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Consumer Innovation Fatigue in Digital Commerce: Scale Development and Validation

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Abstract

Rapid digital transformation has accelerated the frequency with which firms introduce product updates, platform enhancements, and feature innovations in e-commerce environments. While continuous innovation is typically associated with improved functionality and customer value, limited research has examined its potential psychological costs for consumers. This study introduces the concept of consumer innovation fatigue (CIF), defined as a psychological state of exhaustion arising from repeated exposure to ongoing innovation-related changes in digital products and online platforms. Following established scale development procedures, this research develops and validates a measurement scale for CIF. Item generation combined insights from prior literature with qualitative evidence from consumer interviews, followed by expert evaluation to ensure content validity. Using survey data from two independent samples of digital consumers in Saudi Arabia, exploratory factor analysis (n = 225) identified a unidimensional six-item scale. The scale was subsequently validated using partial least squares structural equation modeling (n = 361), confirming its reliability, convergent validity, and discriminant validity. The findings further demonstrate nomological validity by showing that exposure to continuous digital innovation significantly increases CIF, which in turn leads to innovation avoidance in online consumption contexts. By conceptualizing and empirically validating CIF, this study contributes to electronic commerce research by highlighting a previously underexplored psychological consequence of rapid innovation cycles in digital environments. The validated scale provides a useful instrument for future research examining consumer responses to ongoing technological change in e-commerce ecosystems.

Keywords: consumer innovation fatigue; continuous innovation; innovation exposure; innovation avoidance; digital innovation; consumer behavior

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1. Introduction

Innovation is widely recognized as a key driver of competitiveness and economic growth because it enables firms to enhance productivity, develop new products and services, and sustain long-term competitive advantage [1]. In increasingly competitive and digitally mediated markets, firms continuously introduce new products, technological features, and service upgrades to differentiate their offerings and maintain consumer interest [2–4]. As technological progress accelerates and digital transformation reshapes markets, innovation has become a central strategic mechanism for sustaining market relevance and responding to rapidly evolving consumer expectations, particularly within e-commerce platforms, mobile applications, and digitally enabled service ecosystems [5,6].

In many industries, innovation now occurs in continuous cycles rather than through occasional breakthroughs. Firms regularly release new product versions, feature upgrades, and technological enhancements at an increasing pace [7,8]. In digital commerce environments, this pattern is especially evident, as online platforms, consumer electronics, and service providers frequently introduce software updates, interface redesigns, algorithmic changes, and new functionalities that continuously reshape the user experience [9,10]. These ongoing changes require consumers to repeatedly learn, evaluate, and adapt to evolving product and service features. Consequently, consumers are increasingly exposed to persistent streams of innovation that demand continuous cognitive and behavioral adjustments over time [11].

Although innovation is typically associated with positive outcomes such as improved functionality and enhanced consumer value, continuous exposure to innovation may also produce unintended negative consequences. Prior research suggests that rapid technological change can increase cognitive demands, contribute to stress, and create difficulties for consumers attempting to keep up with evolving technologies and digital environments [12,13]. When innovations are introduced frequently, consumers must repeatedly decide whether to adopt, update, or replace existing products and services, often within short time intervals. Over time, this constant need to evaluate and adapt to new innovations may generate psychological strain and reduce consumers' ability to effectively process and respond to ongoing changes.

From a cognitive perspective, individuals possess limited cognitive processing capacity, and each successive learning demand consumes working memory resources, increasing cognitive load and mental effort [14]. In innovation-intensive environments, particularly those characterized by continuous digital updates and platform-based interactions, consumers may experience fatigue as they repeatedly encounter new product features, system updates, and technological improvements that require ongoing learning and adjustment. Rather than continuously stimulating interest and engagement, excessive exposure to innovation may eventually lead to feelings of tiredness, frustration, or disengagement toward new innovations [11,15].

Several streams of research have examined fatigue-related phenomena in technology and consumer contexts. For instance, studies on technostress explain how individuals experience stress due to technology complexity, constant connectivity, and technology-related demands [16]. Research on social media fatigue focuses on the exhaustion arising from excessive interaction and engagement on digital and social networking platforms [17,18]. Similarly, the concept of information overload describes consumers' difficulty in processing excessive information during decision-making processes [19,20]. While these constructs provide important insights into fatigue associated with technology use, digital interaction, or information processing, they do not specifically address fatigue resulting from repeated exposure to continuous innovation-related changes in products, services, and digital platforms.

In contemporary digital commerce environments, consumers face an unbroken sequence of innovation cycles—each requiring them to learn new features, reassess familiar products, and restructure established usage routines [21,22]. These cycles are particularly pronounced in e-commerce ecosystems, where frequent updates, personalized recommendations, interface modifications, and feature enhancements are embedded into everyday consumption experiences. Despite the growing prevalence of such environments, limited research has examined whether the pace of innovation itself, independent of any difficulty in use, may generate fatigue. Existing constructs do not capture the progressive psychological depletion that accumulates when successive change cycles prevent full cognitive recovery.

To address this gap, this study introduces the concept of consumer innovation fatigue (CIF), defined as a psychological state of exhaustion experienced by consumers due to repeated exposure to product innovations, feature upgrades, and technological changes in digital environments. Although research has increasingly acknowledged the potential negative consequences of digital environments and technological engagement, no validated instrument exists to measure this specific form of fatigue. The absence of such a measure limits the ability of researchers to systematically investigate this phenomenon and to understand its implications within rapidly evolving e-commerce contexts.

Saudi Arabia provides a particularly relevant context for examining CIF due to its expanding digital commerce ecosystem and increasing reliance on mobile applications and technology-enabled services [23,24]. Recent digital transformation initiatives have accelerated technology adoption across commerce and everyday life, creating an environment in which consumers are frequently exposed to platform updates, feature enhancements, and continuous technological change [25]. Saudi Arabia therefore offers a suitable empirical setting for investigating psychological responses to recurring innovation exposure.

The objective of this study is therefore to conceptualize CIF and develop a reliable and valid measurement scale for this construct. Following established scale development procedures, the study generates and refines measurement items and empirically validates the resulting scale using survey data collected from consumers engaged in digital and technology-driven consumption. By introducing and validating a measure of CIF, this study contributes to the innovation, consumer behavior, and electronic commerce literature in several ways. First, it advances theoretical understanding by identifying a previously underexplored psychological cost associated with continuous innovation environments. Second, it provides a rigorously validated measurement instrument that enables future research to examine how excessive innovation exposure influences consumer attitudes and behavioral responses. In doing so, the study sheds light on an important but underexamined dark side of innovation in contemporary digital markets.

