reduced conscious awareness. Over the past two decades, this instrument has been empirically refined and widely applied across behavioral sciences to assess the extent to which a given behavior has become habitual.

Conceptual Foundations of the SRHI

Habits are typically defined as learned sequences of acts that are automatic responses to specific cues and are performed with minimal conscious deliberation (Wood et al., 2002). This automaticity is not merely a product of frequent repetition but is facilitated by the presence of stable contextual cues and the formation of strong mental associations between those cues and behavioral responses (Verplanken, 2006). The SRHI builds on this definition by emphasizing three core characteristics of habitual behavior: behavioral frequency, automaticity, and the degree to which the behavior is integrated into one's self-concept (Verplanken & Orbell, 2003).

The original SRHI consists of 12 items, each rated on a 7-point Likert scale, that tap into the behavioral, cognitive, and identity components of habit. These items assess whether a behavior is performed frequently, automatically, without awareness, efficiently, and in a manner consistent with one's identity (e.g., "Behavior X is something I do without thinking" or "Behavior X is something that's typically me"). The scale has demonstrated strong internal consistency ($\alpha > .89$ in most studies), convergent validity, and predictive utility in a wide range of behavioral contexts, including health-related behaviors, transport choices, and dietary practices (Gardner, Lally, & Wardle, 2012; Verplanken et al., 2008).

Measurement Refinements and the Role of Automaticity

A significant development in SRHI research was Gardner et al.'s (2012) proposal to streamline the instrument by isolating its automaticity subscale. This subscale, composed of four items focused exclusively on the automatic execution of behavior, was found to retain much of the predictive validity of the full SRHI while offering a more slimmed down assessment tool. The study demonstrated that the automaticity subscale effectively predicted health behaviors such as exercise and dietary choices, thereby validating its use as a standalone measure in time-sensitive or resource-constrained research contexts.

This refinement aligns with Orbell and Verplanken's (2010) cue-contingent automaticity model, which posits that habits are best understood as stimulus-driven actions that occur when specific environmental or internal cues are present. These authors argue that automaticity is the defining feature of habit and that behaviors that meet this criterion can be reliably differentiated from non-habitual behaviors, even if they occur frequently. Thus, while frequency is important in habit formation, it is the presence of automatic, cue-contingent responses that truly signal the development of a habit.

Although early habit research often equated frequency with habit strength, more recent scholarship has challenged this assumption. Verplanken (2006) argues that frequency-based measures fail to capture the internalization and cognitive architecture of habits. For example, two individuals may brush their teeth twice a day, but one may do so with effortful intention while the other does it automatically without reflection. The SRHI, by incorporating elements of automaticity, identity, and lack of conscious control, offers a more nuanced representation of habit as a mental construct rather than a mere behavioral pattern.

Schmidt and Retelsdorf (2016) contribute to this critique by developing a multidimensional habit scale for reading behavior that highlights affective and motivational dimensions alongside frequency. Their findings suggest that a broader conceptualization of habit, one that includes personal relevance and cognitive-emotional components, is necessary for accurate measurement, particularly when assessing complex or less observable behaviors such as reading or meditation.

Empirical Applications and Contextual Sensitivity

The SRHI has been applied across diverse behavioral domains, most notably in health psychology and behavioral nutrition. For instance, Lally et al. (2010) employed the SRHI in a longitudinal study to model the real-world formation of health habits, such as drinking water or eating fruit with lunch. They found that habit formation follows an asymptotic curve, with initial gains in automaticity occurring quickly and then leveling off after several weeks. The average time to reach a behavioral plateau was 66 days, highlighting the importance of sustained repetition in stable contexts for habit consolidation.

In another applied study, Verplanken et al. (2008) used the SRHI framework to investigate the role of environmental context in travel mode choice. Their findings supported the "habit discontinuity hypothesis," which suggests that changes in context, such as moving to a new home, can disrupt existing habits and provide a critical window for behavior change interventions. The SRHI helped quantify the strength of pre-existing travel habits and demonstrated how disruption in environmental cues could reduce automaticity and open the door for more deliberative decision-making.

Moreover, Gardner (2015) conducted a critical review of how "habit" has been used in health psychology research, emphasizing that inconsistent definitions and measurement strategies have muddied the field. He advocated for a return to theoretically grounded, validated tools like the SRHI and its derivatives to ensure conceptual clarity. Gardner also emphasized that researchers should distinguish between behavioral repetition, goal-directed action, and genuine habitual responses—an analytical distinction that the SRHI is uniquely positioned to uphold.

SRHI Theoretical and Practical Contributions

The SRHI's major theoretical contribution lies in its ability to link subjective experience with observable behavior. By measuring both internal (e.g., automaticity, identity) and external (e.g., frequency) aspects of habit, the index bridges cognitive psychology with behavioral analysis. Practically, the SRHI enables researchers and practitioners to evaluate the effectiveness of habit-based interventions, particularly in areas where behavior change is difficult to sustain through motivation or willpower alone. This has important implications for clinical interventions, public health campaigns, and behavioral economics, where durable behavior change is a central objective.

The SRHI represents a robust, flexible, and theoretically sound instrument for measuring the strength and structure of habitual behaviors. Its multidimensional nature allows for a richer understanding of how habits are formed, maintained, and disrupted, making it a cornerstone in contemporary habit research. As mindfulness and other self-regulatory practices continue to be studied through the lens of habit formation, the SRHI, and particularly its automaticity subscale, offers a valuable framework for operationalizing and assessing behavioral change over time.

CHAPTER III

METHODOLOGY

This chapter describes the philosophical stance, research design, sampling strategy, survey methodology, and ethical protocols underlying this study, which examines the relationship between meditation habit strength, as measured by the Self-Report Habit Index (SRHI), and average session duration among contemporary meditation practitioners. By situating the investigation within established research frameworks, the chapter aims to clearly articulate how these variables are operationalized and analyzed using a cross-sectional, survey-based methodology. The following sections provide a detailed account of the methodological decisions used in service of answering the research question, beginning with the study's philosophical foundations, followed by a discussion of the research approach, data collection procedures, sampling strategy, survey implementation, analytic plan, and ethical considerations.

Philosophical Orientation and Research Approach

This study adopted a post-positivist philosophical stance and an exploratory research approach to examine the relationship between meditation habit strength and session duration. Post-positivism maintains a commitment to empirical measurement and replicability while recognizing that knowledge is inherently partial, context-dependent, and shaped by underlying assumptions (Phillips & Burbules, 2000). This epistemological position supports the use of standardized instruments and statistical analysis, both hallmarks of quantitative research. At the same time, it acknowledges the provisional nature of findings and the need to remain open to complexity and contextual nuance. As Gamage (2025) explains, post-positivist paradigms are particularly appropriate in behavioral research contexts where existing models may be insufficient to explain lived variability, and where patterns must be uncovered rather than imposed.

The study employed an exploratory correlational design grounded in established habit theory. While the research was fundamentally deductive, drawing on Verplanken and Orbell's (2003) validated Self-Report Habit Index and established constructs of behavioral automaticity, it takes an exploratory rather than confirmatory approach. Specifically, it examined associations between SRHI-measured habit strength and self-reported session durations without testing pre-specified directional hypotheses. This exploratory stance is appropriate given the limited empirical research on habit formation specifically within meditation contexts. As Streefkerk (2023) notes, exploratory approaches are particularly well suited to research aims where existing theoretical frameworks require contextual validation or where prior models may not fully account for domain-specific phenomena. By investigating these relationships in a relatively understudied population, the study strove to contribute empirical evidence that can inform future theory development regarding meditation habit formation.

The methodological choices in this study reflected the structure of the Research Onion model (Saunders et al., 2007; Gamage, 2025), moving through the successive layers of philosophy (post-positivism), approach (exploratory deductive), strategy (cross-sectional survey), time horizon (single point in time), and techniques and procedures (quantitative analysis of theory-based self-report measures).

Data Collection and Sampling Strategy

Data were collected through an online survey administered via SurveyMonkey and distributed through the communication channels of the New Leaf Meditation Project, a U.S.-

based online meditation community with approximately 45,000 members. The survey included two primary measures: (1) the Self-Report Habit Index (SRHI), which operationalizes meditation habit strength, and (2) self-reported measures of meditation session duration (in minutes) and practice frequency (sessions per week). The SRHI is a validated 12-item scale widely used to assess behavioral automaticity and identity integration across various health domains, including meditation (Verplanken & Orbell, 2003). All survey questions were closed-ended and standardized to enable statistical analysis of responses.

Eligibility criteria required that participants be members of the New Leaf Meditation Project community, be at least 18 years old, and have meditated at least once within the past 30 days. No additional exclusion criteria were applied. The study sought to capture a sample that varied in age, gender, and meditation experience while remaining reflective of the New Leaf community's broader demographics, which tend to skew toward female, college-educated, and urban-based practitioners.

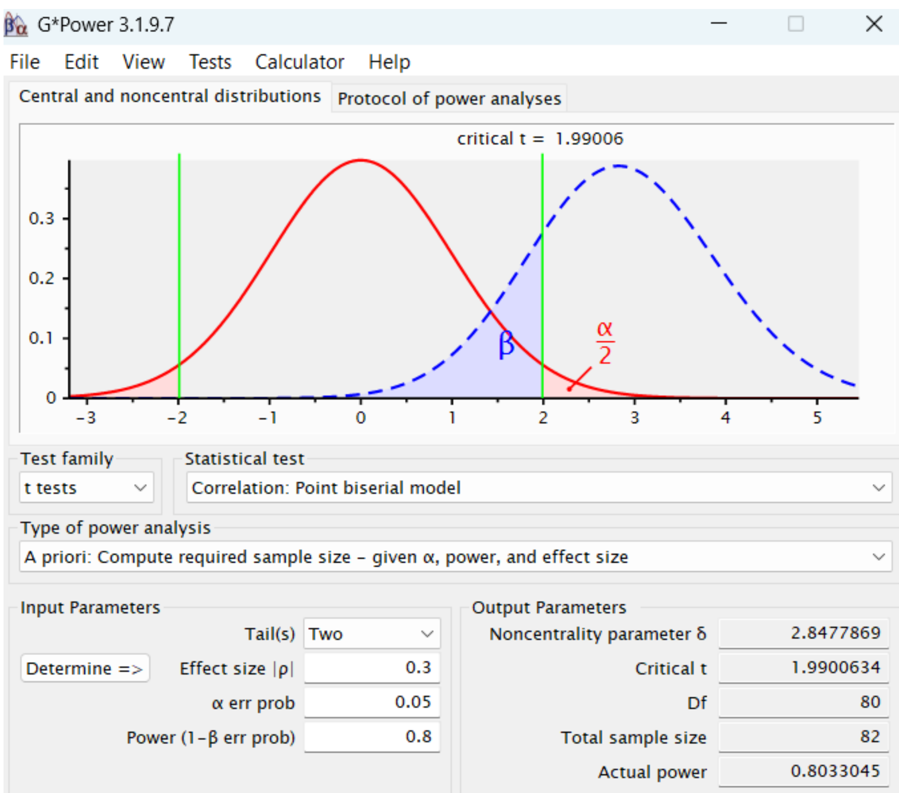
A non-probability, convenience sampling method was used to recruit voluntary participants from within the New Leaf community. While this approach introduced the possibility of self-selection bias, it is methodologically appropriate for exploratory research that aims to identify relational patterns rather than to generate generalizable estimates. As Gamage (2025) emphasizes, methodological alignment with the research aim is paramount; in this case, the objective was to explore potential associations within a self-motivated population of meditation practitioners.

Participants were incentivized through entry into a raffle for one of four $50 Amazon gift cards, offered upon completion of the survey. This incentive was disclosed during the recruitment process and reiterated in the informed consent documentation.

A priori power analysis (G*Power 3.1) for a two-tailed Pearson correlation with $\alpha = .05$ and power = .80 indicated a minimum of $N = 82$ to detect a medium effect of |*r*|=.30|*r*| = .30|*r*|=.30 (Faul et al., 2007, 2009; Cohen, 1988). To accommodate possible exclusions and missing data (~25%), the recruitment target was $N = 110$.

Figure 1

*G*Power Analysis for Sample Size Determination in Pearson Correlation*



The study employed a cross-sectional design, collecting data at a single point in time. This design was well-suited to examining correlational relationships between meditation habit strength and session duration without making causal claims or inferences about longitudinal change. As described in the Research Onion framework (Saunders et al., 2007; Gamage, 2025), the cross-sectional time horizon was appropriate for exploratory research designs that seek to examine correlational patterns within a specific population at one moment in time. Taken together, the survey delivery, sampling method, and time-bound structure reflected a coherent methodological strategy consistent with the study's exploratory aims.

Survey Instruments

The present study employed a structured online questionnaire delivered through SurveyMonkey. The instrument consisted of three sections: (a) a measure of meditation habit strength, (b) meditation practice descriptive items, and (c) demographic questions.

Habit strength was assessed using the Self-Report Habit Index (SRHI; Verplanken & Orbell, 2003), modified to reference meditation as the target behavior. The SRHI consists of 12 items, each beginning with the stem "Meditating is something…" (e.g., "I do frequently," "I do automatically," "I do without thinking"). Responses were recorded on a 7-point Likert-type scale ranging from 1 (strongly disagree) to 7 (strongly agree). This can be found in Appendix 1. Scores were calculated as the mean of all items, with higher scores indicating greater habit strength. The SRHI conceptualizes habit as a multidimensional construct encompassing automaticity, frequency, and identity relevance, and it has been widely used across domains such as health behavior and environmental decision-making (Gardner, 2015; Gardner, Lally, & Wardle, 2012; Lally et al., 2010). Reliability of the full SRHI has been consistently strong, with Cronbach's alphas reported above .89 across multiple studies (Gardner et al., 2012; Verplanken & Orbell, 2003). Evidence of validity includes convergent correlations with behavioral frequency, predictive validity in longitudinal designs, and confirmatory factor analyses supporting its multidimensional structure (Lally et al., 2010; Verplanken et al., 2008). In this study, the total SRHI score was used to examine the relationship between meditation habit strength and session duration.

Meditation Practice Descriptives

Four additional items were included to capture descriptive information about participants' meditation practice. Participants were asked to report: (a) the number of days they meditated in the past seven days, (b) the number of days they typically meditate in a week, (c) the average number of minutes per session, and (d) the number of years and months they have been practicing meditation. These items were analyzed as continuous variables. Session duration served as an independent variable in the main analyses, while other practice descriptives were used for supplementary description of the sample.

Demographic Items

The final section of the survey collected demographic information, including age range, gender identity, highest level of education completed, marital status, and race/ethnicity. These variables were used to describe the sample and to evaluate representativeness relative to the broader population of interest. No demographic variables were included in the primary hypothesis testing.

Administration Procedures

All items were presented in a fixed linear order within a single survey instrument. To preserve anonymity, the survey concluded with a separate link to an external webpage for raffle entry, thereby preventing identifying information from being connected with survey responses.

Survey Implementation

The survey was pre-tested with a small sub-sample ($n \approx 6$) drawn from the target population to assess item clarity, response formatting, and overall usability. The pre-test confirmed that the instrument was comprehensible and functioned as intended. No adjustments were required, and the finalized survey was deemed ready for full distribution. The complete survey instrument is included in Appendix A.

The survey was administered via SurveyMonkey and remained open for a period of two days. Recruitment was conducted through the New Leaf Meditation Project's email list and associated social media platforms.

To ensure data integrity, the survey incorporated several standard quality control measures. SurveyMonkey's settings were configured to restrict each participant to a single submission per device in order to minimize duplicate responses. Although IP addresses were not collected, browser cookies were used to prevent multiple submissions from the same user session. Additionally, response options were presented in consistent formats, and all questions were required to be answered before progressing, thereby eliminating partial data. No attention checks were embedded, as the nature of the survey and its distribution through a trusted community platform were expected to promote conscientious participation.

Data Analysis

Quantitative data were analyzed using IBM SPSS Statistics version 31.0.0.0 (117). Descriptive statistics, including means, standard deviations, ranges, and frequency distributions, were used to summarize demographic characteristics, SRHI scores, session duration, weekly practice frequency, and total meditation experience. These descriptive analyses provided foundational context for subsequent inferential tests.

A multi-step analytic plan was implemented to evaluate the research question and its subcomponents in a manner consistent with post positivist inquiry and contemporary behavioral research. Analyses proceeded in a structured sequence. First, bivariate Pearson correlation coefficients were computed to assess the zero-order associations among the primary variables, including typical meditation duration, weekly meditation frequency, total meditation experience, and SRHI scores. These correlations provided an initial descriptive foundation for understanding the relationships among the constructs.

Second, multiple linear regression models were estimated to evaluate the extent to which meditation duration predicted SRHI scores when entered as the sole predictor. Third, hierarchical multiple regression analyses were conducted to determine whether weekly meditation frequency and total meditation experience contributed additional explanatory power beyond typical session duration. Incremental effects were evaluated through R-squared change statistics and corresponding significance tests.

Fourth, given the possibility that the association between meditation duration and habit strength may follow a nonlinear or plateauing pattern, planned nonlinear analyses were conducted. Polynomial regression models were estimated to test for quadratic and higher-order curvature. These models were complemented by visual inspection of locally estimated scatterplot smoothing (LOESS) curves to identify potential departures from linearity that would not be captured by traditional parametric models.

Fifth, independent samples t-tests were used to examine group differences between practitioners with the strongest meditation habits and the remainder of the sample. To facilitate this comparison, SRHI scores were divided into quartiles using the n-tiles ranking procedure in SPSS. The upper quartile represented practitioners with the highest habit strength, allowing evaluation of whether these individuals differed in typical duration or weekly practice frequency.

Together, these analytic procedures provided a coherent, comprehensive, and theoretically aligned strategy for testing the study's primary research aims.

Ethical Considerations

This study adheres to all ethical guidelines established by the Marywood University Institutional Review Board (IRB). All research materials, including recruitment messages, informed consent language, survey instruments, and data security protocols, received IRB approval prior to data collection.

Informed Consent: Participants were fully informed of the study's purpose, estimated time commitment, voluntary nature, and their rights as research participants. The informed consent statement was presented on the opening screen of the survey. By continuing with the survey, participants provided implied consent. They were informed of their right to withdraw at any time without penalty and that their participation would remain anonymous.

Anonymity and Confidentiality: No personally identifiable information was collected at any stage of the study. IP addresses were not recorded. All data were stored in a passwordprotected, encrypted database accessible only to the primary researcher. Data will be retained for three years following completion of the study and then securely destroyed in accordance with university policy.

Participant Welfare and Risk

The study posed minimal risk to participants, as it involved only non-invasive self-report questions related to meditation habits and practices. There were no foreseeable psychological, physical, legal, or social risks associated with participation.

Compensation

To encourage participation, individuals who completed the survey were given the opportunity to enter a raffle for one of four $50 Amazon gift cards. Entry into the raffle was voluntary and required separate opt-in via a secure, unlinked form that maintained participant anonymity. Winners were selected at random and contacted after data collection was complete. No debriefing procedure was deemed necessary due to the low-risk nature of the study and the absence of deception.

Potential Study Limitations

Although the present study employs a rigorous methodological design, several limitations should be acknowledged. First, because all measures rely on self-report, responses may be influenced by social desirability bias or recall errors. For example, participants may overestimate or underestimate their meditation frequency or session duration, which could affect the accuracy of observed associations. Second, the use of a voluntary, convenience sample introduces the potential for self-selection bias, as those who chose to participate may differ in meaningful ways (e.g., motivation, engagement with meditation) from those who did not.

Sample size considerations also present limitations. While *a priori power analysis* established a minimum threshold for detecting medium-sized effects, actual recruitment and completion rates may influence the precision and robustness of findings. Additionally, participants were recruited exclusively through the New Leaf Meditation Project, a single online community. This reliance on one site constrains the diversity of the sample and limits the generalizability of findings to broader populations of meditators who may vary in cultural background, practice context, or levels of experience.

Taken together, these limitations underscore the importance of interpreting the study's results with caution and situating them within the specific context of the sampled population. Future research would benefit from multi-site recruitment strategies, the inclusion of objective behavioral measures, and longitudinal designs that can more fully capture the dynamics of habit formation in meditation practice.

CHAPTER IV

INTRODUCTION

The purpose of this quantitative study was to examine the extent to which the typical duration of daily meditation practice predicts overall meditation habit strength, as measured by the 12 item Self-Report Habit Index (SRHI; Verplanken & Orbell, 2003), among adult members of the New Leaf Meditation Project. Consistent with the post-positivist philosophical orientation described in Chapter 3 (Phillips & Burbules, 2000), this chapter presents the results of the statistical analyses in an objective, structured manner. The emphasis is placed on identifying empirical patterns of association while recognizing the inherent inferential limits of cross-sectional survey data.