2. Theoretical Background

To provide a theoretical foundation for the concept of CIF, this study draws on two complementary perspectives: diffusion of innovation theory (DIT) and cognitive load theory (CLT). DIT explains how innovations spread through markets and how consumers respond to new products over time, whereas CLT explains how repeated exposure to new information and technological changes can place cognitive demands on individuals. Together, these perspectives help explain why continuous innovation may not only encourage adoption but can generate psychological strain when consumers are repeatedly required to evaluate and adapt to new innovations.

2.1. Diffusion of Innovation Theory (DIT)

DIT explains how new ideas, products, and technologies spread within a social system over time. According to [26], diffusion refers to the process through which innovations are communicated among members of a social system through various channels over time. The theory proposes that individuals adopt innovations at different stages, typically categorized as innovators, early adopters, early majority, late majority, and laggards [26]. This framework has been widely applied to understand how consumers evaluate and adopt technological innovations across markets and industries [26].

A central assumption in diffusion research is that innovations generate positive outcomes for both firms and consumers. Innovations can improve product functionality, enhance service quality, and create new forms of value for consumers [27,28]. Consequently,

much of the literature has focused on identifying the drivers of innovation adoption, such as perceived usefulness, compatibility, and ease of use [29].

However, contemporary markets differ from the traditional diffusion context in which innovations appeared relatively infrequently. Rapid technological development and digital transformation have accelerated the pace at which firms introduce new products, product versions, and technological upgrades [30,31]. In many industries, innovations are now introduced in continuous cycles rather than as occasional breakthroughs. As a result, consumers are repeatedly exposed to innovation-related changes and must continually evaluate whether to adopt, update, or adapt to new products and features.

While DIT provides valuable insights into how innovations spread and how adoption occurs, it pays relatively limited attention to the psychological costs borne by consumers who never exit the adoption cycle [32]. When innovations are introduced frequently, consumers may face repeated demands to reassess products, learn new functionalities, and update existing technologies. Over time, this unrelenting pace of change may erode consumers' enthusiasm for new products and generate fatigue toward future innovations [13]. Diffusion theory therefore helps explain how increasing rates of innovation exposure can create conditions in which fatigue may emerge among consumers.

2.2. Cognitive Load Theory (CLT)

CLT provides an additional perspective for understanding how successive innovation demands accumulate into psychological strain. The theory suggests that individuals possess limited cognitive processing capacity when learning or processing new information [14]. When information complexity or task demands exceed an individual's cognitive capacity, cognitive overload may occur, leading to mental strain, reduced learning efficiency, and fatigue [14,33].

In innovation-intensive consumer environments, individuals frequently encounter new product features, technological updates, and evolving service systems. Consumers must often learn how new functionalities operate, understand interface changes, and evaluate whether innovations offer meaningful benefits compared to existing alternatives [34]. For example, software updates, smartphone upgrades, and digital service enhancements often require consumers to invest time and effort to understand new capabilities and adjust their usage behaviors [16].

Each innovation therefore imposes cognitive demands on consumers, as they must process new information and integrate it into their existing knowledge structures. When innovations occur repeatedly, the cognitive effort required for learning and adaptation accumulates over time. According to CLT, sustained cognitive demands may eventually exceed individuals' processing capacity, resulting in mental fatigue and reduced motivation to engage with new information [19].

In the context of continuous innovation environments, this perspective suggests that consumers may experience psychological exhaustion when repeatedly required to evaluate and adapt to new technologies or product features. Thus, consumer responses to innovation are influenced not only by the perceived benefits of new offerings but also by the cognitive resources required to understand and adopt them.

2.3. Integrating Diffusion of Innovation Theory and Cognitive Load Theory

Diffusion of Innovations Theory (DIT) explains how innovations are introduced, communicated, and adopted within markets. However, it primarily emphasizes the spread and acceptance of innovations rather than the psychological consequences of repeated innovation exposure [26,35]. In contemporary digital environments, innovation rarely occurs as isolated events. Instead, firms increasingly introduce continuous cycles of updates,

feature enhancements, interface redesigns, and system modifications [9,36]. Consequently, consumers are repeatedly required to respond to ongoing product and platform changes. Each innovation cycle independently requires consumers to learn, evaluate, compare, and adapt to revised functionalities. Critically, CLT specifies that each such cognitive operation—schema restructuring, comparative evaluation, routine adjustment—imposes measurable load on working memory and draws from a finite pool of cognitive resources that does not replenish instantaneously [14]. When a second innovation cycle begins before those resources are fully restored from the first, the consumer enters the new cycle in a state of partial depletion. With each successive cycle under these conditions, the residual depletion deepens. This is not mere repetition of effort—it is a theoretically distinct accumulation dynamic grounded in CLT's resource-limitation premise, and it is the mechanism through which innovation exposure transforms progressively into sustained psychological fatigue.

Such recurring exposure creates sustained learning demands and decision pressures. Consumers must understand revised functionalities, evaluate whether changes offer meaningful benefits, and adjust their routines accordingly [37]. They may also need to compare previous and updated versions, relearn familiar processes, and reconsider prior habits. Although DIT explains why consumers face increasing innovation exposure, it does not fully explain how individuals cognitively process these continuing demands over time.

Cognitive Load Theory (CLT) provides the micro-level mechanism that explains the cost consumers bear within each innovation cycle [14]. CLT distinguishes three types of cognitive load: intrinsic load, arising from the inherent complexity of the material being processed; extraneous load, arising from how that material is presented; and germane load, associated with schema formation and knowledge restructuring. In the context of product innovation, each update cycle generates primarily intrinsic and germane load: consumers must mentally compare the revised product with its prior version, assess the functional implications of changes, update their existing product schema, and re-establish usage routines around the modified interface. These operations compete for the same finite pool of working memory resources. CLT establishes a critical theoretical premise: working memory capacity is limited and does not replenish instantaneously following effortful cognitive work [14]. When consumers are continuously required to process new information or adapt to changing systems, cognitive effort accumulates. Once these demands exceed available processing capacity, psychological strain, fatigue, and reduced motivation may emerge [14,19]. This resource-limitation premise is CLT's most theoretically consequential contribution to the present study: it establishes not merely that cognitive demands are costly, but that the cost carries forward—partial depletion from one episode becomes the starting condition for the next.

Drawing on the theoretical foundations of DIT and CLT, this study proposes a four-stage process model through which innovation exposure transforms progressively into sustained consumer fatigue. The model is strictly sequential: each stage is causally dependent on the prior one, and CIF cannot emerge without traversal of all four stages.

Stage 1—Structural Innovation Supply (DIT): In competitive digital markets, firms operate under sustained pressure to innovate, producing a continuous structural pattern of product updates, interface redesigns, and feature modifications [9,26,36]. Unlike episodic innovations of the pre-digital era, this supply is a persistent environmental condition that repeatedly places adaptation demands on consumers. This DIT-grounded condition is the necessary initiating factor; without it, no subsequent stage occurs.