The analytic sequence employed in this chapter aligns with the methodological plan articulated in the previous chapter. The chapter begins with descriptive statistics summarizing the sample's demographic characteristics and meditation practice variables. These descriptives provide essential context for interpreting subsequent analyses and situate the findings within the broader behavioral patterns observed in contemporary meditation research (Cearns & Clark, 2023; Miles et al., 2023).

Following the descriptive section, preliminary analyses assess the psychometric adequacy of the SRHI within the present sample. Although prior studies consistently report strong internal consistency for the full SRHI, typically with alpha coefficients above .89 (Gardner, 2015; Hagger et al., 2015), it remains methodologically necessary to confirm reliability within this specific dataset. Establishing reliability is essential because it justifies the treatment of the SRHI as a coherent continuous measure suitable for use in correlational and regression models.

Data screening and quality checks were then conducted to ensure the appropriateness of the planned analyses. These procedures included examination of scatterplots, evaluation of potential outliers, and review of normality indicators for key variables. Although survey-based behavioral data often depart modestly from ideal normal distributions, parametric techniques remain robust under such conditions (Blanca et al., 2017; Schmider et al., 2010). Consistent with this contemporary methodological literature, Pearson correlations and ordinary least squares regression models were used to address the study's primary research question and related sub-questions.

The primary analysis examined the extent to which typical meditation session duration predicted overall meditation habit strength. Pearson's correlation coefficients were first computed to assess the bivariate association between session duration and SRHI scores. This was followed by multiple regression analyses in which session duration was specified as the independent variable and habit strength as the dependent variable, allowing for evaluation of the unique predictive contribution of session duration while accounting for additional practice related variables. These analytic strategies are widely recommended in behavioral research because they permit clear partitioning of variance and identification of unique predictors of psychological constructs (Gallo & Ottenbreit, 2021).

Because one of the study's research questions (RQ1b) concerns both the incremental contribution of frequency and potential threshold effects in meditation duration, this chapter also includes planned nonlinear analyses. These procedures are aligned with recommendations in habit formation research, where behavioral effects often follow curvilinear or plateauing patterns rather than strictly linear ones (Lally et al., 2010; Kiken et al., 2021). The analyses include polynomial modeling and visual inspection of smoothed scatterplots to identify departures from linearity, along with supplementary categorical comparisons where helpful. Although these methods are exploratory in nature, they addressed a theoretically grounded hypothesis articulated in Chapter 1 regarding potential duration plateaus in early mindfulness practice.

Data Screening and Preparation

A total of 91 survey responses were received. Initial data screening followed established recommendations for psychological and behavioral research (Aguinis et al., 2013; Osborne, 2010). IP-based restrictions were enabled within the survey platform to reduce duplicate submissions. After data collection, additional integrity checks were performed. These included removal of one clearly invalid case, removal of one incomplete response, and ensuring that no repeated response patterns suggested fabrication or mechanical responding. Following these procedures, the final analytic sample consisted of 89 participants, which surpassed the minimum of 82 detailed in Chapter 3.

Missing data were evaluated in accordance with methodological best practices for counseling, educational, and behavioral research (Dong & Peng, 2013; Schlomer et al., 2010). Because the proportion of missingness was small and appeared to be random, listwise deletion was applied. Listwise deletion is a defensible approach under conditions of minimal and random missingness and is widely used in cross-sectional behavioral datasets where imputation would not meaningfully improve model precision (Dong & Peng, 2013; Schlomer et al., 2010).

Outlier inspection followed contemporary guidelines emphasizing the identification of anomalous or influential cases rather than routine removal (Aguinis et al., 2013). Apart from the single invalid response that was excluded during initial screening, no additional outliers were removed. The dataset resulting from these data cleaning and screening steps provided the analytic foundation for the descriptive statistics, reliability analyses, and the inferential models presented in the subsequent sections of this chapter.

Participant Characteristics

Descriptive statistics were calculated for all demographic variables, including age brackets, gender identity, educational attainment, relationship status, meditation experience, and race and ethnicity. The sample was predominantly female (60.7%), college educated, White, and between the ages of 30 and 49 59.6% (Table 1). This demographic profile is consistent not only with published studies of online meditation and digital mindfulness communities (Buchholz et al., 2023; Schumer et al., 2018; Wielgosz et al., 2019), but also with the known characteristics of the New Leaf Meditation Project community from which participants were recruited. Because participation in both meditation communities and online surveys is voluntary, some degree of self-selection bias is expected (Bethlehem, 2010; Conway et al., 2020). The demographic distributions in this study therefore reflect broader tendencies described in Chapter 2 regarding typical participation patterns in contemporary mindfulness research, as well as the methodological considerations discussed in Chapter 3 pertaining to voluntary sampling and recruitment procedures.

Table 1

Descriptive statistics of demographic information

Variable	Category	*n*	%
Age	18 to 29	4	4.5
	30 to 39	25	28.1
	40 to 49	28	31.5
	50 to 59	18	20.2
	60 or older	14	15.7
Gender	Male	33	37.1
	Female	54	60.7
	Prefer not to say	1	1.1
	Other or unspecified	1	1.1
Meditation experience	Less than 1 year	21	23.6
	1 to 3 years	21	23.6
	4 to 7 years	12	13.5
	8 to 10 years	8	9.0
	11 or more years	27	30.3
Education	High school	11	12.4

Variable	Category	*n*	%
	Bachelor's degree	45	50.6
	Master's degree	26	29.2
	Doctorate	7	7.9
Relationship status	Single	30	33.7
	Married	40	44.9
	Divorced	11	12.4
	Widowed	3	3.4
	Domestic partnership	3	3.4
	Other	1	1.1
	Prefer not to say	1	1.1
Hispanic ethnicity	Not Hispanic	82	92.1
	Hispanic	5	5.6
	Other or unspecified	2	2.3
Race	White	84	94.4
	Black or African American	1	1.1

Variable	Category	*n*	%
	Asian	3	3.4
	Prefer not to say	1	1.1

In addition to demographic characteristics, participants provided information about their meditation practice. These variables included typical meditation session duration in minutes, number of days meditated during the past seven days, number of days meditated in a typical week, and total meditation experience expressed in years and months (Table 2). These descriptive statistics offered an overview of the practice patterns represented in the sample and established the empirical context for subsequent analyses of habit strength and meditation duration. This structure aligned with the descriptive framework established in Chapter 3 and supports the examination of meditation behavior outlined in the earlier chapters of the dissertation.

Table 2

Descriptive statistics of meditation experience, typical length of meditation, typical number of days of the week meditated, and the Self Report Habit Index score

Variable	Minimum	Maximum	Mean	SD
Meditation duration	5.00	60.00	21.76	12.56
Frequency per week	0.00	7.00	4.75	1.96
SRHI total score	11.00	77.00	55.16	15.33

Reliability Analysis

Internal consistency reliability for the 12-item Self-Report Habit Index (SRHI) was evaluated using Cronbach's alpha. The SRHI demonstrated an alpha coefficient of .783, which reflects acceptable internal consistency for research purposes and is consistent with the scale's performance in exploratory behavioral studies. This level of reliability aligns with prior validation work in diverse behavioral domains, where the SRHI has typically demonstrated strong internal coherence and stability (Gardner, 2015; Hagger et al., 2015; Verplanken & Orbell, 2003). These findings confirmed that the scale functioned coherently within the present sample and that the items collectively measured the underlying construct of meditation habit strength. This result supported the analytic decision to treat the SRHI as a unidimensional continuous measure in subsequent analyses, consistent with the methodological plan described in Chapter 3.

Primary Analyses

The following sections present the statistical results that correspond to the primary research question and its subcomponents. Analyses proceeded in the order outlined in Chapter 3, beginning with bivariate correlations and followed by multiple regression models and planned moderation and nonlinear analyses. These results are interpreted within the theoretical context established in Chapter 2 regarding habit formation, automaticity, and meditation adherence.

Research Question 1

To what extent does the typical duration of daily meditation practice predict overall habit strength, as measured by the SRHI?

Correlation Analysis

A Pearson product moment correlation coefficient was calculated to examine the association between typical meditation session duration and SRHI total scores. Results indicated a significant positive but modest correlation between session duration and meditation habit strength, $r = .284$, $p = .007$ (Table 3). Although statistically significant, this effect size suggests that the length of an average meditation session accounts for a relatively small portion of the variability in habit strength. This pattern is consistent with contemporary habit formation theory, which posits that while longer behavioral episodes may support consolidation, they play a secondary role relative to repetition and cue-based consistency (Gardner, 2015; Lally et al., 2010). Notably, inspection of the full correlation matrix revealed that typical weekly meditation frequency demonstrated a substantially stronger association with habit strength, $r = .697$, $p < .001$, than session duration. This preliminary finding directly anticipates Research Question 1b, which examines the incremental contribution of frequency beyond duration, and suggests that repetition may play a more central role than session length in the development of meditation habits.

Additionally, total meditation experience exhibited a significant negative correlation with habit strength, $r = -.315$, $p = .003$, a finding that runs counter to the intuitive expectation that more experienced practitioners would report stronger habits. While a full theoretical examination of this relationship is reserved for Chapter V, one possible explanation is that highly experienced meditators may practice in ways that are less regimented and routine-based, resulting in lower scores on a measure designed to capture automaticity through behavioral consistency. The remaining correlations among predictor variables are reported in Table 3 for completeness.

Table 3

Pearson Correlation Matrix for Meditation Habit Strength, Meditation Duration, Weekly Frequency, and Total Experience.

Variable	SRHI	Meditation Duration	Weekly Frequency	Total Experience
SRHI	—	.284**	.697**	−.315**
Meditation Duration	.284**	—	.156	−.214*
Weekly Frequency	.697**	.156	—	−.143
Total Experience	−.315**	−.214*	−.143	—
N	89	89	89	89

Note: * $p < .05$. ** $p < .01$.

Regression Analysis

A hierarchical regression analysis was conducted to evaluate the degree to which session duration predicts meditation habit strength. In Step 1, session duration was entered as the sole predictor of SRHI scores, consistent with the primary research question. Results indicated that session duration significantly predicted habit strength, $F(1, 87) = 7.64$, $p = .007$, $R^2 = .081$, reflecting that duration alone explains a modest proportion of variance in habit strength. The regression equation for Step 1 was SRHI' = 47.609 + 0.347(Time). In Step 2, typical weekly meditation frequency was added to the model to assess its incremental contribution beyond session duration. The addition of frequency produced a large and statistically significant increase in explained variance, $\Delta R^2 = .437$, F change$(1, 86) = 77.785$, $p < .001$, bringing the total variance explained to $R^2 = .517$. The regression equation for Step 2 was SRHI' = 25.537 + 0.219(Time) + 5.229(NormalWeek). These results indicate that weekly meditation frequency contributes substantial predictive value beyond session duration alone, and that the two variables together account for approximately half of the variability in habit strength among participants (Table 4).

Research Question 1a

For meditators in their first year of practice, what is the relationship between daily session duration and SRHI scores?

To examine this question, the dataset was restricted to participants reporting less than one year of total meditation experience. Within this subsample (N=21), a bivariate correlation indicated that session duration was not associated with SRHI scores, $r = -.007$, $p = .977$. A simple linear regression analysis produced consistent findings. Session duration did not significantly predict habit strength, $F(1, 19) = .001$, $p = .977$, and the model explained no variance in SRHI scores ($R^2 = .000$).

Research Question 1b

To what extent does meditation frequency predict habit strength after accounting for session duration?

Incremental Contribution of Frequency

A hierarchical linear regression analysis was conducted to determine whether meditation frequency contributed additional explanatory power beyond daily session duration. In Step 1, typical daily meditation duration significantly predicted SRHI scores, $R^2 = .081$, $F(1, 87) = 7.637$, $p = .007$. In Step 2, the typical number of days meditated in a normal week was added to the model. The inclusion of this frequency variable produced a large and statistically significant increase in explained variance, $\Delta R^2 = .437$, F change$(1, 86) = 77.785$, $p < .001$, raising total explained variance to $R^2 = .517$.

This pattern indicates that meditation frequency provides substantial additional predictive value beyond session duration. These findings support contemporary behavioral models demonstrating that repetition and routine stability are central to the development of automaticity, whereas duration captures only the intensity of individual sessions. Together, these results suggest that frequency plays a stronger role than duration in shaping the consolidation of meditation habits.

Table 4

Hierarchical Regression Predicting SRHI From Session Duration and Weekly Frequency

Model	Predictor	*B*	*SE B*	*β*	*t*	*p*
Step 1	Constant	47.609	3.149	—	15.119	< .001
	Time (minutes)	0.347	0.125	0.284	2.763	.007
Step 2	Constant	25.537	3.396	—	7.521	< .001
	Time (minutes)	0.219	0.093	0.179	2.366	.020
	Frequency (days)	5.229	0.593	0.669	8.820	< .001

Model	*R*	R^2	ΔR^2	*F for* ΔR^2	*df*	*p*
Step 1	0.284	0.081	—	7.637	1, 87	.007
Step 2	0.719	0.517	0.437	77.785	1, 86	< .001

Note: Hierarchical regression values taken directly from SPSS output

Nonlinear and Threshold Effects

To examine whether the relationship between session duration and habit strength follows a nonlinear pattern, two complementary analytical procedures were conducted: hierarchical polynomial regression and SPSS Curve Estimation comparing multiple functional forms.

Polynomial Regression

Three nested models were tested. The linear model (Model 1) accounted for 8.1% of variance in SRHI scores, $F(1, 87) = 7.637$, $p = .007$, consistent with the bivariate correlation reported above. Adding a quadratic term (Model 2) increased explained variance minimally to 10.7% ($\Delta R^2 = .026$), but the quadratic coefficient was not statistically significant, $B = -0.013$, SE = 0.008, p = .113. The cubic model (Model 3) provided no meaningful additional improvement ($R^2 = .108$, $\Delta R^2 = .001$), with all higher-order terms remaining nonsignificant (p values > .33).

Curve Estimation

Five functional forms were compared: linear, logarithmic, quadratic, cubic, and exponential. The linear model ($R^2 = .081$) and logarithmic model ($R^2 = .105$) performed comparably to polynomial alternatives. The quadratic model ($R^2 = .107$) and cubic model ($R^2 =

.108) offered negligible improvement over simpler specifications. Visual inspection of fitted curves across all five models revealed similar trajectories with no evident inflection points, plateaus, or asymptotic patterns within the observed duration range (5 to 60 minutes).

Summary of Nonlinear Findings

Taken together, these analyses provided no evidence of threshold effects or curvilinear relationships between session duration and habit strength. The relationship appeared primarily linear within the behavioral range represented in this sample. The modest incremental variance explained by higher-order polynomial terms (< 3%) did not justify increased model complexity. These findings suggested that duration relates to habit strength consistently across the observed range, with no indication that longer sessions produce diminishing returns or that shorter sessions below a certain threshold are less effective for habit development (Table 5; Figure 2).

Table 5

Model Comparison for Polynomial and Curve Estimation Analyses

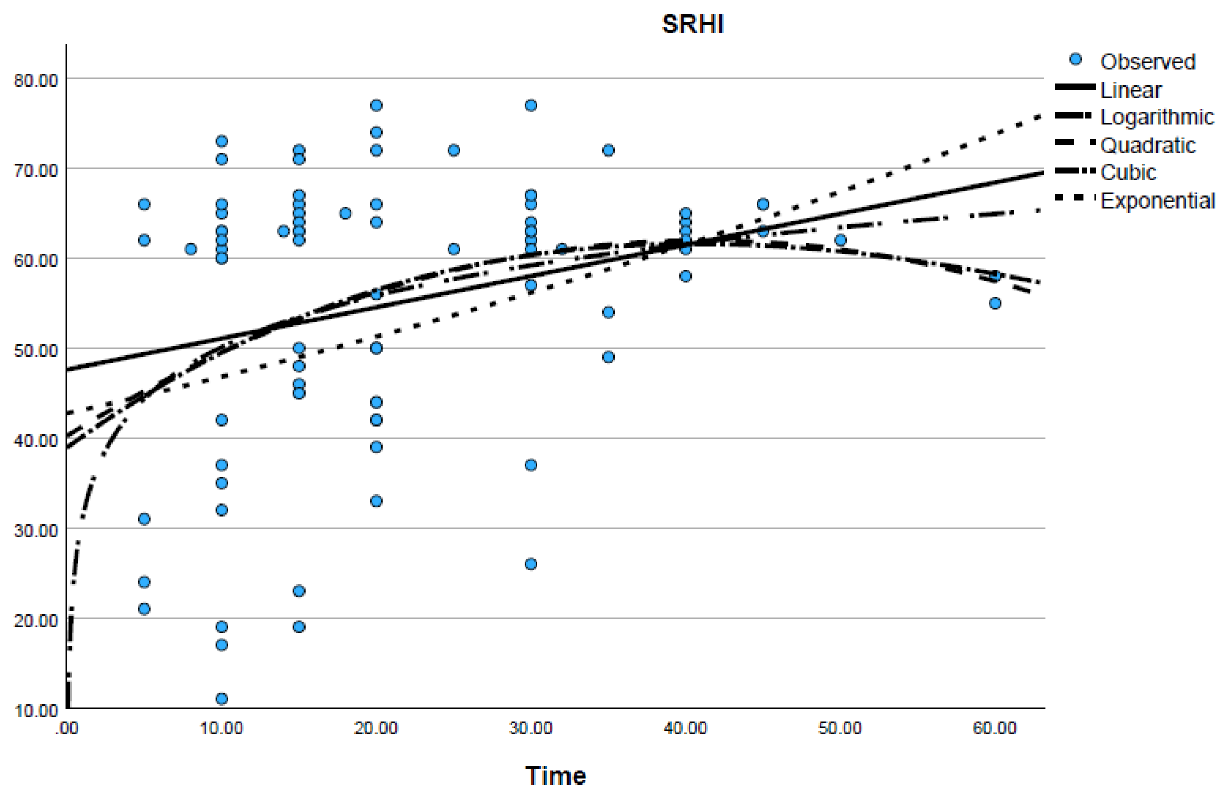
Model Type	R^2	F	df	p	ΔR^2 from Linear
Linear	.081	7.64	1, 87	.007	---
Logarithmic	.105	10.17	1, 87	.002	+.024
Quadratic	.107	5.17	2, 86	.008	+.026
Cubic	.108	3.42	3, 85	.021	+.027

Model Type	R^2	F	df	p	ΔR^2 from Linear
Exponential	.091	8.69	1, 87	.004	+.010

Note. All models treat SRHI total score as the dependent variable and typical session duration (minutes) as the independent variable. ΔR^2 represents the increase in explained variance relative to the linear model.

Figure 2

Fitted Curve Estimation Models Predicting Meditation Habit Strength (SRHI) From Session Duration (Time)



Research Question 1c

How do individuals with the strongest meditation habits differ from the overall sample in their typical meditation duration and weekly frequency?

To address this question, participants were grouped into quartiles based on SRHI scores. The top twenty-five percent of respondents constituted the high habit strength group. Independent samples t-tests were conducted to compare this high SRHI group with the rest of the sample on typical session duration and weekly practice frequency. Typical session duration did not differ significantly between groups, $t(87) = .107$, $p = .915$. In contrast, weekly meditation frequency was significantly higher among high habit strength practitioners, $t(87) = 2.770$, $p = .007$, with a mean difference of more than one additional practice day per week.

Variable	Group	*n*	*M*	*SD*	*t*	*df*	*p*
Session Duration (minutes)	High SRHI	24	22.00	11.34	0.107	87	.915
	Remaining Sample	65	21.68	13.06			
Weekly Frequency (days)	High SRHI	24	5.67	1.55	2.770	87	.007
	Remaining Sample	65	4.42	2.00			

Effect Sizes
Cohen's *d* for weekly frequency = 0.662 (medium to large)
Cohen's *d* for duration = 0.025 (negligible)

Note. High SRHI group defined as the top twenty five percent of SRHI scores. Duration reflects typical meditation time per session. Weekly frequency reflects number of days meditated during a typical week. Values extracted directly from SPSS output

Summary of Findings

The purpose of this study was to examine how meditation habit strength, measured by the Self Report Habit Index (SRHI), relates to typical meditation duration among members of the

New Leaf Meditation Project. The results contribute empirical clarity regarding how duration, frequency, and early experience relate to the development and consolidation of meditation habits.

For the primary research question, longer typical meditation sessions were modestly associated with higher SRHI scores ($r = .284$, $p = .007$), indicating that duration is one behavioral correlate of habit strength within the overall sample, though its effect is limited compared to frequency.

For Research Question 1a, which focused on practitioners in their first year of meditation, the results showed that session duration was not associated with SRHI scores. The correlation was essentially zero, $r = -.007$, $p = .977$, and the regression model accounted for none of the variance in habit strength ($R^2 = .000$). These findings suggest that among new meditators, typical session length does not meaningfully relate to early habit development.