Stage 2—Within-Cycle Cognitive Load (CLT): Each innovation cycle independently activates CLT mechanisms. Consumers must engage in schema restructuring (updating mental models of the product), comparative evaluation (assessing the revised version

against the prior one), and routine re-establishment (adjusting behavioral patterns to the modified interface). These operations place concurrent demands on working memory, consuming cognitive resources proportional to the perceived novelty and scope of each change. At the end of each cycle, the consumer's cognitive resource pool is partially depleted.

Stage 3—Inter-Cycle Non-Recovery (the DIT–CLT causal interaction): This is the theoretical core of the model and the precise point at which DIT and CLT interact rather than operate in parallel. CLT establishes that working memory resources require recovery time following effortful cognitive work. DIT establishes that in high-velocity innovation environments, the interval between successive cycles is shorter than the time required for full recovery. When Stage 2 of a new cycle begins before resources from the prior cycle are restored, the consumer enters it at a reduced cognitive baseline. Each successive cycle deepens that deficit. This inter-cycle non-recovery dynamic—driven by the structural mismatch between DIT's supply rate and CLT's recovery rate—is the mechanism that neither theory produces independently, and that makes CIF theoretically distinct from simple within-session cognitive overload.

Stage 4—Fatigue Crystallization: As the non-recovery dynamic persists across multiple cycles, the consumer's working memory resources reach a chronically depleted state. Cognitive strain is no longer episodic but sustained, and the consumer experiences generalized psychological exhaustion toward the innovation environment. This sustained exhaustion—CIF—represents a qualitative shift from the transient load of any single cycle: it is the accumulated end-state of the full process, not a scaled-up version of within-cycle overload.

Theoretical Proposition (P1): CIF develops when the rate of firm-initiated innovation cycles (Stage 1) generates within-cycle cognitive costs (Stage 2) that are not recovered before the next cycle begins (Stage 3), causing inter-cycle resource depletion to accumulate to a chronic fatigue threshold (Stage 4). Factors that lengthen between-cycle recovery intervals or reduce per-cycle load attenuate CIF; factors that compress those intervals or intensify per-cycle demands accelerate its onset. DIT and CLT together generate this mechanism; neither theory produces it independently.

The intensity of this process may vary across consumers. Individuals with higher digital literacy, stronger innovation orientation, or greater prior experience with evolving technologies may be better able to process updates with lower cognitive strain. In contrast, consumers with lower technological confidence, weaker innovation interest, or limited digital experience may perceive repeated change as more demanding, thereby increasing susceptibility to CIF.

This integrated framework provides a more comprehensive explanation of consumer responses in innovation-intensive environments. Although innovation may initially enhance convenience, value, and engagement, excessive exposure to continual change can create psychological costs that reduce openness toward subsequent innovations.

2.4. Conceptual Boundaries of Consumer Innovation Fatigue (CIF)

In construct development research, clearly distinguishing a new construct from related concepts is essential for establishing theoretical clarity and avoiding conceptual redundancy. The prior scale-development literature emphasizes that newly proposed constructs must demonstrate conceptual distinctiveness from existing constructs in order to justify their theoretical contribution [38,39]. In the context of digital environments and consumer behavior, several constructs have examined fatigue or strain experienced by individuals, including technostress, social media fatigue, and information overload [16,18,19]. While these constructs capture important forms of psychological strain associated with technology

use and digital environments, they do not specifically address fatigue that may arise from repeated exposure to continuous innovation-related changes in the marketplace.

2.4.1. Technostress

Technostress refers to the stress individuals experience due to demands associated with the use of information technologies [16,40]. Prior research identifies several sources of technostress, including technology complexity, information overload, system uncertainty, and constant connectivity [40,41]. These stressors arise primarily from difficulties associated with interacting with technological systems or managing technology-related demands in work or daily life.

Although technostress captures strain associated with technology usage, CIF is distinguished from it along three precise dimensions. First, the locus of the stressor differs: technostress originates within the consumer's interaction with a system—complexity, usability difficulties, or connectivity demands encountered during use—whereas the stressor in CIF is external and supply-side, originating in the rate at which firms introduce successive innovations regardless of the consumer's usage experience. Second, the triggering condition differs: technostress can occur with a single encounter with a difficult system and does not require repeated prior exposure, whereas CIF is inherently historical and accumulative—it cannot arise from a single update but only develops when a pattern of successive change events prevents full cognitive recovery between cycles. Third, and most importantly, the functional state of the technology is irrelevant to CIF but central to technostress: a consumer can experience maximum technostress with a system that never changes but is persistently difficult to use, whereas a consumer experiencing CIF may be using a system that is consistently well-designed, easy to operate, and genuinely useful—one that simply changes too frequently. This third distinction is theoretically decisive: CIF is not a fatigue of difficulty, but a fatigue of pace.

2.4.2. Social Media Fatigue

Social media fatigue refers to the exhaustion individuals experience due to excessive engagement with social networking platforms [18,42]. Social media fatigue typically arises from constant social interaction, continuous information updates, and pressures associated with maintaining an online presence. Research suggests that high levels of social media activity, information sharing, and interpersonal communication demands can contribute to psychological exhaustion and disengagement from social networking platforms.

In contrast, CIF is not primarily driven by social interaction or communication demands. Instead, it reflects consumers' responses to repeated innovation-related changes in products and services. For example, consumers may experience fatigue when they are frequently confronted with new product versions, updated digital features, or redesigned technological interfaces that require ongoing learning and adjustment. Therefore, while social media fatigue emerges from excessive social engagement in digital platforms, CIF results from continuous exposure to innovation cycles in the marketplace.

2.4.3. Information Overload

Information overload refers to situations in which individuals are exposed to more information than they can effectively process during decision-making [19]. This concept emphasizes the quantity and complexity of information available to individuals at a particular point in time [43]. When individuals face excessive information simultaneously, their cognitive processing capacity may be exceeded, resulting in confusion, decision difficulty, or mental strain.

CIF is conceptually distinct from information overload in both antecedent structure and temporal scope. Information overload is a within-episode phenomenon: it arises when

the volume or complexity of information available at a particular moment exceeds an individual's processing capacity, and it dissipates once the decision context is resolved. CIF, by contrast, is an across-episode phenomenon: it does not arise from information volume in any single moment but from the frequency with which the consumer must re-engage with a changed product or system across multiple time points. A consumer can experience information overload while browsing a single cluttered website without ever encountering a product update; a consumer experiencing CIF may interact with a clean, simple interface that has been updated six times in twelve months. The antecedents are categorically different—overload is driven by information quantity per unit time, and CIF is driven by innovation frequency per unit time. Furthermore, information overload is largely context-specific and can be reduced by simplifying the information environment; CIF is driven by firm-level innovation decisions that are outside the consumer's control, making it a structurally different form of strain (see Table 1).