For Research Question 1b, hierarchical regression analyses demonstrated that meditation frequency added a large and statistically significant increment in predictive power beyond daily session duration. After adding frequency, the model's explained variance increased from $R^2 =$ .081 to $R^2 = .517$, with $\Delta R^2 = .437$, $p < .001$. This indicates that frequency contributes substantially to habit strength and carries more explanatory weight than duration when both factors are considered together.

Additional nonlinear analyses conducted as part of Research Question 1b examined whether the duration-habit relationship exhibits threshold or plateau effects. Polynomial regression models (quadratic and cubic) and curve estimation procedures (testing linear, logarithmic, quadratic, cubic, and exponential forms) revealed no evidence of nonlinearity. The relationship between duration and SRHI scores appears primarily linear within the observed range (5-60 minutes), with no indication that longer sessions produce diminishing returns or that briefer sessions below a certain threshold are ineffective for habit development.

For Research Question 1c, practitioners with the strongest habits differed from the broader sample primarily in weekly meditation frequency rather than session duration. High habit strength meditators practiced significantly more days per week, $t(87) = 2.770$, $p = .007$, while their session durations did not differ meaningfully from the remainder of the sample. This pattern underscored that strong meditation habits are associated with consistent repetition rather than longer individual sessions.

Taken together, these findings supported the broader theoretical expectation that sustained engagement, regular repetition, and behavioral consistency contribute meaningfully to the development of automaticity in contemplative practice. Consistent with a post positivist framework, these conclusions are interpreted probabilistically and contextualized within the motivational and behavioral variability present in a large, diverse online meditation community.

CHAPTER V

DISCUSSION

The purpose of this study was to clarify how meditation habit strength, assessed through the Self-Report Habit Index (SRHI), relates to typical meditation session duration among members of the New Leaf Meditation Project. Earlier chapters established that contemporary meditation instruction often assumes that longer sessions contribute meaningfully to the development of stable practice routines. However, empirical research has not yet demonstrated whether duration functions as a mechanism of habit consolidation or whether repetition plays the central role. This study therefore sought to examine how behavioral patterns reported by everyday practitioners align with central principles from habit formation theory and emerging work on meditation adherence. Chapter 5 now turns from presentation of results to a structured interpretation of the observed patterns, situated within the theoretical and applied context outlined throughout the dissertation.

The overarching aim of the study was to determine whether individuals with stronger meditation habits tend to meditate for longer periods on average. This question reflects a broader theoretical interest in how automaticity manifests in contemplative practice. If habit strength is reflected in session endurance, stronger habits should correspond with longer practice durations. If, however, habit strength is primarily shaped by repetition and consistent contextual cues, then duration may function as a secondary or derivative indicator rather than a driver of automaticity. This distinction carries practical implications for meditation instructors, clinicians, and behavioral scientists who seek to understand how novices can reliably establish and maintain a sustainable practice.

Three subsidiary research questions refined the primary aim. Research Question 1a asked whether the duration–habit relationship differs among practitioners in their first year of meditation, a period characterized by weaker routines and more volatile motivation. Research Question 1b examined whether meditation frequency predicts habit strength beyond duration, thereby testing whether repetition offers independent explanatory value. Research Question 1c explored whether practitioners with the strongest habits differed from others in typical duration or weekly frequency. These questions created a coherent analytic structure that situates duration, frequency, and experience within the broader behavioral mechanisms described in Chapter 2.

The interpretive stance of this chapter is shaped by the post positivist orientation detailed in Chapter 3. Post positivism maintains a commitment to empirical inquiry while acknowledging that behavioral phenomena are probabilistic and context dependent (Phillips & Burbules, 2000). This study's cross-sectional design enables the identification of patterns but does not support causal inferences or strong claims about developmental trajectories. The goal is therefore to interpret the results as evidence of tendencies in meditation behavior that are consistent with, or that challenge, established theoretical expectations. This perspective emphasizes theoretical modesty while still valuing the explanatory potential of quantitative data.

The analytic plan described in Chapter 3 was guided by an inductive and exploratory logic, which is appropriate for behavioral domains where theory remains underdeveloped or insufficiently integrated across fields. Meditation research has not fully incorporated principles from habit formation science despite the clear behavioral nature of contemplative practice. Inductive reasoning is therefore justified, since it allows empirical relationships to emerge without requiring strong a priori assumptions about the relative roles of duration and frequency. As argued by Streefkerk (2023) and Gamage (2025), inductive strategies provide a useful foundation in early stage research that seeks to map phenomena rather than to adjudicate among competing hypotheses.

Given this orientation, the findings presented in Chapter 4 offer a set of empirically grounded patterns that require theoretical contextualization. The quantitative analyses demonstrated that while session duration is positively associated with habit strength across the full sample, the magnitude of this relationship is minimal. Among first year meditators, duration showed no association with SRHI scores, which suggests that duration does not meaningfully contribute to the formation of early habits. Weekly frequency, in contrast, emerged as a strong predictor of habit strength and accounted for substantial explanatory variance beyond duration. Furthermore, practitioners with the strongest habits differed not in their session length but in how many days per week they practiced.

These results align with contemporary habit formation models that emphasize repetition within stable contexts as the foundation of automaticity (Gardner, 2015; Lally et al., 2010). They also resonate with emerging evidence that meditation adherence is sustained more reliably through consistent engagement than through longer individual sessions. The findings therefore call for a reinterpretation of traditional duration based recommendations in mindfulness instruction, especially for novices who may struggle to maintain stable routines when asked to meet high time thresholds.

The remainder of this chapter uses these empirical patterns to engage with automaticity theory, motivational processes, and the existing literature on meditation practice. It examines how these findings contribute to theoretical understanding, highlight implications for practice, and identify limitations that constrain the strength of inferences. This interpretive work aims to integrate the study's empirical insights with broader scientific and applied perspectives, thereby clarifying how duration, frequency, and experience interact within the behavioral landscape of contemporary meditation.

Interpretation and Discussion of Findings

RQ1: Duration Modestly Predicts Habit Strength

The results of this study indicate that typical meditation session duration is statistically associated with SRHI scores, yet the magnitude of this relationship is modest. This pattern is consistent with contemporary habit formation theory, which argues that frequency and contextual repetition play a more decisive role in the development of automaticity than the intensity or length of any single behavioral episode (Gardner, 2015; Lally et al., 2010). In the context of meditation, practitioners often assume that longer sessions are the primary indicator of progress. However, the present findings suggest that duration is better conceptualized as supportive rather than determinative.

Several theoretical explanations may account for why duration exerts only a limited influence on habit strength. First, duration may facilitate depth of engagement, attentional absorption, and experiential richness, but these qualities do not reliably reinforce procedural automaticity in the way that repetition does. Automaticity requires frequent pairing of cues, contexts, and behavioral responses, and this pairing strengthens through routine exposure rather than longevity of individual episodes. Second, longer sessions may contribute to identity reinforcement by helping practitioners experience themselves as committed meditators, yet identity effects alone cannot compensate for inconsistency. Without regular repetition, identity based motivation remains aspirational rather than habitual (Kaushal & Rhodes, 2015). In this sense, duration may enhance qualitative aspects of practice while remaining insufficient to independently consolidate long term behavioral stability.

A particularly important implication is that meditators may overvalue duration as a metric of progress. Many contemporary mindfulness communities emphasize thirty- or sixty-minute sessions as markers of seriousness, yet the present findings suggest that such emphasis may misdirect practitioners away from the behavioral regularity that more effectively promotes sustainable practice. Duration retains meaning, but its impact appears secondary.

RQ1a: Duration Is Irrelevant for First-Year Meditators

The absence of any meaningful relationship between duration and SRHI scores among first year meditators aligns closely with theoretical accounts of early-stage behavior change. Early practice is often unstable, effortful, and intention driven rather than automatic. During this motivationally variable period, practitioners rely more on conscious choice and reflective commitment than on stable, cue based routines (Rothman et al., 2009). Because automaticity has not yet begun to form, duration carries little psychological meaning. It therefore cannot differentiate stronger from weaker early habits.

Habit formation typically unfolds in phases. Initial engagement reflects deliberative motivation, followed by the gradual emergence of stable cues and routines, and finally the consolidation of automaticity (Lally et al., 2010). First year meditators are largely situated in the first or early second phase. As a result, the behavioral system that would allow duration to contribute to habit strength has not yet matured. The experience of meditation is also highly variable in the initial months, and practitioners experiment with technique, setting, time of day, and personal goals. This inconsistency reduces the capacity for duration to serve as a meaningful predictor.

Taken together, the null findings reflect the combined influence of motivational fluctuation, irregular practice patterns, and the absence of entrenched cues. Duration becomes psychologically relevant only after a baseline routine has been consistently established.

RQ1b: Frequency as the Primary Driver of Habit Strength

The hierarchical regression results strongly indicate that weekly meditation frequency is the primary driver of SRHI scores. When frequency is added to the model, the predictive contribution of duration diminishes substantially. This pattern aligns closely with the theoretical claim that habit strength is repetition centric. Habits emerge through the repeated coactivation of context and behavior, which strengthens procedural memory and reduces reliance on conscious intention (Wood, 2020).

Frequency supports several psychological mechanisms. First, frequent practice reinforces identity based cues by repeatedly linking the act of meditation with the self concept of being a meditator. Second, repetition strengthens environmental cue behavior linkages, increasing the probability of practice initiation even in the absence of motivational intensity. These mechanisms are central to the SRHI's conceptualization of habit strength as involving both automaticity and identity relevance (Gardner et al., 2012). The present findings therefore support the theoretical integration of SRHI scores with established models of behavioral maintenance.

RQ1b Threshold Interpretation

The nonlinear analyses revealed no evidence of plateau effects within the observed range of session durations. This suggests that increases in session length continue to be associated with incremental increases in habit strength, although the gains are modest relative to the influence of frequency. From a theoretical standpoint, this is consistent with the notion that habits stabilize before duration intensifies. Individuals typically establish a stable routine and automatic cue response cycle before extending session length. Duration escalation often reflects momentary increase in willpower rather than foundational habit consolidation. The linear relationship between SRHI and duration effect further indicates that meditators do not experience diminishing returns.

RQ1c: Differences Among High Habit Practitioners

The comparison between high SRHI practitioners and the broader sample further supports a repetition first model of meditation habit formation. Frequency was the only behavioral variable that differentiated the strongest practitioners. Those with the highest habit strength practiced more often, but not for longer durations. This pattern can be explained by several mechanisms. Higher frequency increases exposure to environmental cues, deepens procedural encoding, and strengthens identity integration. Over time, such factors create an automatic tendency to initiate meditation. Duration does not appear to distinguish experienced practitioners, reinforcing the conclusion that sustainable meditation behavior depends primarily on repetition and contextual regularity.

Integration with Literature

The central empirical pattern emerging from this study is that meditation habit strength is strongly associated with weekly frequency and only modestly associated with typical session duration once frequency is accounted for. This pattern offers several points of theoretical advancement across habit formation, motivation research, and meditation adherence studies. Rather than reiterating prior frameworks, this section focuses on what the present findings contribute to ongoing scholarly debates, where they contradict existing expectations, and what the null effects reveal about the developmental trajectory of meditation habits. The evidence from this sample, taken together with the broader literature, suggests that meditation adheres to the same behavioral principles that govern health habit formation more generally, but it also raises important questions about how contemplative traditions conceptualize practice effort, and developmental progress.

Habit Formation Theory

The findings extend automaticity theory by clarifying the relative roles of behavioral repetition and session duration within contemplative practice. The robust association between weekly practice frequency and SRHI scores replicates the central claim of Gardner (2015), Lally et al. (2010), and Verplanken & Orbell (2003) that habits consolidate when behaviors are repeated in stable contexts rather than performed with high intensity. However, the present study strengthens and refines this claim in two ways.

First, the multivariate models demonstrate that duration substantially loses predictive power once frequency is added. This attenuation is stronger than has typically been documented in general health behaviors, where episode length sometimes contributes marginally to identity integration or perceived commitment. In this sample, duration's unique contribution was small enough that it was no longer statistically significant when repetition was considered. This suggests that for meditation, the context-triggered nature of the behavior may rely even more heavily on recurrence than on the depth or length of sessions.

Second, these findings provide a more nuanced view of the asymptotic curve identified by Lally et al. (2010). Rather than asking how many days it takes to reach a plateau, this study considers where meditators fall on the curve and whether duration meaningfully contributes as practitioners approach asymptote. The first-year meditators in this sample had an average of roughly six months of practice, which is approximately three times the median time to automaticity reported by Lally et al. (2010). Nonetheless, with new meditators duration still showed no association with SRHI scores in this subgroup, suggesting that consistent repetition may be necessary but not sufficient for novice-level automaticity in meditation. Meditation may require more contextual embeddedness, more affective tolerance, or greater cognitive stability than ordinary health habits before duration begins to matter. This nuance is underdeveloped in habit theory and represents a novel contribution of the findings.

Motivation Literature

Motivational science provides an essential complement to habit theory in interpreting why duration failed to predict habit strength among new practitioners and why frequency dominated the multivariate models. While Fogg's Behavior Model is relevant, its application must go beyond the idea that reduce friction predicts repetition. The present study's results invite deeper engagement with self-determination theory (SDT), which is central to understanding meditation motivation but is often missing in habit formation discussions.

SDT distinguishes intrinsic motivation, extrinsic motivation, and introjected motives. Meditation is frequently framed as an intrinsically motivated activity, yet digital meditation communities often reveal substantial extrinsic or instrumental motives, including self-improvement, stress reduction, or social belonging. The present findings suggest that session duration may correlate more with identity- or value-based motives, whereas frequency appears more associated with behavioral integration regardless of motivational quality. This helps explain why first-year meditators, who likely experience fluctuating autonomy, competence, and internalization, show no duration–habit relationship.

Moreover, the strong predictive value of frequency suggests that repetition may facilitate the gradual internalization of meditation motives. In SDT terms, repetition may shift practitioners from controlled to more autonomous motivation, which could in turn influence long-term adherence. The null effect for duration in early practice may reflect that beginners have not yet reached the motivational stability needed to translate longer sessions into reliable automaticity. This speculation opens a new line of inquiry connecting SDT and contemplative practice, an intersection rarely addressed empirically.

Meditation Research and Home Practice Literature

The findings also intersect with a growing literature on meditation adherence, particularly work within clinical and digital mindfulness contexts. The consistency-first pattern resonates with Cearns and Clark (2023), but the implications extend far beyond app research. Several decades of home practice literature in MBSR and MBCT contexts have produced mixed findings on what predicts adherence and improvement. Crane et al. (2021) have emphasized that home practice is a cornerstone of successful outcomes in structured mindfulness programs At the same time, Parsons et al. (2020) and other MBSR adherence scholars have also documented substantial variability in adherence patterns across stress, mood disorders, and chronic pain populations.

How This Study Advances the Literature

First, most MBSR and MBCT studies operationalize adherence primarily through duration-based metrics, often equating longer daily practice with better outcomes. These data challenge this assumption by demonstrating that duration does not meaningfully differentiate strong and weak habit practitioners once repetition is accounted for. This suggests that frequency is the more ecologically valid indicator of behavioral integration, especially as meditation transitions from a structured program requirement to a self-maintained life habit.

Second, the null results for first-year practitioners are especially informative for translational applications. Meditation research has often assumed linear developmental progress, yet these findings reveal that early-stage practice is characterized by motivational volatility and unstable behavioral patterns. This clarifies why many clinical trials report early adherence drop-offs and inconsistent home practice. The present study added empirical detail to this pattern by showing that duration does not predict early habit strength, suggesting that beginner-oriented instruction should prioritize highly repeatable, low-friction practices until stability emerges.

Revisiting and Deepening the Gap Identified in the Literature Review

Rather than restating the gap identified earlier, the present findings refine it. The earlier conceptual question concerned whether novices benefit more from increasing duration or frequency. The evidence now clearly indicates that frequency is the most reliable predictor of habit strength during the first year and remains the dominant predictor for the broader sample.

The more substantive gap that emerges from this study, however, concerns the developmental timing of duration relevance. While contemplative traditions often emphasize longer sessions for insight, concentration, and equanimity, the empirical findings suggest that duration may become relevant only after habit stability is established. This contradicts many instructional norms and points to the need for research that explicitly differentiates between habit formation processes and contemplative depth processes. The present findings therefore offer both empirical resolution to the original gap and a more complex theoretical question for the field: When, how, and for whom does duration begin to matter?

Theoretical Implications

The findings of this study contribute several meaningful implications for contemporary theories of habit formation, meditation pedagogy, and the broader behavioral science literature. Central among these is strong empirical support for automaticity theory, which holds that repetition in consistent contexts, rather than the intensity or duration of any singular behavioral episode, is the primary driver of habit consolidation. This theoretical lens is well established in the works of Lally et al. (2010), Gardner et al. (2012), Verplanken & Orbell (2003), and Wood & Runger (2016), each of whom emphasizes that automaticity emerges through repeated cue–behavior associations rather than prolonged behavioral engagement. The present findings align with this framework by showing that while duration is modestly associated with SRHI scores in the overall sample, it becomes insignificant when frequency is introduced as a predictor. This pattern reinforces the central claim of automaticity theory that repetition is foundational and that duration serves a supplementary role rather than a primary one.

The results further illuminate an important nuance within early stage meditation practice. For first year meditators, session duration did not predict habit strength in any meaningful way. This suggests that the behavioral system supporting habit formation in novices has not yet stabilized sufficiently for duration to exert influence. This finding complements research showing that early habit development is characterized by motivational volatility, limited contextual stability, and weak cue–response encoding (Fogg, 2019; Wood, 2024). It also resonates with neuroscientific accounts indicating that early behavioral repetition strengthens striatal learning processes irrespective of duration, whereas duration-related effects emerge only after stable habit loops have formed (Wyatt, 2024). Thus, the present study clarifies that duration does not impair early habit formation. Rather, it exerts little theoretical relevance during the fragile, inconsistent first months of practice because automaticity has not yet taken root.

A third implication concerns the longstanding assumption embedded within MBSR and similar protocols that session length is a central driver of meditative progress. Traditional approaches, including the influential recommendation of twenty to forty minutes of daily meditation (Kabat-Zinn, 1990; Ludwig, 2008), implicitly treat duration as the principal behavioral metric. Yet findings from this study replicate an emerging empirical critique of this assumption. Consistency, not duration, predicted SRHI scores most strongly. This pattern aligns with contemporary app-based and ecological studies showing that shorter, more frequent sessions outperform longer, inconsistent practice in terms of adherence, emotional regulation, and overall well-being (Cearns & Clark, 2023; Kiken et al., 2021). The present findings therefore challenge duration-focused models and call for a recalibration of pedagogical emphasis. For many practitioners, especially novices, longer sessions may be aspirational but not mechanistically central in the development of habit strength.

From this vantage, duration may be best understood as a secondary enhancer rather than a foundational mechanism of habit formation. The data suggest that longer sessions may deepen psychological engagement, strengthen identity integration, or increase meditative absorption, each of which can contribute to later stage consolidation. However, these effects appear contingent upon repetition. Duration can amplify but cannot substitute for the behavioral stability created through frequent enactment. This interpretation parallels the asymptotic models of habit formation reported by Lally et al. (2010), which demonstrate sharp early gains in automaticity through repetition and only modest incremental improvements thereafter. In this sense, the present study reinforces a tiered conceptual model: frequency establishes the habit architecture and duration contributes to depth once the architecture is in place.

Finally, the implications of these findings reinforce the study's post-positivist framing. As articulated in Chapters 1 and 3, a post-positivist perspective treats findings as probabilistic, contingent on context, and open to revision as additional evidence emerges. The behavioral patterns revealed here should therefore not be construed as universal prescriptive laws but as empirically observed tendencies within a specific population of adult, self-selected meditators in an online mindfulness community. Contextual factors identified in Chapter 2 such as environmental cue stability, motivational architecture, neuroplasticity, and identity relevance likely interact with the observed patterns in complex ways. The modest effect size of duration, the strong predictive value of frequency, and the absence of duration effects in novices should be understood within this probabilistic framework. They indicate trends rather than deterministic rules, and they underscore the necessity of contextualized behavioral interpretation rather than simplistic generalization.

In sum, the theoretical implications of this study reinforce central tenets of automaticity theory, revise duration-focused assumptions in mindfulness pedagogy, situate duration as a secondary enhancer of habit strength, and affirm a post-positivist interpretation of empirical findings. Together, these insights advance theoretical clarity in a field that has long relied on tradition, intuition, or clinical convention rather than empirical guidance for determining optimal practice parameters. The evidence presented here offers a more behaviorally grounded account of how meditation habits are formed, challenging long-standing assumptions and providing new conceptual scaffolding for instructors and researchers seeking to support sustained contemplative practice.