Table 1. Theoretical Differentiation of CIF from Adjacent Fatigue Constructs.

Construct	Core Focus	Key Difference from Consumer Innovation Fatigue (CIF)
Technostress	Stress resulting from technology complexity, connectivity, and technological demands	CIF arises from the pace of firm-driven innovation cycles, not from difficulty or complexity in using a system
Social Media Fatigue	Exhaustion resulting from excessive engagement and interaction on social networking platforms	CIF stems from continuous innovation cycles rather than social interaction pressures
Information Overload	Cognitive strain caused by excessive information during decision-making	CIF reflects fatigue resulting from innovation frequency over time, not from information volume at a given moment

2.5. Theoretical Positioning of Consumer Innovation Fatigue (CIF)

The theoretical originality of CIF rests on a specific combination of properties that has not been theorized, measured, or empirically tested in the prior literature. Consumer fatigue research to date has focused on three classes of antecedent: system difficulty (technostress), information volume (overload), and social interaction pressure (social media fatigue). All three locate the stressor within the consumer's usage experience. CIF introduces a fourth class: firm-imposed innovation velocity. This is not a marginal distinction. A consumer can be cognitively capable, informationally unencumbered, and socially disengaged and still experience CIF if the firm releases updates faster than the consumer cognitive recovery allows. Conversely, a consumer can use a system that is persistently complex, information-dense, and socially demanding without ever experiencing CIF if that system never changes. This logical independence means CIF cannot be predicted, measured, or explained by any existing construct. It occupies an empirical space that is currently unmapped in the literature and that space is precisely what this study targets.

CIF occupies a theoretically distinct position that is not reducible to any existing fatigue construct. The key to understanding this distinctiveness lies not in what CIF shares with other constructs—all involve psychological strain associated with technology—but in what uniquely defines it: the stressor is the firm's innovation pace, not the consumer's usage experience. Technostress, cognitive overload, and social media fatigue are all demand-side constructs: they originate in what the consumer is asked to do (use a complex system, process excessive information, maintain an online presence). CIF is a supply-side construct: it originates in what the firm continuously delivers (successive versions, redesigned interfaces, new feature sets) at a rate that structurally exceeds the consumer's cognitive

recovery capacity. This supply-side origin is not a minor variation—it represents a categorically different theoretical mechanism. Existing fatigue constructs could in principle be eliminated if technology were made simpler, information made less abundant, or social demands made lower. CIF persists even under ideal usability conditions, even with excellent system design, even when every update is objectively valuable—as long as the pace of change prevents consumers from cognitively resetting between cycles [16,17,19]. This supply-side origin gives CIF a logically independent theoretical standing: its presence or absence is determined by the firm's innovation decisions, not by the consumer's interaction capabilities, information environment, or social engagement level.

The theoretical independence of CIF is established through three defining characteristics that set it apart from all adjacent constructs. First, the antecedent: CIF is triggered by innovation velocity—the rate at which firms release successive versions, updates, and redesigns—rather than by system complexity, information volume, or social demands. The same system that causes no technostress because it is simple and easy to use can cause CIF if it is updated repeatedly. Second, the temporal structure: CIF cannot arise from a single exposure event. A consumer cannot develop CIF from a single update. Technostress and cognitive overload can occur in a single session; CIF only emerges after a pattern of change events whose frequency exceeds the consumer's cognitive recovery rate. This non-recovery dynamic—the accumulation of unresolved adaptation demands across successive cycles—is the generative mechanism unique to CIF. Third, the locus of control: existing fatigue constructs involve stressors that are at least partially addressable through better system design, reduced information, or managed social use. CIF persists regardless of design quality because its source is the pace of the firm's innovation decisions, not the design of any particular release. Together, these three properties—supply-side antecedent, cumulative temporal structure, and firm-determined locus—constitute the theoretical core that distinguishes CIF as an independent construct requiring dedicated measurement and analysis. Accordingly, CIF explains how consumers may become psychologically disengaged from future innovations even when technologies remain functional, useful, and easy to use.

A defining characteristic of CIF is its temporal nature. Unlike information overload, which often reflects excessive information encountered at a specific moment, or technostress, which is commonly linked to system complexity and technology-related demands, CIF develops gradually through recurring exposure to change over time [16,19]. CIF is thus cumulative rather than episodic.

Conceptually, CIF is theorized as a holistic fatigue response to high-velocity innovation cycles. Empirically, it manifests as tiredness from frequent updates, cognitive strain from ongoing adaptation, feelings of overwhelm, and declining motivation to engage with new innovations. The dimensional structure of these manifestations was subsequently examined through the empirical scale validation stages of this study.

The case for CIF as a distinct construct ultimately rests on a single, testable proposition that no existing construct captures: consumers can experience fatigue from innovation even when every individual innovation is well-designed, easy to use, and genuinely beneficial—provided the pace of successive changes exceeds their cognitive recovery capacity. This proposition is empirically falsifiable, theoretically grounded in CLT's account of resource depletion across repeated demands, and practically significant because it predicts avoidance behavior in scenarios where technostress-based models would predict none. Consider a consumer using a smartphone app that receives monthly interface redesigns, each one well-engineered and user-tested: no episode is difficult, no single update is cognitively overwhelming, yet the cumulative pattern produces fatigue and eventual disengagement. Neither technostress (which requires usability difficulty), nor cognitive overload

(which requires simultaneous information excess), nor social media fatigue (which requires interaction pressure) predicts this outcome. CIF does. This predictive gap is the clearest justification for treating CIF as a theoretically independent construct that extends rather than duplicates the existing literature.

The primary behavioral relevance of CIF lies in explaining declining receptiveness toward future innovations. Consumers experiencing CIF may postpone updates, ignore newly introduced features, retain familiar systems, or avoid further innovations. CIF thus explains innovation avoidance not because consumers oppose innovation itself, but because they become fatigued by the relentless pace of change.

CIF is especially relevant in high-velocity innovation environments such as digital platforms, mobile applications, e-commerce ecosystems, smart devices, and technology-enabled services, where updates and feature enhancements occur continuously [9,36]. CIF therefore offers a valuable lens for understanding consumer behavior in contemporary digital markets, where continuous innovation has become the norm rather than the exception.

3. Materials and Methods

3.1. Scale Development Procedure

The development of the CIF scale followed established guidelines for construct development and validation in behavioral research [38,39]. These guidelines recommend a multi-stage process covering item generation, content validation, exploratory factor analysis, and construct validation. Following this approach, the present study employed both deductive and inductive methods to generate measurement items and then empirically validated the resulting scale through a series of statistical analyses.