Practical Implications for Psychotherapists and Meditation Instructors

The applied implications of this study concern how clinicians and meditation teachers can use the present findings to support sustainable meditation routines. The core empirical pattern, demonstrated across correlations, hierarchical regressions, and group comparisons, is that frequency during the week is the strongest predictor of meditation habit strength, while typical session duration plays a comparatively modest role once frequency is taken into account (see Chapter 4, including correlations and regression models showing that duration predicts only 8.1 percent of variance while frequency adds 43.7 percent) . These patterns align with contemporary habit research emphasizing repeated enactment in stable contexts as the primary engine of automaticity (Gardner, 2015; Lally et al., 2010). However, several methodological considerations must temper how these findings are applied in therapeutic or instructional settings.

Caveat on Generalizability to Clinical Populations

This study drew from a convenience sample of self-selected adult meditators within an established online community. The participants were largely White, female, college educated, and already engaged in contemplative practices. Although these demographics are consistent with the New Leaf Meditation Project community and with typical mindfulness research samples, they do not match the demographic or symptomatic profiles commonly seen in psychotherapy settings that treat depression, anxiety, trauma, or emotional dysregulation. Because the study did not assess clinical symptoms or diagnostic categories, findings must not be generalized to clinical populations without caution. The behavioral patterns observed here may operate differently among individuals who struggle with motivation, anhedonia, avoidance, chronic stress, or attentional instability. For clinicians, this means that the recommendations can guide psychoeducation and habit support, but should always be adapted to client-specific functional capacities, symptom severity, and treatment goals.

Clarifying What the Study Does and Does Not Show

The data indicate that repetition predicts SRHI scores more strongly than duration, but the study did not examine whether longer sessions produce affective, attentional, or clinical improvements. Therefore, the implication is not that long sessions are ineffective or unnecessary. Instead, duration should be understood as a practice-enhancing feature rather than the foundation of habit consolidation. Instructors must take care not to misinterpret these findings as discouraging deeper or longer practice for students who desire it or whose traditions emphasize it.

Practical Recommendations Informed by the Findings

1. Emphasize frequency as the primary behavioral target

Professionals should encourage a daily or near-daily meditation routine, even if the duration remains brief. Repetition strengthens cue–behavior associations and increases the likelihood that meditation becomes part of an automatic behavioral repertoire. In Chapter 4, the strongest habits were observed among practitioners who meditated more days per week, not those who sat for longer sessions (high SRHI participants practiced approximately one additional day per week on average) . This suggests that clinicians and teachers should prioritize consistency above ambitious duration targets, particularly for beginners and those with unstable routines.

2. Introduce duration increases only after routine stability

Duration remains relevant once the behavior is anchored as a stable habit. Longer sessions may support experiential depth, identity reinforcement, or contemplative insight, but the study's data show that duration did not distinguish high-habit practitioners from the broader sample. Instructors should therefore frame longer sessions as an advanced practice option rather than a requirement for habit formation. A graded progression, such as adding two to five minutes after two to four weeks of consistent practice, respects both the empirical data and the developmental arc of many contemplative traditions.

3. Specify the types of friction that impede early practice

A range of frictions can impede early meditation practice, and although friction reduction is well supported in behavioral science, the present study did not directly measure these mechanisms. Instructors and clinicians should emphasize meditation-specific frictions that have been documented in prior qualitative and observational research. These include the complexity involved in setting up practice environments, such as locating cushions, timers, or quiet spaces;

uncertainty about how to perform or structure meditation techniques; anticipatory cognitive load related to concerns about performing the practice correctly; competing morning or evening routines that limit available time or disrupt behavioral flow; emotional discomfort that arises during stillness or silence; and forgetting to practice due to an absence of effective environmental cues. Such frictions mirror barriers reported in digital mindfulness usage studies and are consistent with the motivational volatility described by Fogg (2019). Although the present study did not measure friction directly, the finding that repetition was the strongest predictor of SRHI scores supports a reasonable inference that minimizing initiation barriers is likely to facilitate the repetition required for habit formation. Nevertheless, it is important to emphasize that specific friction-reduction strategies were not tested within this dataset and should therefore be framed as theoretically supported rather than empirically validated for meditation practice in particular.

4. Use scaffolding systems to promote cue consistency while acknowledging the evidence limitations

In addition to reducing friction, it is appropriate to use behavioral scaffolding systems that promote cue consistency while also acknowledging the limitations of the present evidence. Systems such as implementation intentions, stable practice anchors, digital reminders, and social accountability groups have demonstrated broad effectiveness in general habit research. Although this study did not examine the direct influence of these supports on meditation adherence, they remain appropriate as optional tools for instructors and clinicians to offer. These strategies should be framed as theoretically grounded in automaticity and habit formation research rather than as empirically verified mechanisms within the specific domain of meditation. When presented in this way, scaffolding systems can support practitioners in organizing practice routines while maintaining flexibility and respecting individual needs.

5. Offer clear guidance for students who prefer longer sessions

Finally, meditation professionals should offer clear and balanced guidance for students who prefer engaging in longer meditation sessions. Many practitioners value the contemplative depth, somatic awareness, and reflective insight that longer sessions can facilitate. It is therefore appropriate to frame long sessions as potentially deepening concentration and inner attunement while simultaneously clarifying that extended practice is not required for the development of a stable meditation habit. A practical approach is to emphasize that habit formation should precede duration increases. Once a reliable routine is established, longer sessions can be added in accordance with personal goals or traditional expectations. This balanced framing honors both the empirical findings of the present study, which indicate that repetition rather than duration is the central driver of habit strength, and the experiential aspects of meditative traditions that continue to hold value for many students and clinicians.

6. Contextualize all practice plans within individual differences

The study found no association between duration and habit strength among first-year meditators, suggesting that beginners may experience too much variability and instability for duration to meaningfully predict automaticity. Clinicians who work with early-stage meditators, especially those with anxiety or trauma histories, should provide small, predictable practice expectations that minimize overwhelm. For experienced practitioners with stable routines, expanding duration may be both feasible and beneficial.

Limitations of the Study

This study offers an empirically grounded examination of the relationship between meditation habit strength and typical session duration. However, several limitations should be acknowledged to contextualize the findings within a post positivist framework. These limitations reflect constraints in measurement, sampling, construct validity, and research design. Taken together, they underscore that the relationships identified in this study are probabilistic, contingent, and subject to meaningful uncertainty.

1. Self report measurement of "typical" session duration introduces substantial error

A primary limitation concerns the measurement of meditation duration. Participants provided a single self report estimate of their "typical" session length. Such global self estimations are vulnerable to considerable recall inaccuracy, anchoring effects, rounding biases, and socially desirable inflation. Behavioral research consistently shows that single item duration estimates can deviate markedly from logged behavior, particularly when the target behavior varies across days (Conway et al., 2020). Because this study did not obtain objective time stamps or app based duration logs, typical duration represents an imprecise proxy rather than a robust behavioral measure. This limitation likely attenuates effect sizes and restricts the interpretive strength of duration related findings.

2. The SRHI measures multiple constructs rather than pure automaticity

Although the Self Report Habit Index is widely used and theoretically coherent, its multidimensional structure represents a limitation for the present study. The SRHI conflates automaticity, frequency, and identity related sentiments within a single composite construct. Scholars have noted that this structure makes it difficult to isolate the core automaticity component that habit theory identifies as the central mechanism of habit formation (Gardner et al., 2012). In the context of meditation, identity related items may inflate SRHI scores for individuals who view meditation as personally meaningful even when their behavioral patterns are inconsistent. Conversely, automaticity items may function differently for novice meditators who have not yet formed stable routines. This construct heterogeneity complicates interpretation of the observed relationships between SRHI and duration.

3. Internal consistency of α = .783 suggests nontrivial measurement noise

The Cronbach's alpha of .783 obtained in this study, while acceptable, is lower than the coefficients typically reported for the SRHI, which often exceed .89 (Hagger et al., 2015; Verplanken & Orbell, 2003). Rather than treating this as a minor deviation, a post positivist interpretation requires recognition that reduced internal consistency indicates greater measurement error. This error may attenuate correlations with duration and frequency and may limit the interpretability of regression findings. It may also reflect that meditation is a more heterogeneous behavioral domain than the health habits for which the SRHI was originally validated. Future work may benefit from using the automaticity subscale alone or employing meditation specific measures of routine stability.

4. Absence of measures of meditation quality, style, or technique

The study did not assess the quality of meditation, the technique practiced, or the degree of attentional engagement. Duration alone does not necessarily capture meaningful practice. A twenty minute session characterized by distraction and inconsistent technique may differ substantially from a shorter but more focused session. Meditation quality may moderate the relationship between duration and habit strength, and the absence of such measures limits the conceptual precision of the findings.

5. Motivational heterogeneity was not assessed

Participants were not asked about their reasons for meditating, such as stress reduction, spiritual development, emotional regulation, or clinical treatment. Prior research suggests that motivation meaningfully shapes persistence, identity integration, and self regulatory behavior. Differences in purpose could plausibly moderate the association between duration and habit strength. Without measuring motivation, the study cannot assess whether practitioners who meditate for psychological relief, for contemplative depth, or for social belonging differ in the way duration and frequency relate to their habits.

6. Cross sectional design precludes causal inference and allows for reverse causation

Although the analyses identified associations between duration, frequency, and SRHI scores, the cross sectional design does not support conclusions about causal direction. It remains possible that individuals with strong habits choose longer durations rather than the reverse. It is also possible that strong identity based commitment inflates SRHI scores, which then appear correlated with behavioral measures in a manner that reflects reverse causation. Longitudinal designs would be required to determine whether increases in duration lead to stronger habits or whether habit consolidation leads practitioners to lengthen their sessions.

7. Community context may provide unmeasured support structures

All participants were members of the New Leaf Meditation Project, a community that provides email reminders, social belonging, challenges, and peer support. These contextual features were not measured but may influence habit strength independent of individual behavior. Community mediated scaffolding may inflate SRHI scores or stabilize routines in ways that do not generalize to independent meditators. This contextual embeddedness limits external validity and suggests that the associations observed here may differ in settings without communal reinforcement.

8. Restricted range of meditation durations limits detection of nonlinear effects

The behavioral range of session duration in the sample was relatively narrow. Most practitioners reported durations between fifteen and thirty minutes, with an overall range of five to sixty minutes. This distribution excludes extremely short sessions, such as one to three minute micro practices, which are commonly recommended by instructors and which the practical implications chapter encourages. The absence of micro practices in the dataset limits the ability to make data driven claims about their effectiveness or their relationship to habit strength. The restricted range also reduces sensitivity to potential threshold or asymptotic effects that may occur at very long or very short durations. As a result, conclusions about linearity or the absence of plateaus should be interpreted cautiously.

9. Single community, convenience sample limits generalizability

Because participants were drawn from one online community, findings may not extend to practitioners from other cultural, socioeconomic, or spiritual contexts. The study reflects the behavior of a particular self-selected group with shared norms and expectations. This limitation reinforces the need for future research using multi-site sampling strategies and more diverse populations.

Taken together, these limitations highlight that the study’s conclusions should be interpreted with appropriate caution. They also identify new areas for future research aimed at improving measurement precision, contextual diversity, and theoretical specificity in the study of meditation habit formation.

Recommendations for Future Research

The findings of this study highlight several promising directions for further inquiry into meditation habit formation. As Chapter 5 makes clear, meditation habits appear to develop through processes that are not uniform across time or across levels of practitioner experience. The empirical patterns uncovered here, combined with the theoretical perspectives outlined in earlier chapters, point toward a need for nuanced, phase specific, and longitudinally oriented research. The following recommendations outline the most important priorities for advancing the science of meditation habits in ways that honor the complexity revealed in this study.

1. Investigate Distinct Phases of Habit Development

One of the clearest implications of the findings is the importance of treating habit formation as a phase based developmental process rather than a single trajectory. Chapter 4 demonstrated that meditators with less than one year of experience showed no relationship between duration and SRHI scores, whereas more experienced meditators demonstrated patterns consistent with automaticity theory. This divergence suggests that early-stage habit development may be governed by fundamentally different mechanisms than those involved in later consolidation.

The habit formation literature strongly supports the value of stage specific models. Automaticity develops gradually and often nonlinearly (Lally et al., 2010), with early practice heavily influenced by volatility, inconsistent execution, and greater motivational fluctuation

(Fogg, 2019). Research should therefore aim to differentiate at least three phases: initiation, early stabilization, and consolidation. The early to intermediate transition is particularly important because this period appears to involve shifts from deliberative action to cue driven repetition (Gardner, 2015).

Future studies should explicitly isolate these developmental periods and consider designs that stratify participants by experience level or practice stability. This may include experimental studies manipulating frequency, duration, or cue based supports differentially across phases. Such work would allow researchers to test whether findings like those in the present study hold across diverse contexts or shift meaningfully once foundational behavioral regularity has been established.

2. Conduct Longitudinal Studies Examining Trajectories of Habit Strength Over Time

The cross-sectional nature of the current study, although appropriate for an exploratory analysis, restricts the ability to draw conclusions about developmental pathways or causal mechanisms. Automaticity theory posits that habit strength emerges gradually through repeated exposure to consistent cues and stable behavioral contexts (Wood, 2020). Longitudinal research is therefore essential for assessing how meditation habits strengthen, weaken, or plateau over time.

There are two particularly compelling designs. First, high frequency longitudinal panel studies could track changes in SRHI scores, duration, and weekly frequency over periods of several weeks or months. Prior work has shown that habit formation curves often follow asymptotic growth trajectories (Lally et al., 2010). Replicating this approach within meditation populations would provide critical insight into whether meditation follows similar patterns or exhibits a more variable developmental course.

Second, ecological momentary assessment (EMA) methods could capture real time fluctuations in practice behavior, contextual cues, and motivational states. Because meditation practice interacts with personal meaning making, emotional regulation, and daily stress levels, EMA offers a uniquely rich approach for understanding when and why individuals maintain or interrupt their routines. This would extend the descriptive work in earlier chapters by situating habit strength within dynamic lived environments rather than static self-report estimates.

3. Identify Mechanistic Differences Between Early and Later Habit Consolidation

The findings of this study demonstrate that session duration plays a modest role in predicting habit strength, whereas frequency provides robust predictive value once routines stabilize. However, this pattern is likely an aggregate indicator that masks important mechanistic distinctions between early and later phases of practice. Early habit formation may be more strongly influenced by motivational scaffolding, environmental supports, and perceived identity alignment. In contrast, later consolidation may be driven by distinct processes such as contextual cueing, procedural fluency, and automaticity of initiation.

Recent behavioral theories emphasize that different psychological systems underlie behavior in different stages of habit acquisition (Gardner et al., 2012). For example, early behavior may be shaped by intentionality and self-regulatory effort, while later behavior is more strongly governed by automatic cue response processes. Meditation, with its dual identity as both a health behavior and a meaning oriented contemplative practice, may exhibit even more pronounced mechanistic variation across developmental stages.

Future research should therefore examine whether frequency, duration, identity relevance, environmental cues, self-determination theory constructs, or emotional regulation variables differentially predict early versus later habit strength. Experimental and longitudinal methods would permit more precise modeling of these mechanisms. Multi-level modeling approaches would also enable researchers to examine within person and between person differences simultaneously.

Contribution to Knowledge

This study contributes to the emerging behavioral science of meditation by offering empirically grounded insights into how habit strength relates to the basic structural features of practice. Although modest in scope, the study advances knowledge in four areas: methodological innovation, measurement insight, theoretical refinement, and preliminary guidance for practice.

1. Methodological contribution: Applying the SRHI to meditation behavior

A primary contribution of this dissertation is the application of the Self Report Habit Index to meditation practice, a domain in which habit processes have been theorized but rarely measured quantitatively. The use of the SRHI in this context demonstrates both the feasibility and the challenges of applying an automaticity based instrument to a contemplative behavior. The reliability findings, which were lower than those often observed in health behavior studies, provide initial evidence that meditation may activate the SRHI's multidimensional components in uneven ways. This methodological extension offers a foundation for future research seeking to refine or adapt automaticity measures for contemplative contexts.

2. Measurement insight: Clarifying what operationalizations work and where they fall short

The study also offers important measurement observations. The reliance on self reported "typical" duration revealed substantial variability and potential imprecision in participant estimations, which suggests that duration may be a less stable construct than often assumed. The restricted range of reported session times further illustrates the difficulty of capturing the diversity of real world practice. These insights highlight the need for better operationalizations, including ecological momentary assessment, app based logging, or multi item duration measures. By documenting the constraints of current measurement strategies, the study identifies clear pathways for improving behavioral assessment in meditation research.

3. Theoretical refinement: Modifying expectations about duration and habit development

The findings refine existing theoretical models by clarifying the limited role of duration in predicting meditation habit strength. Duration demonstrated a small positive association with SRHI scores, which indicates that it contributes to habit development but not as strongly as commonly believed. The absence of a duration effect among first year meditators challenges assumptions that longer sessions accelerate early habit formation. These patterns support a theoretical shift toward understanding duration as a secondary characteristic that may signal maturity rather than drive it.

4. Empirical reinforcement of repetition-based mechanisms

The clearest contribution of this study is its empirical support for repetition-based mechanisms of habit formation. Weekly practice frequency, rather than duration, accounted for the largest proportion of variance in SRHI scores. This result aligns with automaticity theory, which identifies repeated cue-based enactment as the central pathway to habit development. Although the study does not validate a full "habit first" framework, it provides evidence that any such framework must prioritize routine stability before session lengthening.

Taken together, these contributions matter because they illuminate how individuals build stable contemplative routines in contemporary life. In a behavioral landscape marked by distraction, competing demands, and limited time, understanding the mechanisms that support sustainable meditation is essential for both scientific progress and public well being. By demonstrating that repetition rather than duration best predicts habit strength, this study advances the science of habit formation, challenges long standing assumptions within contemplative pedagogy, and opens new directions for designing accessible, realistic, and sustainable pathways into meditation practice.

Conclusion

The purpose of this study was to clarify how meditation habit strength relates to typical session duration within a large online community of contemporary practitioners. Framed within a post positivist philosophical orientation and guided by an inductive analytic approach, the investigation sought to determine whether duration functions as a central mechanism of habit formation or whether repetition plays the dominant role in the development of automaticity. The findings provide a coherent and empirically grounded response to the questions raised in the introductory chapters. They indicate that although session duration is modestly associated with higher SRHI scores in the overall sample, its influence is limited and context dependent. Duration did not predict habit strength among first year meditators, nor did it distinguish the most experienced or most consistent practitioners from the broader sample. In contrast, weekly practice frequency emerged as the strongest behavioral correlate of habit strength across all analyses.

Taken together, these results offer a clear resolution to the central problem that motivated this study. The behavioral consolidation of meditation habits is driven primarily by repetition and secondarily supported by length. This pattern was evident in the large incremental variance explained by weekly frequency in hierarchical regression models, the absence of duration effects among novices, and the distinctive consistency of practice among individuals with the strongest habits. These findings align closely with automaticity theory, which emphasizes repeated cue-based enactment as the foundation of habit formation, and they challenge long standing assumptions within contemplative training that place duration at the center of practice design. The study therefore contributes empirical clarity to a topic that has historically been guided more by tradition and intuition than by systematic behavioral evidence.

By demonstrating that frequency is the most reliable behavioral predictor of habit strength, this research offers a refined conceptual model for understanding how meditation routines develop over time. Duration can enrich practice, deepen engagement, and support identity integration, but it does not serve as the primary mechanism through which meditation becomes automatic. Instead, frequent enactment within stable contexts appears to be the behavioral architecture that sustains long term practice. This insight has important implications for meditation instruction, clinical intervention, and future research design, particularly in recognizing that early practice should prioritize small, repeatable behaviors over longer, aspirational sessions.

There are substantial benefits associated with a regular meditation habit; however, these benefits are not realized without consistent practice. This researcher hopes the present study will encourage meditation instructors, therapists, and other wellness professionals to prioritize helping their students establish consistent routines, emphasizing frequency of practice first and then increased duration last.

REFERENCES

Aguinis, H., Gottfredson, R. K., & Joo, H. (2013). Best-practice recommendations for defining, identifying, and handling outliers. *Organizational Research Methods*, *16*(2), 270–301. https://doi.org/10.1177/1094428112470848

Ashby, F. G., Turner, B. O., & Horvitz, J. C. (2010). Cortical and basal ganglia contributions to habit learning and Automaticity. *Trends in Cognitive Sciences*, *14*(5), 208–215. https://doi.org/10.1016/j.tics.2010.02.001

Balleine, B. W., & Dezfouli, A. (2019). Hierarchical action control: Adaptive collaboration between actions and habits. *Frontiers in Psychology*, *10*. https://doi.org/10.3389/fpsyg.2019.02735

Balleine, B. W., & O'Doherty, J. P. (2009). Human and rodent homologies in action control: Corticostriatal determinants of goal-directed and habitual action. *Neuropsychopharmacology*, *35*(1), 48–69. https://doi.org/10.1038/npp.2009.131

Barceló-Soler, A., Morillo-Sarto, H., Fernández-Martínez, S., Monreal-Bartolomé, A., Chambel, M. J., Gardiner, P., López-del-Hoyo, Y., García-Campayo, J., & Pérez-Aranda, A. (2023). A systematic review of the adherence to home-practice meditation exercises in patients with chronic pain. *International Journal of Environmental Research and Public Health*, *20*(5), 4438. https://doi.org/10.3390/ijerph20054438

Berkman, E. T. (2018). The neuroscience of goals and behavior change. *Consulting Psychology Journal: Practice and Research*, *70*(1), 28–44. https://doi.org/10.1037/cpb0000094

Beshears, J., Choi, J., Laibson, D., & Madrian, B. (2019). *Active Choice, Implicit Defaults, and the Incentive to Choose*. https://doi.org/10.3386/w25473

Bethlehem, J. (2010). Selection bias in web surveys. *International Statistical Review*, *78*(2), 161–188. https://doi.org/10.1111/j.1751-5823.2010.00112.x

Bishop, S. R. (2002). What do we really know about mindfulness-based stress reduction? *Psychosomatic Medicine*, *64*(1), 71–83. https://doi.org/10.1097/00006842-200201000-00010

Bishop, S. R., Lau, M., Shapiro, S., Carlson, L., Anderson, N. D., Carmody, J., Segal, Z. V., Abbey, S., Speca, M., Velting, D., & Devins, G. (2004). Mindfulness: A proposed operational definition. *Clinical Psychology: Science and Practice*, *11*(3), 230–241. https://doi.org/10.1093/clipsy.bph077

Blanca, M., Alarcón, R., Arnau, J., Bono, R., & Bendayan, R. (2017). Non-normal data: Is anova still a valid option? *Psicothema*, *4*(29), 552–557. https://doi.org/10.7334/psicothema2016.383

Bornstein, A. M., & Daw, N. D. (2011). Multiplicity of control in the basal ganglia: Computational roles of striatal subregions. *Current Opinion in Neurobiology*, *21*(3), 374–380. https://doi.org/10.1016/j.conb.2011.02.009

Bowen, M., & Beam, M. (2025). Mapping mindfulness: Assessing the stages of meditation habit formation in the USA using the sussex mindfulness meditation (summed) model. *Mindfulness*, *16*(5), 1340–1351. https://doi.org/10.1007/s12671-025-02555-2

Cearns, M., & Clark, S. R. (2023a). The effects of dose, practice habits, and objects of focus on digital meditation effectiveness and adherence: Longitudinal Study of 280,000 digital meditation sessions across 103 countries. *Journal of Medical Internet Research*, *25*. https://doi.org/10.2196/43358

Chivers, M. L., Rieger, G., Latty, E., & Bailey, J. M. (2004). A sex difference in the specificity of sexual arousal. *Psychological Science*, *15*(11), 736–744. https://doi.org/10.1111/j.0956-7976.2004.00750.x

Cloughesy, J. N., Mrazek, A. J., Mrazek, M. D., & Schooler, J. W. (2020). Planning to practice: Action and coping plans increase days of meditation practiced. *Psi Chi Journal of Psychological Research*, *25*(2), 203–209. https://doi.org/10.24839/2325-7342.jn25.2.203

Duhigg, C. (2021). *The Power of Habit*. Memories of Ages Press.

Faul, F., Erdfelder, E., Buchner, A., & Lang, A.-G. (2009). Statistical Power analyses using G*Power 3.1: Tests for correlation and regression analyses. *Behavior Research Methods*, *41*(4), 1149–1160. https://doi.org/10.3758/brm.41.4.1149

Faul, F., Erdfelder, E., Lang, A.-G., & Buchner, A. (2007). G*Power 3: A flexible statistical power analysis program for the social, Behavioral, and Biomedical Sciences. *Behavior Research Methods*, *39*(2), 175–191. https://doi.org/10.3758/bf03193146

Fincham, G. W., Mavor, K., & Dritschel, B. (2023). Effects of mindfulness meditation duration and type on well-being: An online dose-ranging randomized controlled trial. *Mindfulness*, *14*(5), 1171–1182. https://doi.org/10.1007/s12671-023-02119-2

Fogg, B. J. (2021). *Tiny Habits: The small changes that change everything*. Mariner Books.

Frey, E., & Rogers, T. (2014a). Persistence. *Policy Insights from the Behavioral and Brain Sciences*, *1*(1), 172–179. https://doi.org/10.1177/2372732214550405

Gardner, B. (2014). A review and analysis of the use of 'habit' in understanding, predicting and influencing health-related behaviour. *Health Psychology Review*, *9*(3), 277–295. https://doi.org/10.1080/17437199.2013.876238

Gardner, B., & Rebar, A. L. (2019). Habit formation and behavior change. *Oxford Research Encyclopedia of Psychology*. https://doi.org/10.1093/acrefore/9780190236557.013.129

Gardner, B., Arden, M. A., Brown, D., Eves, F. F., Green, J., Hamilton, K., Hankonen, N., Inauen, J., Keller, J., Kwasnicka, D., Labudek, S., Marien, H., Masaryk, R., McCleary, N., Mullan, B. A., Neter, E., Orbell, S., Potthoff, S., & Lally, P. (2021). Developing habit-based health behaviour change interventions: Twenty-one questions to guide future research. *Psychology & Health*, *38*(4), 518–540. https://doi.org/10.1080/08870446.2021.2003362

Gardner, B., Lally, P., & Wardle, J. (2012). Making health habitual: The psychology of 'habit-formation' and general practice. *British Journal of General Practice*, *62*(605), 664–666. https://doi.org/10.3399/bjgp12x659466

Greco, L. A., & Hayes, S. C. (2008). *Acceptance & Mindfulness Treatments for Children & Adolescents: A practitioner's guide* (1st ed., Vol. 1). Context Press.

Grossman, P, Niemann, L., Schmidt, S., & Walach, H. (2003a). Mindfulness-based stress reduction and health benefits: A meta-analysis. *Focus on Alternative and Complementary Therapies*, *8*(4), 500–500. https://doi.org/10.1111/j.2042-7166.2003.tb04008.x

Grossman, Paul, Niemann, L., Schmidt, S., & Walach, H. (2004). Mindfulness-based stress reduction and health benefits. *Journal of Psychosomatic Research*, *57*(1), 35–43. https://doi.org/10.1016/s0022-3999(03)00573-7

Hagger, M. S., Chatzisarantis, N. L., Alberts, H., Anggono, C. O., Batailler, C., Birt, A. R., Brand, R., Brandt, M. J., Brewer, G., Bruyneel, S., Calvillo, D. P., Campbell, W. K., Cannon, P. R., Carlucci, M., Carruth, N. P., Cheung, T., Crowell, A., De Ridder, D. T., Dewitte, S., … Zwienenberg, M. (2016). A multilab preregistered replication of the egodepletion effect. *Perspectives on Psychological Science*, *11*(4), 546–573. https://doi.org/10.1177/1745691616652873

Hardwick, R. M., Forrence, A. D., Krakauer, J. W., & Haith, A. M. (2019). Time-dependent competition between goal-directed and habitual response preparation. *Nature Human Behaviour*, *3*(12), 1252–1262. https://doi.org/10.1038/s41562-019-0725-0

Havranek, T., Rusnak, M., & Sokolova, A. (2017). Habit formation in consumption: A meta-analysis. *European Economic Review*, *95*, 142–167. https://doi.org/10.1016/j.euroecorev.2017.03.009

Judah, G., Gardner, B., & Aunger, R. (2012). Forming a flossing habit: An exploratory study of the psychological determinants of habit formation. *British Journal of Health Psychology*, *18*(2), 338–353. https://doi.org/10.1111/j.2044-8287.2012.02086.x

Kaushal, N., & Rhodes, R. E. (2015). Exercise habit formation in new gym members: A longitudinal study. *Journal of Behavioral Medicine*, *38*(4), 652–663. https://doi.org/10.1007/s10865-015-9640-7

Kermavnar, T., & Desmet, P. M. (2024a). Technology and meditation: Exploring the challenges and benefits of a physical device to support meditation routine. *Multimodal Technologies and Interaction*, *8*(2), 9. https://doi.org/10.3390/mti8020009

Killeen, T. K., & Brewerton, T. D. (2024b). More is less pain and less opioid misuse: A mindful remedy. *American Journal of Psychiatry*, *181*(2), 89–91. https://doi.org/10.1176/appi.ajp.20231001

Lally, P., van Jaarsveld, C. H., Potts, H. W., & Wardle, J. (2009). How are habits formed: Modelling Habit Formation in the real world. *European Journal of Social Psychology*, *40*(6), 998–1009. https://doi.org/10.1002/ejsp.674

Lam, S. U., Riordan, K. M., Simonsson, O., Davidson, R. J., & Goldberg, S. B. (2023). Who sticks with meditation? rates and predictors of persistence in a population-based sample in the USA. *Mindfulness*, *14*(1), 66–78. https://doi.org/10.1007/s12671-022-02061-9

Leaf, C., Wasserman, C., Leaf, A., Kopooshian, N., Turner, R., & Paulson, R. (2024). Habit formation and automaticity: Psychoneurobiological correlates of Gamma Activity. *NeuroRegulation*, *11*(1), 2–24. https://doi.org/10.15540/nr.11.1.2

Ma, H., Wang, A., Pei, R., & Piao, M. (2023). Effects of habit formation interventions on physical activity habit strength: Meta-analysis and meta-regression. *International Journal of Behavioral Nutrition and Physical Activity*, *20*(1). https://doi.org/10.1186/s12966-023-01493-3

Maksudul Shadat Akash, & Shahanaz Chowdhury. (2025). Small changes, big impact: A mini review of habit formation and behavioral change principles. *World Journal of Advanced Research and Reviews*, *26*(1), 3098–3106. https://doi.org/10.30574/wjarr.2025.26.1.1333

Meyer, J. D., & Torres, E. R. (2018). Benefits of 8-WK mindfulness-based stress reduction or aerobic training on seasonal declines in physical activity. *Medicine & Science in Sports & Exercise*, *50*(9), 1850–1858. https://doi.org/10.1249/mss.0000000000001636

Miles, E., Matcham, F., Strauss, C., & Cavanagh, K. (2023a). Making mindfulness meditation a healthy habit. *Mindfulness*, *14*(12), 2988–3005. https://doi.org/10.1007/s12671-023-02258-6

Neifeld, M. R. (1924). Formulas for facilitating the computation of the mean of the distribution obtained by combining component distributions. *Journal of Educational Psychology*, *15*(9), 588–591. https://doi.org/10.1037/h0073354

Norcross, J. C., & Vangarelli, D. J. (1988). The Resolution Solution: Longitudinal Examination of New Year's change attempts. *Journal of Substance Abuse*, *1*(2), 127–134. https://doi.org/10.1016/s0899-3289(88)80016-6

Orbell, S., & Verplanken, B. (2010). The automatic component of habit in health behavior: Habit as cue-contingent automaticity. *Health Psychology*, *29*(4), 374–383. https://doi.org/10.1037/a0019596

Orbell, S., & Verplanken, B. (2020). Changing behavior using habit theory. *The Handbook of Behavior Change*, 178–192. https://doi.org/10.1017/9781108677318.013

Roozenbeek, J., Culloty, E., & Suiter, J. (2023). Countering misinformation. *European Psychologist*, *28*(3), 189–205. https://doi.org/10.1027/1016-9040/a000492

Schlomer, G. L., Bauman, S., & Card, N. A. (2010). Best practices for missing data management in counseling psychology. *Journal of Counseling Psychology*, *57*(1), 1–10. https://doi.org/10.1037/a0018082

Schmider, E., Ziegler, M., Danay, E., Beyer, L., & Bühner, M. (2010). Is it really robust? *Methodology*, *6*(4), 147–151. https://doi.org/10.1027/1614-2241/a000016

Singh, B., Murphy, A., Maher, C., & Smith, A. E. (2024a). Time to form a habit: A systematic review and meta-analysis of health behaviour habit formation and its determinants. *Healthcare*, *12*(23), 2488. https://doi.org/10.3390/healthcare12232488

Slemp, G. R., Jach, H. K., Chia, A., Loton, D. J., & Kern, M. L. (2019b). Contemplative interventions and employee distress: A meta-analysis. *Stress and Health*, *35*(3), 227–255. https://doi.org/10.1002/smi.2857

Stecher, C., Sullivan, M., & Huberty, J. (2021a). Using personalized anchors to establish routine meditation practice with a mobile app: Randomized Controlled Trial. *JMIR mHealth and uHealth*, *9*(12). https://doi.org/10.2196/32794

Stojanovic, M., & Wood, W. (2024b). Beyond deliberate self-control: Habits automatically achieve long-term goals. *Current Opinion in Psychology*, *60*, 101880. https://doi.org/10.1016/j.copsyc.2024.101880

Tang, S. (2023). *Underestimating Habits: Explanations of Habitual Behavior in the Adult Population* (dissertation). National College of Ireland, Dublin.

Tricomi, E., Balleine, B. W., & O'Doherty, J. P. (2009). A specific role for posterior dorsolateral striatum in human habit learning. *European Journal of Neuroscience*, *29*(11), 2225–2232. https://doi.org/10.1111/j.1460-9568.2009.06796.x

Verplanken, B. (2006). Beyond frequency: Habit as mental construct. *British Journal of Social Psychology*, *45*(3), 639–656. https://doi.org/10.1348/014466605x49122

Verplanken, B., & Orbell, S. (2003). Reflections on past behavior: A Self-report index of Habit Strength¹. *Journal of Applied Social Psychology*, *33*(6), 1313–1330. https://doi.org/10.1111/j.1559-1816.2003.tb01951.x

Verplanken, B., & Sui, J. (2019). Habit and identity: Behavioral, cognitive, affective, and motivational facets of an integrated self. *Frontiers in Psychology*, *10*. https://doi.org/10.3389/fpsyg.2019.01504

Verplanken, B., Walker, I., Davis, A., & Jurasek, M. (2008). Context change and travel mode choice: Combining the habit discontinuity and self-activation hypotheses. *Journal of Environmental Psychology*, *28*(2), 121–127. https://doi.org/10.1016/j.jenvp.2007.10.005

Wilhelm, M. O., Brown, E., Rooney, P. M., & Steinberg, R. (2008). The intergenerational transmission of generosity. *Journal of Public Economics*, *92*(10–11), 2146–2156. https://doi.org/10.1016/j.jpubeco.2008.04.004

Wood, W., & Neal, D. T. (2007). A new look at habits and the habit-goal interface. *Psychological Review*, *114*(4), 843–863. https://doi.org/10.1037/0033-295x.114.4.843

Wood, W., & Rünger, D. (2016). Psychology of habit. *Annual Review of Psychology*, *67*(1), 289–314. https://doi.org/10.1146/annurev-psych-122414-033417

Wood, W., Quinn, J. M., & Kashy, D. A. (2002). Habits in everyday life: Thought, emotion, and action. *Journal of Personality and Social Psychology*, *83*(6), 1281–1297. https://doi.org/10.1037/0022-3514.83.6.1281

Wyatt, Z. (2024). The Neuroscience of Habit Formation. *Neurology and Neuroscience*, *5*(1). https://doi.org/10.33425/2692-7918.1063

Yin, H. H., & Knowlton, B. J. (2006). The role of the basal ganglia in habit formation. *Nature Reviews Neuroscience*, *7*(6), 464–476. https://doi.org/10.1038/nrn1919

Zgierska, A. E., Burzinski, C. A., Cox, J., Kloke, J., Stegner, A., Cook, D. B., Singles, J., Mirgain, S., Coe, C. L., & Bačkonja, M. (2016). Mindfulness meditation and cognitive behavioral therapy intervention reduces pain severity and sensitivity in opioid-treated chronic low back pain: Pilot findings from a randomized controlled trial. *Pain Medicine*, *17*(10), 1865–1881. https://doi.org/10.1093/pm/pnw006

APPENDIX A

Survey Instrument

Meditating is something . . .

1. I do frequently. (Strongly disagree to strongly agree)

2. I do automatically. (Strongly disagree to strongly agree)

3. I do without having to consciously remember. (Strongly disagree to strongly agree)

4. that makes me feel weird if I do not do it. (Strongly disagree to strongly agree)

5. I do without thinking. (Strongly disagree to strongly agree)

6. that would require effort not to do it. (Strongly disagree to strongly agree)

7. that belongs to my daily routine. (Strongly disagree to strongly agree)

8. I start doing before I realize I'm doing it. (Strongly disagree to strongly agree)

9. I would find hard not to do. (Strongly disagree to strongly agree)

10. I have no need to think about doing. (Strongly disagree to strongly agree)

11. that's typically "me." (Strongly disagree to strongly agree)

12. I have been doing for a long time. (Strongly disagree to strongly agree)

Meditation Practice Descriptives:

13. In the past seven days I meditated: (0-7 days)

14. In a typical seven day week I meditate: (0-7 days)

15. When I meditate, I typically meditate for ____ minutes (0-999)

16. I have been meditating for ____ years and ______ months

Demographics:

17. Age range ("Under 18", "18-24", "25-34", "35-44", etc.)

18. Gender ("Male", "Female", "Non-binary/Third gender", "Prefer not to say")

19. "What is the highest level of education you have completed?" ("Less than high school", "High school diploma or equivalent", "Some college", "Associate degree", "Bachelor's degree", "Master's degree", "Doctoral degree", "Professional degree")

20. "What is your marital status?"("Single", "Married", "In a domestic partnership/civil union", "Divorced", "Widowed")

21. What is your race/ethnicity? (Select all that apply)

White, Black or African American, American Indian or Alaska Native, Asian, Native Hawaiian or Other Pacific Islander, Hispanic or Latino, Some Other Race (please specify): __________

APPENDIX B

MARYWOOD UNIVERSITY
EXEMPT REVIEW COMMITTEE
Immaculata Hall, 2300 Adams Avenue, Scranton, PA 18509

DATE:	November 20, 2025
TO:	Anthony Cernera, M.Ed.
FROM:	Marywood University Exempt Review Committee
STUDY TITLE:	[2208161-4] *Doctoral Research*
MU ERC #:	
SUBMISSION TYPE:	Amendment/Modification
ACTION:	APPROVED
APPROVAL DATE:	November 20, 2025
CHECK IN DUE DATE:	November 20, 2026
REVIEW TYPE:	Exempt Review
EXEMPT CATEGORY:	45 CFR 46.104 (d)()()

Dear Mr./Mrs/Ms./Dr. Cernera:

Thank you for your submission of Amendment/Modification materials to your Exemption Request for this research study. Marywood University's ERC has **APPROVED** your submission. The project meets federal exemption criteria and involves minimal risk to subjects participating in the research. All research must be conducted in accordance with this approved submission.

Please remember that informed consent is a process beginning with a complete description of the study and assurance of subject understanding.

We have applied the ERC's approval stamp to the following documents, which have been uploaded with this letter in IRBNet. The stamp must appear on versions shared with subjects wherever possible. If it is not feasible to use the stamped versions online (e.g. some email systems or survey platforms), please ensure that the language in the transmitted versions is identical to the stamped versions.

1. Informed Consent Form
2. Advertisement

Please also note that:

- **CLOSURE REPORTING:** Upon completion of the research, you must file a closure report form via IRBNet.
- **CHECK IN REPORTING:** While there is no expiration date for exempted studies, the ERC maintains oversight of open projects. If activities will continue beyond your approval's one-year anniversary of __11/20/26____, file a check in form by that date.
- **RECORDS RETENTION:** While there is no minimum retention period for exempted studies, you must retain records for the length of time stated in your application and informed consent form.
- **DEVIATION, UNANTICIPATED PROBLEM OR SERIOUS ADVERSE EVENT REPORTING:** If any of these events occur, you must file the appropriate form immediately via IRBNet.
- **REVISION REQUESTS:** If you decide to make procedural or document changes to your approved project, you must file a revision request form for review and approval prior to implementation, except when necessary to eliminate apparent, immediate hazards to the subjects. In hazardous situations, you must file the form immediately afterward.

Forms for the reports mentioned above may be found on the ERC's website or in IRBNet's Forms library. The library appears after you begin a follow-up package within your existing project and then click the Designer button on the left menu, followed by the blue "Need forms" link on the main screen (opens library under Step 1).

If you have any questions, please contact the Research Office at 570-348-6211, x.2418 or irbhelp@marywood.edu. Please include your study title and IRBNet number in all correspondence with this office.

Thank you and good luck with your research!