The scale development process consisted of three main stages. First, an initial pool of items was generated using both theoretical insights from the existing literature and qualitative insights from consumers' experiences with continuous innovation environments. Second, content validity was assessed through expert evaluation to ensure that the items accurately represented the construct domain. Third, the refined items were empirically tested through exploratory factor analysis to identify the underlying factor structure, followed by validation analyses using an independent sample. This multi-stage procedure ensures that the resulting scale is both conceptually grounded and empirically reliable.

3.2. Study 1: Item Generation and Content Validity

Following recommended scale development procedures [38], Study 1 focused on generating an initial pool of items and establishing content validity for the construct of CIF. To ensure both theoretical rigor and practical relevance, item generation was conducted using deductive and inductive approaches. This combined strategy allows measurement items to reflect theoretical insights from the prior literature while also capturing consumers' real experiences with innovation-related changes.

3.2.1. Deductive Item Generation

To initiate the scale development process, a deductive approach was employed to generate preliminary measurement items grounded in prior literature. Deductive item generation is widely recommended in scale development because it enables researchers to derive indicators from established theoretical and empirical work, thereby improving construct representativeness and content validity [38,39]. As CIF is a newly proposed construct and no validated measurement scale was available, the relevant literature from conceptually related domains was systematically reviewed to identify recurring themes suitable for item development.

A structured literature search was conducted using Scopus, Web of Science, ScienceDirect, and Google Scholar. Search terms included combinations of innovation fatigue, technostress, digital fatigue, social media fatigue, information overload, cognitive load, innovation resistance, product updates, technology change, and consumer technology stress. Priority was given to peer-reviewed journal articles and highly cited studies in marketing, consumer behavior, information systems, psychology, and technology management. The objective was to identify recurring psychological responses associated with repeated technological or innovation-related change.

Because no direct CIF scale existed, items were informed by adjacent theoretical domains rather than adopted from a single prior instrument. Research on technostress informed items related to stress, pressure, and mental exhaustion caused by recurring technological demands [16]. Studies on social media fatigue and digital fatigue informed items reflecting tiredness and declining motivation following repeated digital engagement or platform changes [17,44,45]. The literature on information overload informed items associated with confusion and feelings of overwhelm resulting from excessive or frequent changes [12,19,46]. In addition, cognitive load theory informed items related to repeated learning burden and cognitive effort required to understand new functionalities [14,47–49]. Research on innovation resistance further informed items capturing reduced willingness to engage with additional innovations [37,50,51].

Based on these recurring themes, 13 preliminary deductive items were drafted to capture the conceptual domain of CIF. Specifically, items were developed to reflect tiredness from frequent updates (CIF1), difficulty keeping pace with continuous feature introductions (CIF2), mental exhaustion caused by new functionalities (CIF3), feelings of overwhelm due to ongoing upgrades (CIF4), repeated learning burden (CIF5), reduced interest in trying new updates (CIF6), stress caused by frequent product changes (CIF7), frustration with excessive upgrades (CIF8), confusion created by repeated innovation (CIF9), preference for product stability over constant change (CIF10), declining enjoyment resulting from recurring feature modifications (CIF11), pressure to keep pace with new versions (CIF12), and mental drain caused by continuous innovation (CIF13). The complete list of deductively generated items is presented in Appendix A.

All items were written in concise consumer-oriented language to reflect experiences in contemporary digital consumption settings, including mobile applications, digital platforms, and technology-enabled products or services. During the drafting stage, duplicate wording, overly technical language, and items not sufficiently aligned with the conceptual meaning of CIF were removed. The resulting set of 13 deductively generated items was subsequently combined with items derived from the inductive qualitative phase for expert review and further empirical purification.

3.2.2. Inductive Item Generation

To complement the deductive approach, an inductive method was employed to capture consumers' lived experiences of innovation-driven cognitive strain in real consumption contexts. Inductive qualitative inquiry is particularly valuable in scale development when existing literature does not fully capture emerging phenomena or context-specific meanings, as it enables researchers to identify expressions, perceptions, and experiences directly from participants [38,39]. Accordingly, semi-structured interviews were conducted with consumers residing in Saudi Arabia who regularly used technology-driven products and digital services characterized by frequent updates or feature changes, such as mobile applications, digital platforms, streaming services, and consumer electronics.

Participant Selection and Sampling

Participants were recruited through online consumer communities and social media groups using purposive sampling. This approach was appropriate because the study required respondents who were actively exposed to recurring innovation cycles in their everyday consumption activities. Prior to participation, individuals were screened to ensure that they regularly used digital products or services involving frequent technological updates, interface modifications, or new feature releases. Only those meeting these criteria were invited to participate. A total of 15 interviews were completed. The participant group included 9 males and 6 females. In terms of age, 5 participants were between 18 and 25 years, 6 were between 26 and 35 years, and 4 were above 35 years. All participants reported regular use of mobile applications, e-commerce platforms, and other digitally enabled services. This sample size was considered suitable for exploratory qualitative inquiry, as thematic saturation is often achieved in relatively small yet information-rich samples when participants share relevant experiences [52].

Interview Procedure

The interviews followed a semi-structured format, which ensured consistency across respondents while allowing sufficient flexibility for participants to describe their experiences in their own words [53]. Participants were asked questions designed to explore their reactions to frequent updates, the extent to which technological upgrades influenced their product usage, and whether they experienced feelings of difficulty, pressure, frustration, or fatigue when attempting to keep pace with evolving product features and functionalities. Each interview lasted approximately 15 to 20 min and was conducted online. Prior to participation, informed consent was obtained, and respondents were assured that their identities would remain anonymous and that their responses would be used solely for academic research purposes. The semi-structured interview guide is presented in Appendix A.

Data Analysis and Trustworthiness

All interviews were recorded with permission and subsequently transcribed for analysis. The transcripts were analyzed using thematic analysis to identify recurring patterns and themes in consumers' accounts of innovation-related exhaustion [54]. Two researchers independently reviewed the transcripts and coded the data to identify themes associated with fatigue, frustration, cognitive effort, adaptation burden, reduced motivation, and difficulties responding to frequent innovation-related changes. After completing the independent coding process, the researchers compared their interpretations and discussed discrepancies until consensus was reached. This multiple-coder procedure enhanced the credibility, consistency, and trustworthiness of the findings.