Regards,
Exempt Review Committee

APPENDIX C

Curve Fit

Notes

Output Created		22-NOV-2025 20:19:26
Comments		
Input	Data	C: \Users\acernera\Documents\Survey Data with Rankings.sav
	Active Dataset	DataSet1
	Filter	<none>
	Weight	<none>
	Split File	<none>
	N of Rows in Working Data File	89
Missing Value Handling	Definition of Missing	User-defined missing values are treated as missing.
	Cases Used	Cases with a missing value in any variable are not used in the analysis.
Syntax		CURVEFIT /VARIABLES=SRHI WITH Time /CONSTANT /MODEL=LINEAR LOGARITHMIC QUADRATIC CUBIC EXPONENTIAL /PLOT FIT.
Resources	Processor Time	00:00:00.39
	Elapsed Time	00:00:00.18
Use	From	First observation
	To	Last observation
Predict	From	First Observation following the use period
	To	Last observation
Time Series Settings (TSET)	Amount of Output	PRINT = DEFAULT
	Saving New Variables	NEWVAR = NONE
	Maximum Number of Lags in Autocorrelation or Partial Autocorrelation Plots	MXAUTO = 16
	Maximum Number of Lags Per Cross-Correlation Plots	MXCROSS = 7

Notes

	Maximum Number of New Variables Generated Per Procedure	MXNEWVAR = 60
	Maximum Number of New Cases Per Procedure	MXPREDICT = 1000
	Treatment of User-Missing Values	MISSING = EXCLUDE
	Confidence Interval Percentage Value	CIN = 95
	Tolerance for Entering Variables in Regression Equations	TOLER = .0001
	Maximum Iterative Parameter Change	CNVERGE = .001
	Method of Calculating Std. Errors for Autocorrelations	ACFSE = IND
	Length of Seasonal Period	Unspecified
	Variable Whose Values Label Observations in Plots	Unspecified
	Equations Include	CONSTANT

Model Description

Model Name		MOD_1
Dependent Variable	1	SRHI
Equation	1	Linear
	2	Logarithmic
	3	Quadratic
	4	Cubic
	5	Exponential[a]
Independent Variable		Time
Constant		Included
Variable Whose Values Label Observations in Plots		Unspecified
Tolerance for Entering Terms in Equations		.0001

a. The model requires all non-missing values to be positive.

Case Processing Summary

	N
Total Cases	89
Excluded Cases[a]	0
Forecasted Cases	0
Newly Created Cases	0

a. Cases with a missing value in any variable are excluded from the analysis.

Variable Processing Summary

		Variables	
		Dependent	Independent
		SRHI	Time
Number of Positive Values		89	89
Number of Zeros		0	0
Number of Negative Values		0	0
Number of Missing Values	User-Missing	0	0
	System-Missing	0	0

Model Summary and Parameter Estimates

Dependent Variable: SRHI

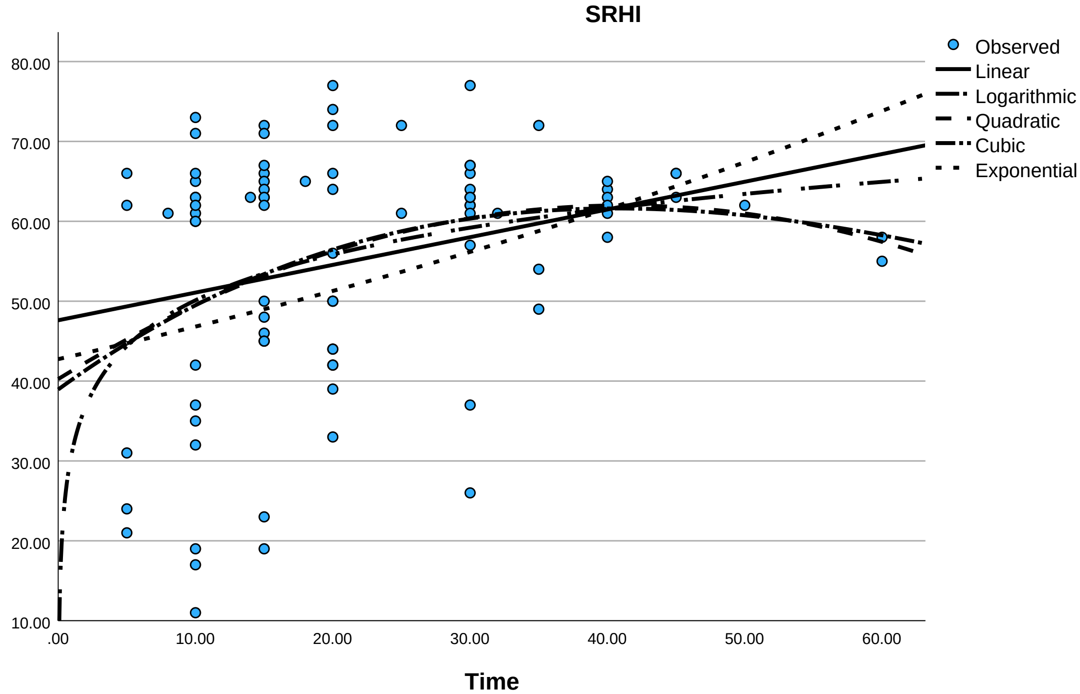
	Model Summary					Parameter Estimates	
Equation	R Square	F	df1	df2	Sig.	Constant	b1
Linear	.081	7.637	1	87	.007	47.609	.347
Logarithmic	.105	10.168	1	87	.002	31.060	8.274
Quadratic	.107	5.170	2	86	.008	40.247	1.056
Cubic	.108	3.416	3	85	.021	38.945	1.249
Exponential	.091	8.688	1	87	.004	42.743	.009

Model Summary and Parameter Estimates

Dependent Variable: SRHI

	Parameter Estimates	
Equation	b2	b3
Linear		
Logarithmic		
Quadratic	-.013	
Cubic	-.020	8.052E-5
Exponential		

The independent variable is Time.


SRHI
Observed
Linear
Logarithmic
Quadratic
Cubic
Exponential
80.00
70.00
60.00
50.00
40.00
30.00
20.00
10.00
.00
10.00
20.00
30.00
40.00
50.00
60.00
Time

Frequencies

Notes

Output Created		22-NOV-2025 15:31:20
Comments		
Input	Data	C: \Users\acernera\Documents\Survey Data.sav
	Active Dataset	DataSet0
	Filter	<none>
	Weight	<none>
	Split File	<none>
	N of Rows in Working Data File	89
Missing Value Handling	Definition of Missing	User-defined missing values are treated as missing.
	Cases Used	Statistics are based on all cases with valid data.
Syntax		FREQUENCIES VARIABLES=Age Gender Experience Education Relationship Hispanic Race /ORDER=ANALYSIS.
Resources	Processor Time	00:00:00.02
	Elapsed Time	00:00:00.01

```
[DataSet0] C:\Users\acernera\Documents\Survey Data.sav
```

Statistics

		Age	Gender	Experience	Education	Relationship	Hispanic	Race
N	Valid	89	89	89	89	89	89	89
	Missing	0	0	0	0	0	0	0

Frequency Table

Age

	N	%
18 to 29	4	4.5%
30 to 39	25	28.1%
40 to 49	28	31.5%
50 to 59	18	20.2%
60+	14	15.7%

Gender

	N	%
Male	33	37.1%
Female	54	60.7%
Prefer not to say	1	1.1%
9.00	1	1.1%

Experience

	N	%
Less than 1 Year	21	23.6%
1 to 3 years	21	23.6%
4 to 7 years	12	13.5%
8 to 10 years	8	9.0%
11 or more years	27	30.3%

Education

	N	%
High School	11	12.4%
Bachelor's Degree	45	50.6%
Master's Degree	26	29.2%
Doctorate	7	7.9%

Relationship

	N	%
Single	30	33.7%
Married	40	44.9%
Divorced	11	12.4%
Widower	3	3.4%
In a domestic partnership	3	3.4%
Other	1	1.1%
Prefer not to say	1	1.1%

Hispanic

	N	%
Not of Hispanic origin	82	92.1%
Yes of Hispanic origin	5	5.6%
3.00	1	1.1%
Prefer not to say	1	1.1%

Race

	N	%
White	84	94.4%
Black	1	1.1%
Asian	3	3.4%
Prefer not to say	1	1.1%

Descriptives

Notes

Output Created		22-NOV-2025 15:35:54
Comments		
Input	Data	C: \Users\acernera\Documents\Survey Data.sav
	Active Dataset	DataSet0
	Filter	<none>
	Weight	<none>
	Split File	<none>
	N of Rows in Working Data File	89
Missing Value Handling	Definition of Missing	User defined missing values are treated as missing.
	Cases Used	All non-missing data are used.
Syntax		DESCRIPTIVES VARIABLES=Time ThisWeek NormalWeek Experience SRHI /STATISTICS=MEAN STDDEV MIN MAX.
Resources	Processor Time	00:00:00.00
	Elapsed Time	00:00:00.00

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
Time	89	5.00	60.00	21.7640	12.55716
ThisWeek	89	.00	7.00	4.1573	1.90632
NormalWeek	89	.00	7.00	4.7528	1.96145
Experience	89	1.00	5.00	2.9888	1.58469
SRHI	89	11.00	77.00	55.1573	15.33038
Valid N (listwise)	89				

Explore

Notes

Output Created		22-NOV-2025 15:38:54
Comments		
Input	Data	C:\Users\acernera\Documents\Survey Data.sav
	Active Dataset	DataSet0
	Filter	<none>
	Weight	<none>
	Split File	<none>
	N of Rows in Working Data File	89
Missing Value Handling	Definition of Missing	User-defined missing values for dependent variables are treated as missing.
	Cases Used	Statistics are based on cases with no missing values for any dependent variable or factor used.
Syntax		EXAMINE VARIABLES=SRHI Time ThisWeek NormalWeek Experience /PLOT BOXPLOT HISTOGRAM NPPLOT /COMPARE GROUPS /STATISTICS DESCRIPTIVES /CINTERVAL 95 /MISSING LISTWISE /NOTOTAL.
Resources	Processor Time	00:00:05.09
	Elapsed Time	00:00:02.60

Case Processing Summary

	Cases					
	Valid		Missing		Total	
	N	Percent	N	Percent	N	Percent
SRHI	89	100.0%	0	0.0%	89	100.0%
Time	89	100.0%	0	0.0%	89	100.0%
ThisWeek	89	100.0%	0	0.0%	89	100.0%
NormalWeek	89	100.0%	0	0.0%	89	100.0%
Experience	89	100.0%	0	0.0%	89	100.0%

Descriptives

			Statistic	Std. Error
SRHI	Mean		55.1573	1.62502
	95% Confidence Interval for Mean	Lower Bound	51.9279	
		Upper Bound	58.3867	
	5% Trimmed Mean		56.1816	
	Median		62.0000	
	Variance		235.020	
	Std. Deviation		15.33038	
	Minimum		11.00	
	Maximum		77.00	
	Range		66.00	
	Interquartile Range		19.50	
	Skewness		-1.130	.255
	Kurtosis		.490	.506
Time	Mean		21.7640	1.33106
	95% Confidence Interval for Mean	Lower Bound	19.1188	
		Upper Bound	24.4092	
	5% Trimmed Mean		20.9675	
	Median		20.0000	
	Variance		157.682	
	Std. Deviation		12.55716	
	Minimum		5.00	
	Maximum		60.00	
	Range		55.00	
	Interquartile Range		20.00	
	Skewness		.958	.255
	Kurtosis		.530	.506
ThisWeek	Mean		4.1573	.20207
	95% Confidence Interval for Mean	Lower Bound	3.7557	
		Upper Bound	4.5589	

Descriptives

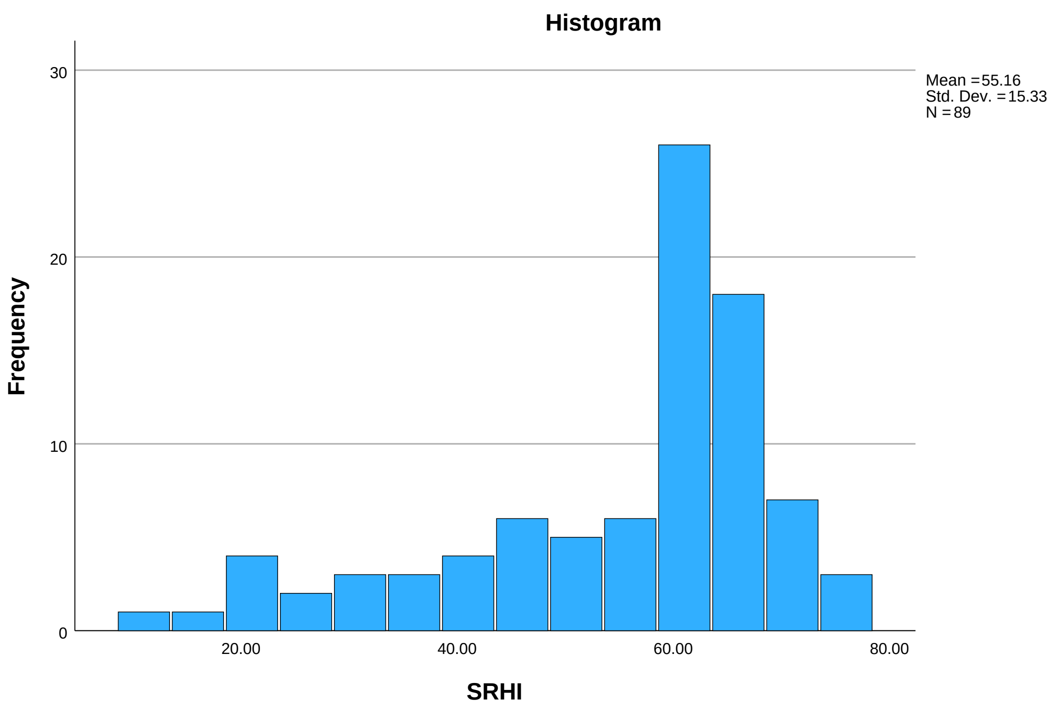
			Statistic	Std. Error
	5% Trimmed Mean		4.2122	
	Median		4.0000	
	Variance		3.634	
	Std. Deviation		1.90632	
	Minimum		.00	
	Maximum		7.00	
	Range		7.00	
	Interquartile Range		2.00	
	Skewness		-.210	.255
	Kurtosis		-.547	.506
NormalWeek	Mean		4.7528	.20791
	95% Confidence Interval for Mean	Lower Bound	4.3396	
		Upper Bound	5.1660	
	5% Trimmed Mean		4.8489	
	Median		5.0000	
	Variance		3.847	
	Std. Deviation		1.96145	
	Minimum		.00	
	Maximum		7.00	
	Range		7.00	
	Interquartile Range		4.00	
	Skewness		-.542	.255
	Kurtosis		-.636	.506
Experience	Mean		2.9888	.16798
	95% Confidence Interval for Mean	Lower Bound	2.6549	
		Upper Bound	3.3226	
	5% Trimmed Mean		2.9875	
	Median		3.0000	
	Variance		2.511	
	Std. Deviation		1.58469	
	Minimum		1.00	
	Maximum		5.00	
	Range		4.00	
	Interquartile Range		3.00	
	Skewness		.124	.255
	Kurtosis		-1.564	.506

Tests of Normality

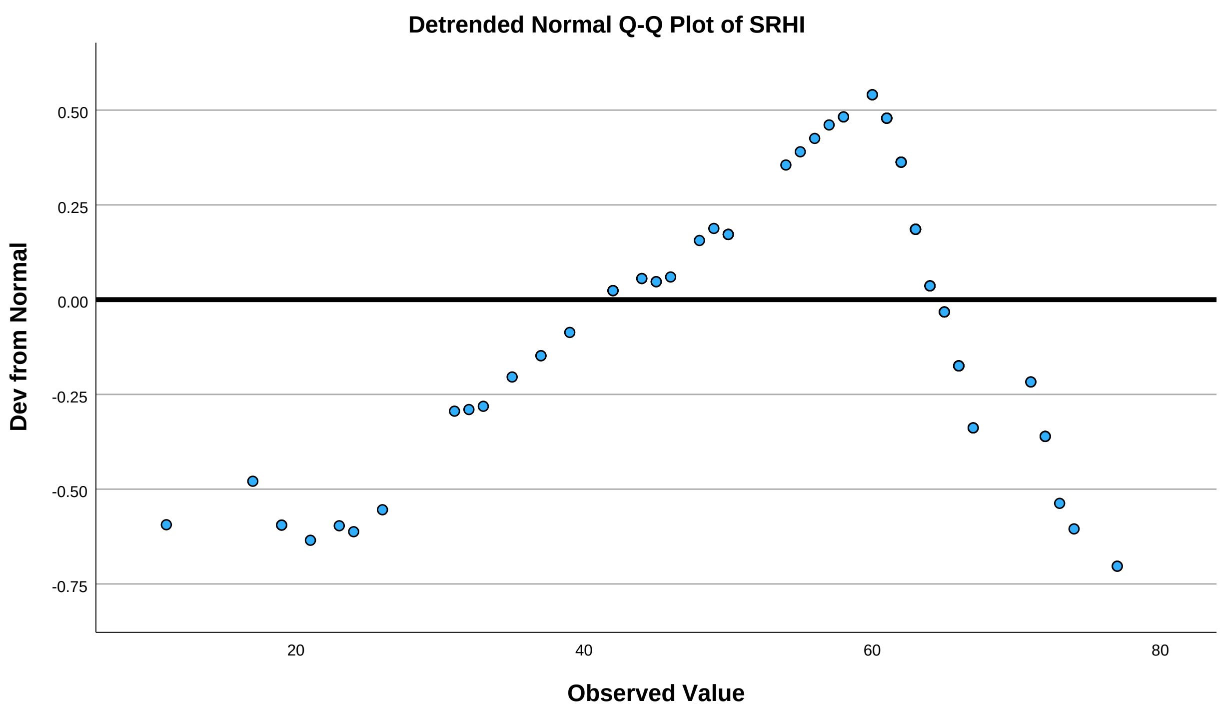
	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
SRHI	.231	89	<.001	.872	89	<.001
Time	.196	89	<.001	.905	89	<.001
ThisWeek	.109	89	.011	.939	89	<.001
NormalWeek	.191	89	<.001	.889	89	<.001
Experience	.206	89	<.001	.835	89	<.001

a. Lilliefors Significance Correction

SRHI




Normal Q-Q Plot of SRHI
Expected Normal
2
0
-2
-4
0
20
40
60
80
100
Observed Value


Detrended Normal Q-Q Plot of SRHI
Dev from Normal
0.50
0.25
0.00
-0.25
-0.50
-0.75
20
40
60
80
Observed Value

Notes

Syntax		REGRESSION /MISSING LISTWISE /STATISTICS COEFF OUTS R ANOVA /CRITERIA=PIN(.05) POUT(.10) TOLERANCE(.0001) /NOORIGIN /DEPENDENT SRHI /METHOD=ENTER Time /SCATTERPLOT=(*ZRESID ,*ZPRED) /RESIDUALS HISTOGRAM(ZRESID) NORMPROB(ZRESID).
Resources	Processor Time	00:00:00.36
	Elapsed Time	00:00:00.33
	Memory Required	2848 bytes
	Additional Memory Required for Residual Plots	896 bytes

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	Time[b]	.	Enter

a. Dependent Variable: SRHI

b. All requested variables entered.

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.284[a]	.081	.070	14.78305

a. Predictors: (Constant), Time

b. Dependent Variable: SRHI

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1668.938	1	1668.938	7.637	.007[b]
	Residual	19012.859	87	218.539		
	Total	20681.798	88			

a. Dependent Variable: SRHI

b. Predictors: (Constant), Time

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	47.609	3.149		15.119	<.001
	Time	.347	.125	.284	2.763	.007

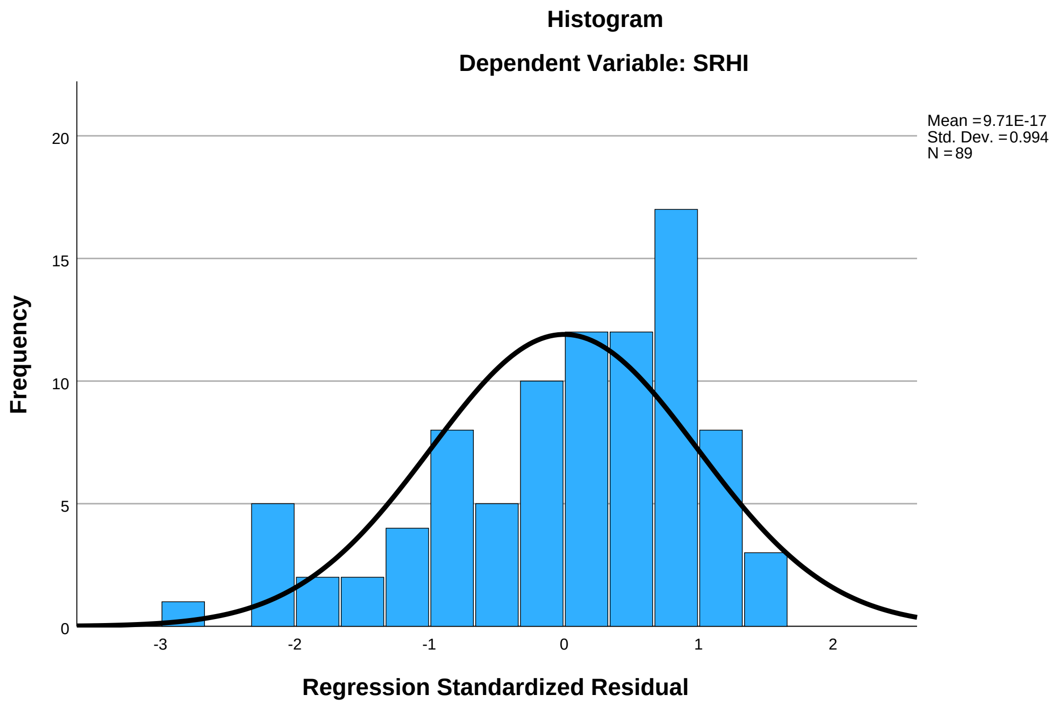
a. Dependent Variable: SRHI

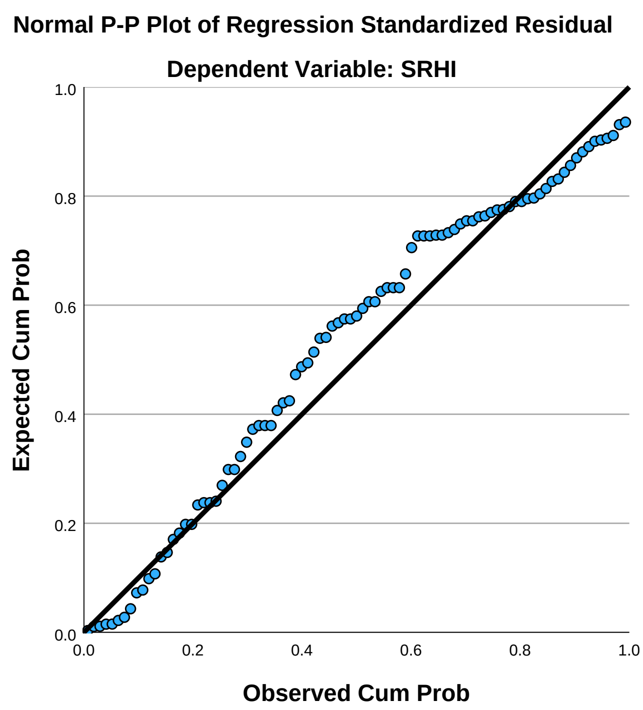
Residuals Statistics[a]

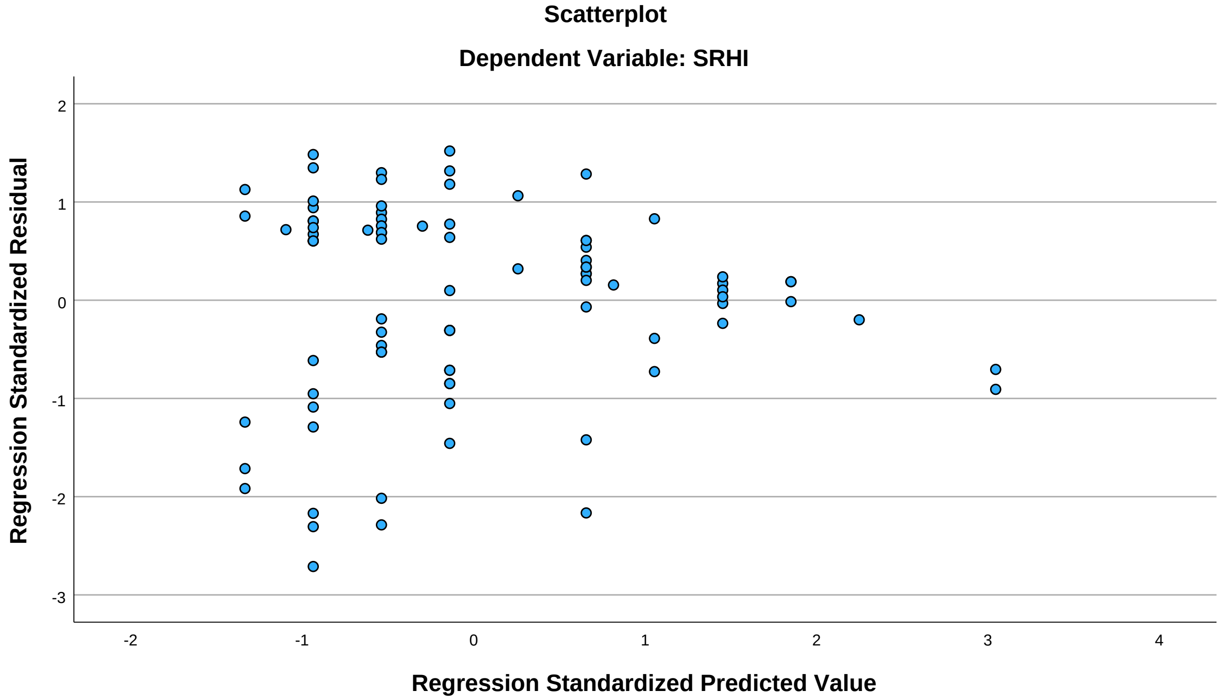
	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	49.3434	68.4178	55.1573	4.35491	89
Residual	-40.07745	22.45448	.00000	14.69882	89
Std. Predicted Value	-1.335	3.045	.000	1.000	89
Std. Residual	-2.711	1.519	.000	.994	89

a. Dependent Variable: SRHI

Charts


Histogram
Dependent Variable: SRHI
Mean =9.71E-17
Std. Dev. =0.994
N =89
Frequency
20
15
10
5
0
-3
-2
-1
0
1
2
Regression Standardized Residual


Normal P-P Plot of Regression Standardized Residual
Dependent Variable: SRHI
Expected Cum Prob
1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.2
0.4
0.6
0.8
1.0
Observed Cum Prob



Correlations

Notes

Output Created		22-NOV-2025 15:44:00
Comments		
Input	Data	C:\Users\acernera\Documents\Survey Data.sav
	Active Dataset	DataSet0
	Filter	<none>
	Weight	<none>
	Split File	<none>
	N of Rows in Working Data File	89
Missing Value Handling	Definition of Missing	User-defined missing values are treated as missing.
	Cases Used	Statistics for each pair of variables are based on all the cases with valid data for that pair.

Notes

Syntax		CORRELATIONS /VARIABLES=SRHI Time ThisWeek NormalWeek Experience /PRINT=TWOTAIL NOSIG FULL /MISSING=PAIRWISE.
Resources	Processor Time	00:00:00.00
	Elapsed Time	00:00:00.01

Correlations

		SRHI	Time	ThisWeek	NormalWeek	Experience
SRHI	Pearson Correlation	1	.284**	.688**	.697**	-.315**
	Sig. (2-tailed)		.007	<.001	<.001	.003
	N	89	89	89	89	89
Time	Pearson Correlation	.284**	1	.041	.156	-.214*
	Sig. (2-tailed)	.007		.700	.144	.044
	N	89	89	89	89	89
ThisWeek	Pearson Correlation	.688**	.041	1	.710**	.061
	Sig. (2-tailed)	<.001	.700		<.001	.572
	N	89	89	89	89	89
NormalWeek	Pearson Correlation	.697**	.156	.710**	1	-.143
	Sig. (2-tailed)	<.001	.144	<.001		.180
	N	89	89	89	89	89
Experience	Pearson Correlation	-.315**	-.214*	.061	-.143	1
	Sig. (2-tailed)	.003	.044	.572	.180	
	N	89	89	89	89	89

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Pearson Correlations

Highly Positive : *(None)*

Positive : *(SRHI <---> Time), (SRHI <---> ThisWeek), (SRHI <---> NormalWeek), (Time <---> ThisWeek), (Time <---> NormalWeek), (ThisWeek <---> NormalWeek), (ThisWeek <---> Experience)*

Positive : *(Time <---> Model 1), (Time <---> Model 2), (NormalWeek <---> Model 2)*

No Linear Correlation : *(None)*

Negative : *(Experience <---> Model 2)*

Highly Negative : *(None)*

Correlations Part

Highly Positive : *(None)*

Positive : *(Time <---> Model 1), (Time <---> Model 2), (NormalWeek <---> Model 2)*

No Linear Correlation : *(None)*

Negative : *(Experience <---> Model 2)*

Highly Negative : *(None)*

Note: Curated Help is calculated based on actual cell values, not the formatted values.

Excluded Variables[a]

Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics
						Tolerance
1	NormalWeek	.669[b]	8.820	<.001	.689	.976
	Experience	-.266[b]	-2.613	.011	-.271	.954

a. Dependent Variable: SRHI

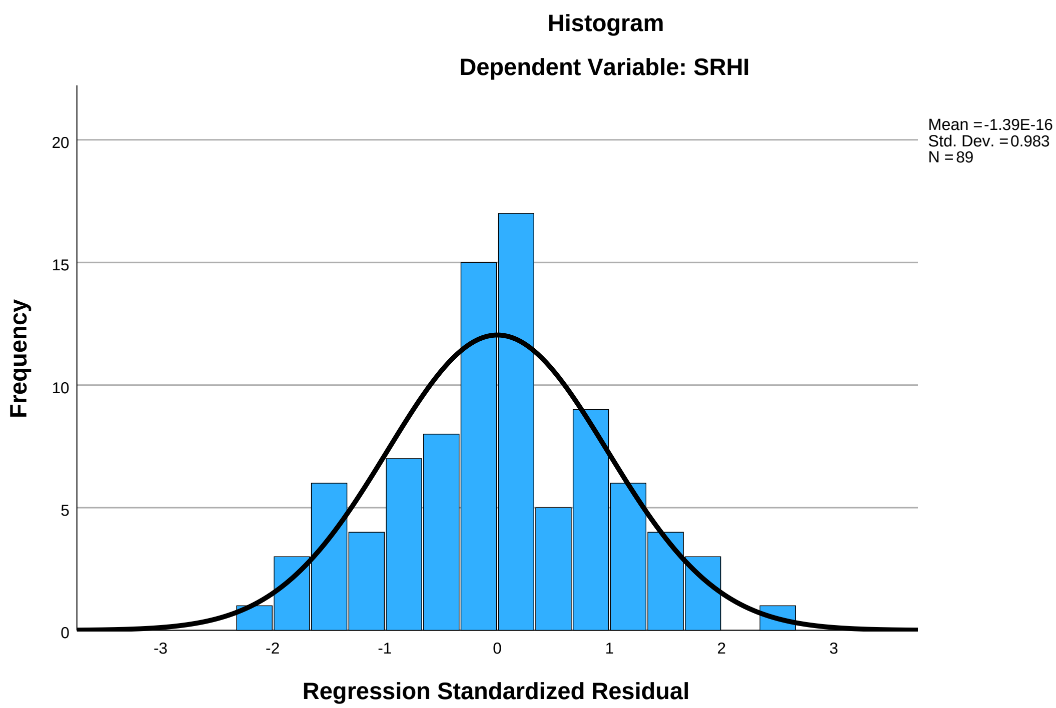
b. Predictors in the Model: (Constant), Time

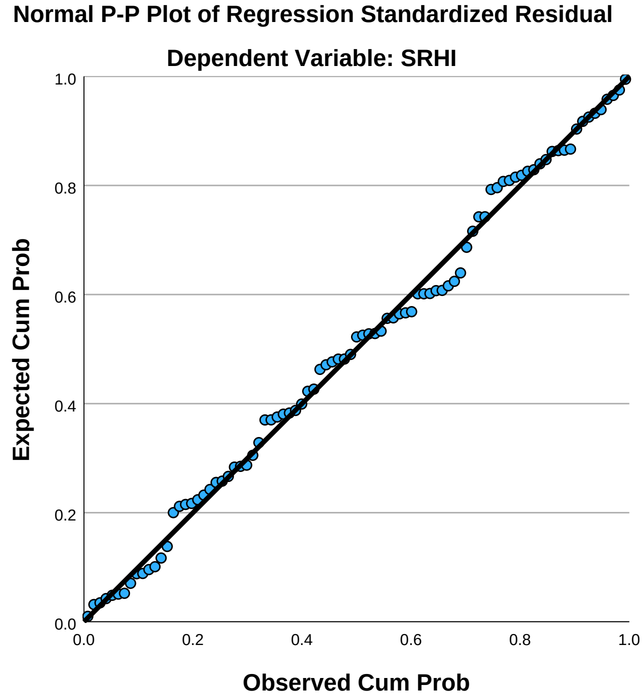
Residuals Statistics[a]

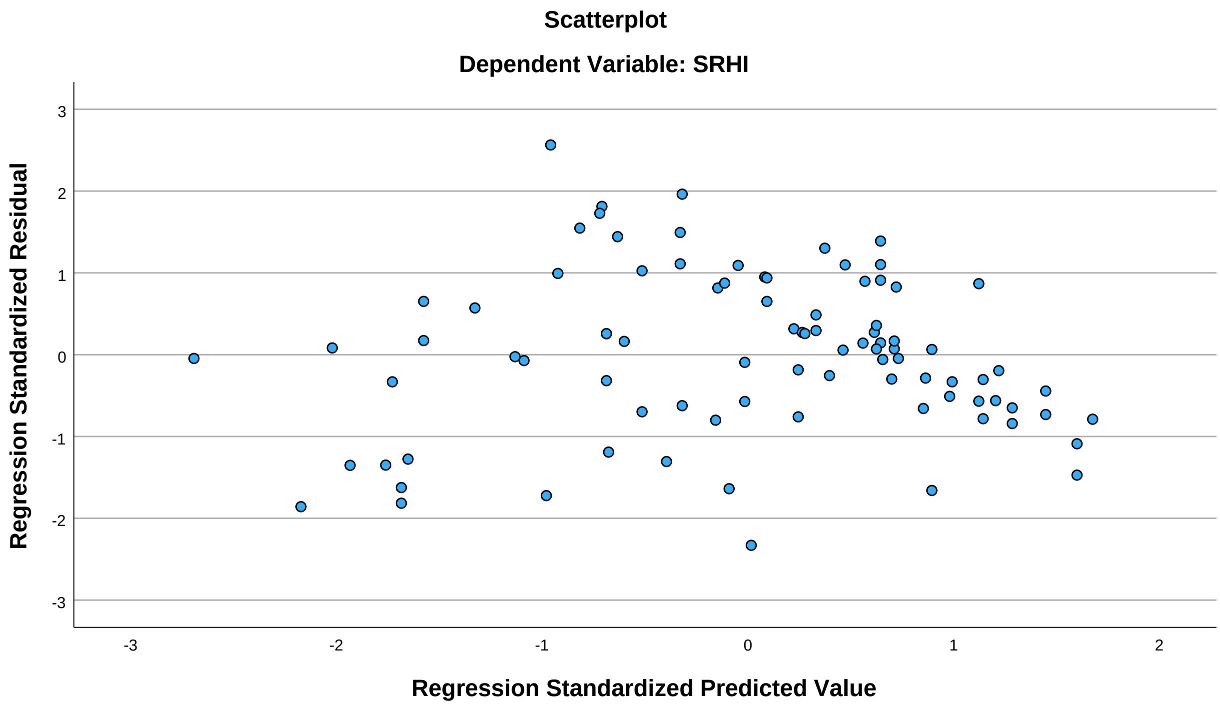
	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	24.4781	74.2387	55.1573	11.38828	89
Residual	-24.33464	26.77097	.00000	10.26292	89
Std. Predicted Value	-2.694	1.676	.000	1.000	89
Std. Residual	-2.330	2.564	.000	.983	89

a. Dependent Variable: SRHI

Charts




Normal P-P Plot of Regression Standardized Residual
Dependent Variable: SRHI
Expected Cum Prob
Observed Cum Prob
0.0
0.2
0.4
0.6
0.8
1.0


Scatterplot
Dependent Variable: SRHI
Regression Standardized Residual
Regression Standardized Predicted Value
3
2
1
0
-1
-2
-3

Regression

Notes

Output Created		22-NOV-2025 15:50:48
Comments		
Input	Data	C:\Users\acernera\Documents\Survey Data.sav
	Active Dataset	DataSet0
	Filter	<none>
	Weight	<none>
	Split File	<none>
	N of Rows in Working Data File	89
Missing Value Handling	Definition of Missing	User-defined missing values are treated as missing.
	Cases Used	Statistics are based on cases with no missing values for any variable used.
Syntax		REGRESSION /DESCRIPTIVES MEAN STDDEV CORR SIG N /MISSING LISTWISE /STATISTICS COEFF OUTS R ANOVA CHANGE ZPP /CRITERIA=PIN(.05) POUT(.10) TOLERANCE(.0001) /NOORIGIN /DEPENDENT SRHI /METHOD=ENTER Time /METHOD=ENTER NormalWeek /SCATTERPLOT=(*ZRESID ,*ZPRED) /RESIDUALS HISTOGRAM(ZRESID) NORMPROB(ZRESID).
Resources	Processor Time	00:00:00.44
	Elapsed Time	00:00:00.32
	Memory Required	3424 bytes
	Additional Memory Required for Residual Plots	880 bytes

Descriptive Statistics

	Mean	Std. Deviation	N
SRHI	55.1573	15.33038	89
Time	21.7640	12.55716	89
NormalWeek	4.7528	1.96145	89

Correlations

		SRHI	Time	NormalWeek
Pearson Correlation	SRHI	1.000	.284	.697
	Time	.284	1.000	.156
	NormalWeek	.697	.156	1.000
Sig. (1-tailed)	SRHI	.	.003	<.001
	Time	.003	.	.072
	NormalWeek	.000	.072	.
N	SRHI	89	89	89
	Time	89	89	89
	NormalWeek	89	89	89

Pearson Correlation

Highly Positive : *(None)*

Positive : *(SRHI <---> Time), (SRHI <---> NormalWeek), (Time <---> NormalWeek)*

No Linear Correlation : *(None)*

Negative : *(None)*

Highly Negative : *(None)*

Note: Curated Help is calculated based on actual cell values, not the formatted values.

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	Time[b]	.	Enter
2	NormalWeek[b]	.	Enter

a. Dependent Variable: SRHI

b. All requested variables entered.

Model Summary[c]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	Change Statistics: F Change	Change Statistics: df1	Change Statistics: df2	Change Statistics: Sig. F Change
1	.284[a]	.081	.070	14.78305	.081	7.637	1	87	.007
2	.719[b]	.517	.506	10.77423	.437	77.785	1	86	<.001

a. Predictors: (Constant), Time

b. Predictors: (Constant), Time, NormalWeek

c. Dependent Variable: SRHI

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1668.938	1	1668.938	7.637	.007[b]
	Residual	19012.859	87	218.539		
	Total	20681.798	88			
2	Regression	10698.569	2	5349.285	46.081	<.001[c]
	Residual	9983.229	86	116.084		
	Total	20681.798	88			

a. Dependent Variable: SRHI

b. Predictors: (Constant), Time

c. Predictors: (Constant), Time, NormalWeek

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	Correlations Zero-order
1	(Constant)	47.609	3.149		15.119	<.001	
	Time	.347	.125	.284	2.763	.007	.284
2	(Constant)	25.537	3.396		7.521	<.001	
	Time	.219	.093	.179	2.366	.020	.284
	NormalWeek	5.229	.593	.669	8.820	<.001	.697

Coefficients[a]

Model		Correlations Partial	Correlations Part
1	(Constant)		
	Time	.284	.284
2	(Constant)		
	Time	.247	.177
	NormalWeek	.689	.661

a. Dependent Variable: SRHI

Correlations Zero-order

Highly Positive : *(None)*

Positive : *(Time <---> Model 1), (Time <---> Model 2), (NormalWeek <---> Model 2)*

No Linear Correlation : *(None)*

Negative : *(None)*

Highly Negative : *(None)*

Correlations Partial

Highly Positive : *(None)*

Positive : *(Time <---> Model 1), (Time <---> Model 2), (NormalWeek <---> Model 2)*

No Linear Correlation : *(None)*

Negative : *(None)*

Highly Negative : *(None)*

Correlations Part

Highly Positive : *(None)*

Positive : *(Time <---> Model 1), (Time <---> Model 2), (NormalWeek <---> Model 2)*

No Linear Correlation : *(None)*

Negative : *(None)*

Highly Negative : *(None)*

Note: Curated Help is calculated based on actual cell values, not the formatted values.