Item Generation Outcomes

The qualitative phase generated 10 additional items reflecting consumers' natural expressions and perceptions of innovation-related fatigue. Representative themes included feeling tired of repeated updates, difficulty keeping pace with changing features, reduced motivation to explore new functionalities, frustration with continual technological change, and effort associated with repeatedly learning revised systems. These themes were subsequently translated into concise first-person survey statements suitable for quantitative measurement of CIF. Illustrative qualitative themes, representative participant statements, and corresponding inductively generated items are presented in Appendix A.

These items were combined with the 13 items derived from the deductive literature review, resulting in an initial pool of 23 measurement items for subsequent expert review

and empirical purification during the scale development process. The complete list of initial items and subsequent refinement stages is presented in Appendix A.

3.2.3. Content Validity Assessment

To assess content validity, the initial pool of 23 measurement items was reviewed by a panel of five academic experts with recognized expertise in marketing, consumer behavior, and scale development. Content validity assessment is an important stage in construct development because it helps determine whether proposed items adequately represent the conceptual domain of a construct prior to empirical testing [38,39]. The experts were provided with the conceptual definition of Consumer Innovation Fatigue (CIF) together with instructions for evaluating each item independently.

Specifically, the panel members were asked to assess each item in terms of (1) clarity of wording, (2) conceptual relevance to CIF, (3) representativeness of the construct domain, and (4) potential overlap or redundancy with other items in the pool. In addition, they were invited to recommend wording improvements, identify ambiguous statements, and suggest the removal of items that did not sufficiently capture the intended meaning of CIF.

Based on the feedback received, several items were revised to improve wording precision, readability, and contextual suitability for digitally intensive consumption settings. Items that were repeatedly identified as conceptually redundant, insufficiently aligned with the CIF definition, overly narrow in scope, or vague in wording were removed from the pool. Certain items reflected preferences for product stability or enjoyment rather than fatigue, while others focused on behavioral delay rather than the psychological state represented by CIF.

Following this refinement process, eight items were removed and the scale was reduced from 23 to 15 items, which were retained for empirical testing in the subsequent exploratory factor analysis stage. Details of the deleted items, reasons for removal, and subsequent purification stages are presented in Appendix A.

3.3. Study 2: Exploratory Factor Analysis

The purpose of Study 2 was to examine the underlying factor structure of the CIF construct and refine the measurement scale by eliminating weak or redundant items. Following the item generation and content validation procedures in Study 1, a set of 15 items was retained for empirical testing. Exploratory factor analysis (EFA) was conducted to assess the dimensionality of the construct and identify the items that most accurately represent CIF.

3.3.1. Sample and Data Collection

Data were collected through an online self-administered questionnaire distributed among consumers in Saudi Arabia. Participants were recruited through social media platforms and online consumer communities. To ensure that respondents had relevant experience with the phenomenon under investigation, a screening question was included at the beginning of the survey asking whether respondents regularly used digital products or services that frequently introduce updates or new technological features. Only individuals meeting this criterion were allowed to proceed with the survey.

A total of 248 responses were initially collected. The dataset was screened for incomplete questionnaires and potential careless responses. Responses showing patterns of inattentive responding, such as straight-lining across scale items or extremely short completion times, were removed. After this data-cleaning procedure, the final sample consisted of 225 valid responses, which were used for the exploratory factor analysis.

Participation in the study was voluntary and anonymous. Respondents were informed about the academic purpose of the research and provided informed consent prior to

completing the questionnaire. All measurement items were measured using a seven-point Likert scale ranging from 1 (strongly disagree) to 7 (strongly agree), which is commonly used in consumer behavior and innovation research to capture respondents' perceptions and attitudes. The adapted scale items are given in Appendix B.

3.3.2. Exploratory Factor Analysis

Exploratory factor analysis (EFA) was conducted to examine the underlying structure of the proposed scale and to refine the measurement items. Consistent with established guidelines for scale development [38,39,55], principal axis factoring was used as the extraction method because it is more appropriate for identifying latent constructs than principal component analysis. Because the objective at this stage was to determine whether the item pool reflected a clear and interpretable underlying structure, varimax rotation was employed to obtain a simpler loading pattern during the initial purification stage. Although psychological constructs may sometimes be correlated, the EFA results supported a single-factor solution, thereby reducing concerns regarding inter-factor correlations in the present analysis.

Before performing the factor analysis, the suitability of the dataset for EFA was assessed. The Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy was 0.837, which exceeds the recommended threshold of 0.70, indicating that the sample size and correlations among variables were adequate for factor analysis. In addition, Bartlett's test of sphericity was statistically significant ($\chi^2 = 1083.334$, $p < 0.001$), suggesting that the correlation matrix contained sufficient inter-item correlations to justify factor extraction.

The factor solution revealed one dominant factor with an eigenvalue greater than 1.00, supporting the unidimensional nature of the construct. The retained factor explained 49.205% of the total variance, indicating that a substantial proportion of common variance among the items was captured by a single latent dimension. Accordingly, the findings indicate that CIF represents a coherent unidimensional construct.

During the item purification stage, measurement items were evaluated based on their factor loadings, potential cross-loadings, and conceptual alignment with the construct definition. Following commonly accepted guidelines for scale development, items with factor loadings below 0.50 were removed, together with items demonstrating conceptual redundancy or insufficient alignment with the construct domain. Through this purification process, nine items were eliminated from the original pool, resulting in a refined measurement scale consisting of six items.

The retained items demonstrated satisfactory factor loadings ranging from 0.681 to 0.710, indicating meaningful relationships between the indicators and the underlying latent construct. Although some loadings were marginally below the ideal 0.70 threshold, they were considered acceptable for early-stage scale development given the clear unidimensional structure and the subsequent evidence of reliability and convergent validity obtained in Study 3. These findings provide empirical support for the unidimensional structure of CIF and result in a parsimonious six-item measurement scale. The refined scale was subsequently carried forward to the next stage of the research, where its reliability and validity were further assessed using an independent sample.

4. Results

4.1. Study 3: Measurement Model Validation and Nomological Assessment

The final empirical stage aimed to validate the psychometric properties of the CIF scale and assess its nomological validity. Following the exploratory factor analysis conducted in Study 2, the refined six-item scale was evaluated using partial least squares structural equation modeling (PLS-SEM). Structural equation modeling can be approached

through covariance-based SEM (CB-SEM) or variance-based SEM (PLS-SEM). CB-SEM is generally preferred for theory confirmation, global model fit assessment, and validation of well-established measurement models. In contrast, PLS-SEM is particularly suitable for prediction-oriented research, exploratory model development, and the assessment of newly proposed constructs.

PLS-SEM was selected in the present study for both conceptual and methodological reasons. First, Consumer Innovation Fatigue (CIF) is a newly developed construct, and the primary objective at this stage was construct validation and theory development rather than strict covariance-based confirmation. Second, the study sought to simultaneously assess the psychometric properties of the CIF scale and examine the nomological relationships among innovation exposure, CIF, and innovation avoidance within a single analytical framework. Third, PLS-SEM performs well with moderate sample sizes and does not require strict multivariate normality assumptions, making it appropriate for early-stage scale development research.

Accordingly, PLS-SEM has been widely recommended for emerging construct validation and prediction-oriented consumer research [56]. The analysis was conducted using SmartPLS 4. The evaluation followed recommended PLS-SEM procedures, including the assessment of indicator reliability, internal consistency reliability, convergent validity, and discriminant validity. In addition, nomological validity was examined by testing the theoretically expected relationships among innovation exposure, CIF, and innovation avoidance.

4.2. Data Collection and Sample

Data were collected from consumers in Saudi Arabia who regularly use technology-driven products and digital services characterized by frequent innovation updates, such as mobile applications, digital platforms, and consumer electronics. Participants were recruited through online consumer communities and social media platforms. A screening question ensured that respondents had prior experience with products or services that frequently introduce technological upgrades or new features. A total of 386 responses were initially collected. After removing incomplete questionnaires and responses indicating inattentive responding, the final dataset consisted of 361 valid responses.

The demographic profile of the respondents reflects a diverse consumer sample. Approximately 52% of respondents were male and 48% were female. Regarding age distribution, 35% were between 18 and 25 years, 43% were between 26 and 35 years, 16% were between 36 and 45 years, and 6% were above 45 years. In terms of education, 60% held a bachelor's degree, 24% had postgraduate qualifications, and 16% reported other educational levels. With respect to employment status, 55% were employed, 30% were students, and 15% were self-employed or engaged in other occupations. While the sample includes respondents from multiple age categories, it is relatively concentrated in younger age groups. This distribution is consistent with the study context, as younger consumers are generally more engaged with digital platforms, mobile applications, and rapidly evolving online services, and tend to adopt new technologies at higher rates than older cohorts [57]. However, older consumers may differ in digital literacy, technology confidence, and their ability to adapt to continuous technological change [58,59]. Therefore, the present findings should be interpreted primarily in relation to digitally active consumer segments rather than the broader population. The sample size of 361 respondents exceeds recommended thresholds for structural equation modeling and is considered adequate for reliable measurement model assessment using PLS-SEM.

4.3. Measurement Model Assessment

The measurement model was evaluated following the recommended procedures for partial least squares structural equation modeling (PLS-SEM) as outlined by Hair et al. [56]. The assessment focused on examining indicator reliability, internal consistency reliability, convergent validity, and discriminant validity to ensure that the constructs were measured accurately and consistently.

Because the data for all constructs were collected from the same respondents using a single questionnaire, the potential for common method bias (CMB) was assessed. Following Harman's single-factor test, all measurement items were entered into an unrotated exploratory factor analysis. The results showed that the first factor accounted for less than 50% of the total variance, indicating that common method bias is unlikely to pose a serious concern in this study.

Indicator reliability was first assessed by examining the outer loadings of each measurement item on its corresponding construct. The results indicate that all items demonstrated satisfactory factor loadings exceeding the recommended threshold of 0.50. Specifically, the items measuring innovation exposure showed loadings ranging from 0.753 to 0.821, while the items measuring CIF ranged from 0.684 to 0.717. Similarly, the indicators for innovation avoidance demonstrated loadings between 0.715 and 0.834. These results suggest that the measurement items are strongly associated with their respective latent constructs and provide adequate support for indicator reliability.

Internal consistency reliability was then evaluated using composite reliability (CR), which is considered a more appropriate reliability measure in PLS-SEM than Cronbach's alpha because it accounts for the different outer loadings of indicators [56].The results show that the composite reliability values for all constructs exceeded the recommended threshold of 0.70. Specifically, innovation exposure demonstrated a composite reliability value of 0.876, CIF exhibited a composite reliability value of 0.881, and innovation avoidance showed a composite reliability value of 0.869. These values indicate that the measurement items within each construct consistently measure the same underlying concept and therefore demonstrate satisfactory internal consistency reliability.

Convergent validity was subsequently assessed using the average variance extracted (AVE), which measures the proportion of variance captured by a construct relative to the variance due to measurement error. The results indicate that the AVE values for all constructs exceed the recommended threshold of 0.50 [56]. In particular, innovation exposure demonstrated an AVE value of 0.640, CIF showed an AVE value of 0.553, and innovation avoidance exhibited an AVE value of 0.626. These values confirm that each construct explains more than half of the variance of its associated indicators, thereby supporting the presence of adequate convergent validity. The results indicate that the measurement model demonstrates satisfactory levels of indicator reliability, internal consistency reliability, and convergent validity. The detailed results of the measurement model evaluation are presented in Table 2.

Discriminant Validity

Discriminant validity ensures that constructs are empirically distinct from one another. It was assessed using both the Fornell–Larcker criterion and the Heterotrait–Monotrait ratio (HTMT).

According to the Fornell–Larcker criterion, the square root of the AVE for each construct should exceed its correlations with other constructs [60]. As shown in Table 3, this condition is satisfied for all constructs, indicating adequate discriminant validity.

Table 2. Reliability and Convergent Validity.

Construct	Source	Items	Loadings	CR	AVE
Innovation Exposure	Adapted scale	IE1	0.803	0.876	0.640
		IE2	0.821		
		IE3	0.753		
		IE4	0.821		
Consumer Innovation Fatigue (CIF)	Newly developed	CIF1	0.714	0.881	0.553
		CIF2	0.696		
		CIF3	0.681		
		CIF4	0.703		
		CIF5	0.705		
		CIF6	0.710		
Innovation Avoidance	Adapted scale	IA1	0.826	0.869	0.626
		IA2	0.834		
		IA3	0.783		
		IA4	0.715		

Table 3. Fornell–Larcker Criterion.

Constructs	Consumer Innovation Fatigue	Innovation Avoidance	Innovation Exposure
Consumer Innovation Fatigue	0.744		
Innovation Avoidance	0.699	0.791	
Innovation Exposure	0.709	0.607	0.800

Discriminant validity was further evaluated using HTMT values. As shown in Table 4, all HTMT values are below the recommended threshold of 0.90, confirming adequate discriminant validity [61].

Table 4. Discriminant Validity (HTMT).

Constructs	Consumer Innovation Fatigue	Innovation Avoidance	Innovation Exposure
Consumer Innovation Fatigue	—		
Innovation Avoidance	0.851	—	
Innovation Exposure	0.858	0.751	—

In addition to the statistical evidence provided through the Fornell–Larcker criterion and HTMT ratios, the distinctiveness of CIF was further supported through its conceptual positioning relative to adjacent constructs discussed in Sections 2.4 and 2.5. Unlike technostress, social media fatigue, and information overload, CIF specifically captures the psychological exhaustion generated when successive innovation cycles exceed the consumer's cognitive recovery capacity. This supply-side origin sets CIF apart from all adjacent fatigue constructs.