Excluded Variables[a]

Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics Tolerance
1	NormalWeek	.669[b]	8.820	<.001	.689	.976

a. Dependent Variable: SRHI

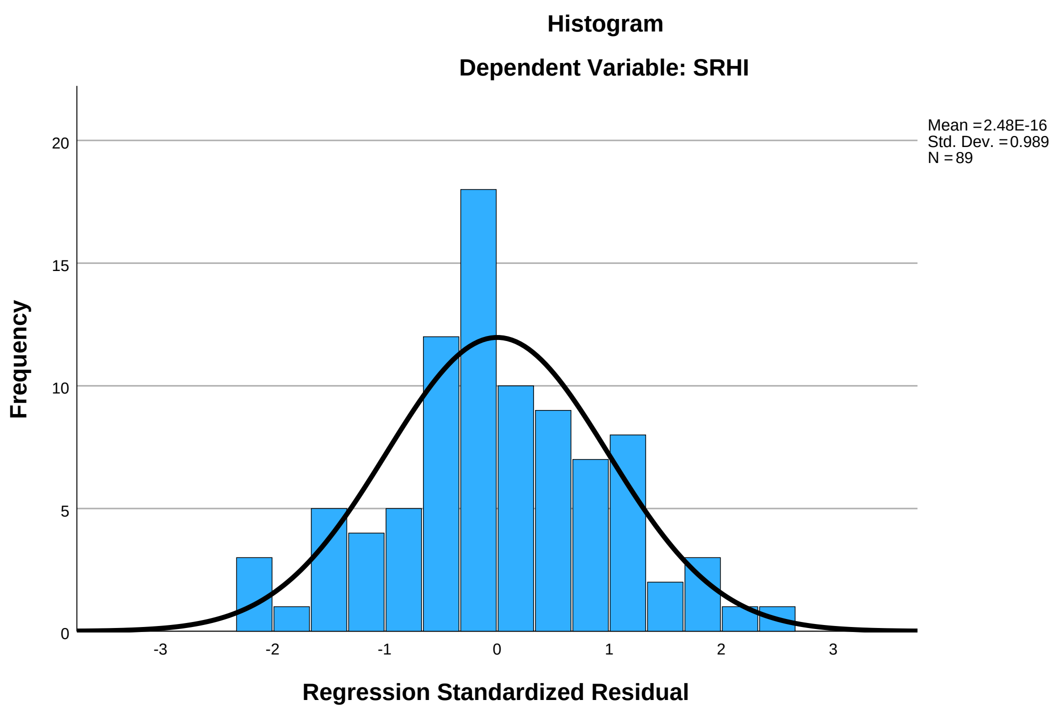
b. Predictors in the Model: (Constant), Time

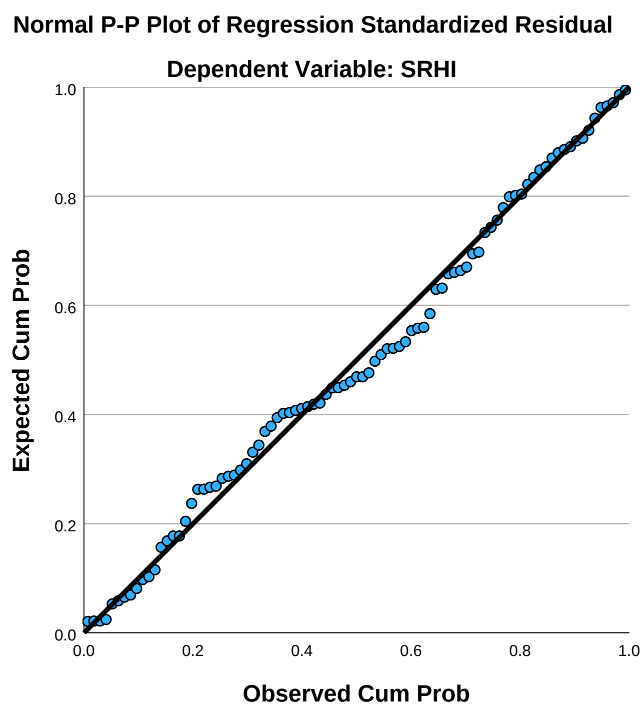
Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	26.6330	71.9990	55.1573	11.02609	89
Residual	-21.95728	27.58546	.00000	10.65109	89
Std. Predicted Value	-2.587	1.527	.000	1.000	89
Std. Residual	-2.038	2.560	.000	.989	89

a. Dependent Variable: SRHI

Charts


Histogram
Dependent Variable: SRHI
Mean = 2.48E-16
Std. Dev. = 0.989
N = 89
Frequency
0
5
10
15
20
-3
-2
-1
0
1
2
3
Regression Standardized Residual


Normal P-P Plot of Regression Standardized Residual
Dependent Variable: SRHI
Expected Cum Prob
Observed Cum Prob
0.0
0.2
0.4
0.6
0.8
1.0

Regression

Notes

Output Created		22-NOV-2025 20:07:57
Comments		
Input	Data	C:\Users\acernera\Documents\Survey Data with Rankings.sav
	Active Dataset	DataSet1
	Filter	<none>
	Weight	<none>
	Split File	<none>
	N of Rows in Working Data File	89
Missing Value Handling	Definition of Missing	User-defined missing values are treated as missing.
	Cases Used	Statistics are based on cases with no missing values for any variable used.
Syntax		REGRESSION /MISSING LISTWISE /STATISTICS COEFF OUTS R ANOVA /CRITERIA=PIN(.05) POUT(.10) TOLERANCE(.0001) /NOORIGIN /DEPENDENT SRHI /METHOD=ENTER Time /METHOD=ENTER Time2 /METHOD=ENTER Time3.
Resources	Processor Time	00:00:00.02
	Elapsed Time	00:00:00.01
	Memory Required	4304 bytes
	Additional Memory Required for Residual Plots	0 bytes

```
[DataSet1] C:\Users\acernera\Documents\Survey Data with Rankings.sav
```

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	Time[b]	.	Enter
2	Time2[b]	.	Enter
3	Time3[b]	.	Enter

a. Dependent Variable: SRHI

b. All requested variables entered.

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.284[a]	.081	.070	14.78305
2	.328[b]	.107	.087	14.65175
3	.328[c]	.108	.076	14.73545

a. Predictors: (Constant), Time

b. Predictors: (Constant), Time, Time2

c. Predictors: (Constant), Time, Time2, Time3

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1668.938	1	1668.938	7.637	.007[b]
	Residual	19012.859	87	218.539		
	Total	20681.798	88			
2	Regression	2219.855	2	1109.928	5.170	.008[c]
	Residual	18461.943	86	214.674		
	Total	20681.798	88			
3	Regression	2225.454	3	741.818	3.416	.021[d]
	Residual	18456.344	85	217.133		
	Total	20681.798	88			

a. Dependent Variable: SRHI

b. Predictors: (Constant), Time

c. Predictors: (Constant), Time, Time2

d. Predictors: (Constant), Time, Time2, Time3

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	47.609	3.149		15.119	<.001
	Time	.347	.125	.284	2.763	.007
2	(Constant)	40.247	5.556		7.244	<.001
	Time	1.056	.460	.865	2.296	.024
	Time2	-.013	.008	-.604	-1.602	.113
3	(Constant)	38.945	9.847		3.955	<.001
	Time	1.249	1.288	1.023	.970	.335
	Time2	-.020	.047	-.954	-.430	.668
	Time3	8.052E-5	.001	.204	.161	.873

a. Dependent Variable: SRHI

Excluded Variables[a]

Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics Tolerance
1	Time2	-.604[b]	-1.602	.113	-.170	.073
	Time3	-.335[b]	-1.549	.125	-.165	.223
2	Time3	.204[c]	.161	.873	.017	.007

a. Dependent Variable: SRHI

b. Predictors in the Model: (Constant), Time

c. Predictors in the Model: (Constant), Time, Time2

Correlations

Notes

Output Created		22-NOV-2025 17:53:41
Comments		
Input	Data	C:\Users\acernera\Desktop\Survey Data.sav
	Active Dataset	DataSet1
	Filter	Experience = 1 (FILTER)
	Weight	<none>
	Split File	<none>
	N of Rows in Working Data File	21
Missing Value Handling	Definition of Missing	User-defined missing values are treated as missing.
	Cases Used	Statistics for each pair of variables are based on all the cases with valid data for that pair.
Syntax		CORRELATIONS /VARIABLES=Time SRHI /PRINT=TWOTAIL NOSIG FULL /MISSING=PAIRWISE.
Resources	Processor Time	00:00:00.00
	Elapsed Time	00:00:00.01

```
[DataSet1] C:\Users\acernera\Desktop\Survey Data.sav
```

Correlations

		Time	SRHI
Time	Pearson Correlation	1	-.007
	Sig. (2-tailed)		.977
	N	21	21
SRHI	Pearson Correlation	-.007	1
	Sig. (2-tailed)	.977	
	N	21	21

Pearson Correlations

Highly Positive : *(None)*

Positive : *(None)*

No Linear Correlation : *(None)*

Negative : *(Time <---> SRHI)*

Highly Negative : *(None)*

Note: Curated Help is calculated based on actual cell values, not the formatted values.

Regression

Notes

Output Created		22-NOV-2025 17:54:50
Comments		
Input	Data	C:\Users\acernera\Desktop\Survey Data.sav
	Active Dataset	DataSet1
	Filter	Experience = 1 (FILTER)
	Weight	<none>
	Split File	<none>
	N of Rows in Working Data File	21
Missing Value Handling	Definition of Missing	User-defined missing values are treated as missing.
	Cases Used	Statistics are based on cases with no missing values for any variable used.
Syntax		REGRESSION /MISSING LISTWISE /STATISTICS COEFF OUTS R ANOVA /CRITERIA=PIN(.05) POUT(.10) TOLERANCE(.0001) /NOORIGIN /DEPENDENT SRHI /METHOD=ENTER Time.
Resources	Processor Time	00:00:00.02
	Elapsed Time	00:00:00.01

Notes

	Memory Required	2880 bytes
	Additional Memory Required for Residual Plots	0 bytes

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	Time[b]	.	Enter

a. Dependent Variable: SRHI

b. All requested variables entered.

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.007[a]	.000	-.053	2.48398

a. Predictors: (Constant), Time

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	.005	1	.005	.001	.977[b]
	Residual	117.233	19	6.170		
	Total	117.238	20			

a. Dependent Variable: SRHI

b. Predictors: (Constant), Time

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	63.553	1.134		56.036	<.001
	Time	-.001	.040	-.007	-.029	.977

a. Dependent Variable: SRHI

Regression

Notes

Output Created		22-NOV-2025 18:00:12
Comments		
Input	Data	C:\Users\acernera\Desktop\Survey Data.sav
	Active Dataset	DataSet1
	Filter	<none>
	Weight	<none>
	Split File	<none>
	N of Rows in Working Data File	89
Missing Value Handling	Definition of Missing	User-defined missing values are treated as missing.
	Cases Used	Statistics are based on cases with no missing values for any variable used.
Syntax		REGRESSION /MISSING LISTWISE /STATISTICS COEFF OUTS R ANOVA CHANGE /CRITERIA=PIN(.05) POUT(.10) TOLERANCE(.0001) /NOORIGIN /DEPENDENT SRHI /METHOD=ENTER Time /METHOD=ENTER NormalWeek.
Resources	Processor Time	00:00:00.00
	Elapsed Time	00:00:00.01
	Memory Required	3440 bytes
	Additional Memory Required for Residual Plots	0 bytes

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	Time[b]	.	Enter
2	NormalWeek[b]	.	Enter

a. Dependent Variable: SRHI

b. All requested variables entered.

Model Summary

					Change Statistics		
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1
1	.284[a]	.081	.070	14.78305	.081	7.637	1
2	.719[b]	.517	.506	10.77423	.437	77.785	1

Model Summary

	Change Statistics	
Model	df2	Sig. F Change
1	87	.007
2	86	<.001

a. Predictors: (Constant), Time

b. Predictors: (Constant), Time, NormalWeek

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1668.938	1	1668.938	7.637	.007[b]
	Residual	19012.859	87	218.539		
	Total	20681.798	88			
2	Regression	10698.569	2	5349.285	46.081	<.001[c]
	Residual	9983.229	86	116.084		
	Total	20681.798	88			

a. Dependent Variable: SRHI

b. Predictors: (Constant), Time

c. Predictors: (Constant), Time, NormalWeek

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	47.609	3.149		15.119	<.001
	Time	.347	.125	.284	2.763	.007
2	(Constant)	25.537	3.396		7.521	<.001
	Time	.219	.093	.179	2.366	.020
	NormalWeek	5.229	.593	.669	8.820	<.001

a. Dependent Variable: SRHI

Excluded Variables[a]

Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics Tolerance
1	NormalWeek	.669[b]	8.820	<.001	.689	.976

a. Dependent Variable: SRHI

b. Predictors in the Model: (Constant), Time

RANK

Notes

Output Created		22-NOV-2025 18:02:56
Comments		
Input	Data	C: \Users\acernera\Desktop\Survey Data.sav
	Active Dataset	DataSet1
	Filter	<none>
	Weight	<none>
	Split File	<none>
	N of Rows in Working Data File	89
Missing Value Handling	Definition of Missing	User-defined missing values are treated as missing.
	Cases Used	All non-missing data are used.
Syntax		RANK VARIABLES=SRHI (A) /RANK /NTILES(4) /PRINT=YES /TIES=MEAN.
Resources	Processor Time	00:00:00.02
	Elapsed Time	00:00:00.01
Variables Created or Modified	RSRHI	Rank of SRHI
	NSRHI	Percentile Group of SRHI

Created Variables[a]

Source Variable	Function	New Variable	Label
SRHI[b]	Rank	RSRHI	Rank of SRHI
	Percentile Group[c]	NSRHI	Percentile Group of SRHI

a. Mean rank of tied values is used for ties.

b. Ranks are in ascending order.

c. 4 groups are generated.

T-Test

Notes

Output Created		22-NOV-2025 18:09:41
Comments		
Input	Data	C: \Users\acernera\Documents\Survey Data with Rankings.sav
	Active Dataset	DataSet1
	Filter	<none>
	Weight	<none>
	Split File	<none>
	N of Rows in Working Data File	89
Missing Value Handling	Definition of Missing	User defined missing values are treated as missing.
	Cases Used	Statistics for each analysis are based on the cases with no missing or out-of-range data for any variable in the analysis.
Syntax		T-TEST GROUPS=BestSRHI(1 0) /MISSING=ANALYSIS /VARIABLES=Time NormalWeek /ES DISPLAY(TRUE) /HOMOGENEITY DISPLAY(FALSE) /CRITERIA=CI(.95).
Resources	Processor Time	00:00:00.00
	Elapsed Time	00:00:00.01

```
[DataSet1] C:\Users\acernera\Documents\Survey Data with Rankings.sav
```

Group Statistics

	Best	N	Mean	Std. Deviation	Std. Error Mean
Time	1.00	24	22.0000	11.34058	2.31489
	.00	65	21.6769	13.06009	1.61990
NormalWeek	1.00	24	5.6667	1.55106	.31661
	.00	65	4.4154	1.99916	.24797

Independent Samples Test

		t-test for Equality of Means			
				Significance	
		t	df	One-Sided p	Two-Sided p
Time	Equal variances assumed	.107	87	.457	.915
	Equal variances not assumed	.114	46.991	.455	.909
NormalWeek	Equal variances assumed	2.770	87	.003	.007
	Equal variances not assumed	3.111	52.738	.002	.003

Independent Samples Test

		t-test for Equality of Means		
				95% Confidence Interval of the ...
		Mean Difference	Std. Error Difference	Lower
Time	Equal variances assumed	.32308	3.01632	-5.67218
	Equal variances not assumed	.32308	2.82538	-5.36089
NormalWeek	Equal variances assumed	1.25128	.45168	.35351
	Equal variances not assumed	1.25128	.40215	.44457

Independent Samples Test

		t-test for Equality ..
		95% Confidence Interval of the ...
		Upper
Time	Equal variances assumed	6.31834
	Equal variances not assumed	6.00704
NormalWeek	Equal variances assumed	2.14905
	Equal variances not assumed	2.05800

Independent Samples Effect Sizes

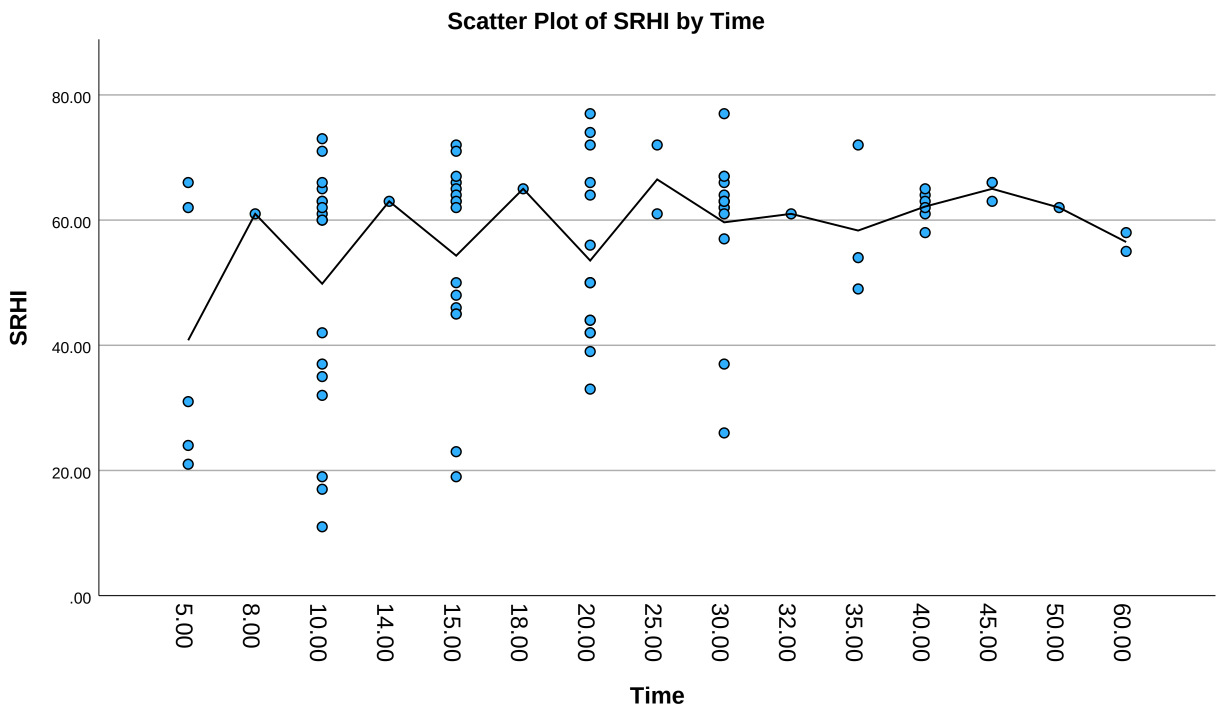
		Standardizer[a]	Point Estimate	95% Confidence Interval Lower	Upper
Time	Cohen's d	12.62829	.026	-.443	.494
	Hedges' correction	12.73848	.025	-.439	.489
	Glass's delta	13.06009	.025	-.444	.493
NormalWeek	Cohen's d	1.89105	.662	.182	1.138
	Hedges' correction	1.90755	.656	.180	1.128
	Glass's delta	1.99916	.626	.143	1.104

a. The denominator used in estimating the effect sizes.
Cohen's d uses the pooled standard deviation.
Hedges' correction uses the pooled standard deviation, plus a correction factor.
Glass's delta uses the sample standard deviation of the control (i.e., the second) group.

GGraph

Notes

Output Created		22-NOV-2025 20:15:44
Comments		
Input	Data	C: \Users\acernera\Documents\Survey Data with Rankings.sav
	Active Dataset	DataSet1
	Filter	<none>
	Weight	<none>
	Split File	<none>
	N of Rows in Working Data File	89
Syntax		GGRAPH /GRAPHDATASET NAME="graphdataset" VARIABLES=Time SRHI MISSING=LISTWISE REPORTMISSING=NO /GRAPHSPEC SOURCE=INLINE /FITLINE TOTAL=NO SUBGROUP=NO. BEGIN GPL SOURCE: s=userSource(id("graphdataset")) DATA: Time=col(source(s), name("Time"), unit.category()) DATA: SRHI=col(source(s), name("SRHI")) GUIDE: axis(dim(1), label("Time")) GUIDE: axis(dim(2), label("SRHI")) GUIDE: text.title(label("Scatter Plot of SRHI by Time")) SCALE: linear(dim(2), include(0)) ELEMENT: point(position(Time*SRHI)) END GPL.
Resources	Processor Time	00:00:00.20
	Elapsed Time	00:00:00.12


Scatter Plot of SRHI by Time
80.00
60.00
40.00
20.00
.00
SRHI
5.00
8.00
10.00
14.00
15.00
18.00
20.00
25.00
30.00
32.00
35.00
40.00
45.00
50.00
60.00
Time