4.4. Model Fit Assessment

Model fit was assessed using the standardized root mean square residual (SRMR). The SRMR value for the saturated model was 0.061, while the estimated model produced an SRMR value of 0.067. Both values fall below the recommended threshold of 0.08, indicating satisfactory model fit [62].

4.5. Nomological Validity

To further establish the nomological validity of CIF, the construct was examined within a theoretically relevant network of antecedent and outcome variables. Nomological validity refers to the extent to which a construct relates to other variables as theory predicts. In the present study, innovation exposure was modeled as an antecedent of CIF, while innovation avoidance was modeled as a behavioral outcome.

Innovation exposure reflects the frequency with which consumers encounter technological updates, product upgrades, interface modifications, and new features in the products and services they use. In contemporary digital environments, consumers are increasingly exposed to continuous cycles of innovation that require repeated attention, evaluation, and adaptation. Prior research suggests that frequent technological change increases the cognitive effort required to understand and adjust to evolving products and services [9,63]. From the perspective of Cognitive Load Theory (CLT), repeated exposure to such changes may gradually consume individuals' limited cognitive resources and generate psychological strain over time [14]. Similarly, research on technostress indicates that recurring technological changes may overwhelm users and create feelings of exhaustion [40]. Consumers who frequently encounter innovation-related changes are more likely to experience CIF.

H1. *Innovation exposure positively influences consumer innovation fatigue.*

Innovation avoidance refers to a consumer's tendency to delay, resist, ignore, or disengage from new innovations, product updates, or technological changes. Prior research on innovation resistance suggests that consumers may avoid innovations when they are perceived as cognitively demanding, effortful, or disruptive to established usage routines [64,65]. When fatigue from successive innovation cycles accumulates, consumers become less willing to engage with additional product features, system changes, or technological upgrades. Rather than actively adopting further innovations, fatigued consumers may prefer familiar usage patterns or postpone interaction with new developments. Consequently, CIF is expected to increase innovation avoidance.

H2. *Consumer innovation fatigue positively influences innovation avoidance.*

CIF is also expected to serve as a mediating mechanism linking innovation exposure with innovation avoidance. Repeated exposure to updates and technological changes may not directly result in avoidance unless such exposure first generates feelings of fatigue, overwhelm, or mental exhaustion. Prior research suggests that psychological strain often operates as an internal mechanism through which external demands influence subsequent behavioral responses [14,40,65]. Once fatigue develops, consumers may become less receptive to further innovations and more likely to disengage from new developments. Thus, innovation exposure is expected to indirectly increase innovation avoidance through CIF.

H3. *Consumer innovation fatigue mediates the relationship between innovation exposure and innovation avoidance.*

4.6. Structural Model

The structural model results support both hypotheses. Innovation exposure has a significant positive effect on CIF ($\beta = 0.709$, $t = 19.830$, $p < 0.001$). In addition, CIF significantly influences innovation avoidance ($\beta = 0.699$, $t = 14.941$, $p < 0.001$). These findings provide evidence of nomological validity, demonstrating that CIF operates consistently within a theoretically meaningful network of innovation-related consumer responses.

The mediation analysis further indicates that CIF significantly transmits the effect of innovation exposure on innovation avoidance. The indirect effect of innovation exposure on innovation avoidance through CIF was positive and significant ($\beta = 0.320$, $t = 11.684$, $p < 0.001$), supporting the mediating role of CIF. This finding suggests that repeated high innovation frequency increases avoidance by first generating the psychological exhaustion captured by CIF.

The explanatory power of the model was assessed using the coefficient of determination (R^2). The results indicate that innovation exposure explains 50.3% of the variance in CIF ($R^2 = 0.503$). Furthermore, CIF explains 48.9% of the variance in innovation avoidance ($R^2 = 0.489$), suggesting that the proposed model demonstrates moderate explanatory power in explaining consumers' responses to continuous innovation environments.

In addition, the effect sizes (f^2) were examined to assess the relative impact of the exogenous constructs on the endogenous variables. According to the guidelines proposed by Hair et al. [56]. f^2 values of 0.02, 0.15, and 0.35 represent small, medium, and large effects, respectively. The results indicate that innovation exposure has a very strong effect on CIF ($f^2 = 0.236$), while CIF also exhibits a substantial effect on innovation avoidance ($f^2 = 1.159$), indicating large effect sizes for both structural relationships.

Finally, the predictive relevance of the model was evaluated using the Stone–Geisser Q^2 statistic obtained through the PLSpredict procedure. Q^2 values greater than zero indicate that the model has predictive relevance for the endogenous constructs. The results show that CIF demonstrates a Q^2 value of 0.186, while innovation avoidance exhibits a Q^2 value of 0.181. Since both values are greater than zero, these findings confirm that the model has satisfactory predictive relevance for explaining consumer responses to high-frequency digital innovation.

5. Discussion

The primary objective of this study was to conceptualize and develop a reliable measurement scale for Consumer Innovation Fatigue (CIF), a phenomenon that has received limited attention in the innovation and consumer behavior literature, particularly within digital commerce environments. In contemporary platform-based markets, firms operate under competitive pressure to continuously update their products, services, and interfaces—a structural condition that places escalating adaptation demands on consumers who never reach a stable post-adoption state. While prior research has largely examined the benefits of innovation and the factors driving consumer acceptance, the potential psychological costs accumulated across multiple successive innovation cycles have remained theoretically underexplored. This study addresses this gap by conceptualizing CIF, grounding it in a four-stage DIT–CLT process model, and developing a validated measurement scale to enable systematic empirical investigation of this construct in digital contexts.

The scale development findings provide strong empirical support for the proposed construct. The exploratory factor analysis and subsequent validation procedures indicate that CIF represents a coherent and unidimensional psychological state associated with repeated exposure to innovation-related change. The final six-item scale demonstrated satisfactory reliability, convergent validity, and discriminant validity, suggesting that the proposed instrument offers a parsimonious yet robust measure of consumers' fatigue toward persistent innovation cycles. Importantly, the findings support the conceptualization of CIF as a distinct fatigue-related construct rooted in innovation velocity rather than system difficulty or momentary information excess.

Beyond scale validation, the findings illuminate the antecedents and behavioral consequences of CIF. Innovation exposure significantly predicts CIF, confirming that consumers who frequently encounter product updates, interface modifications, and technological

changes develop escalating psychological strain. This result is consistent with the process model proposed in Section 2.3: DIT-driven innovation cycles establish the structural condition for recurring consumer demands, CLT mechanisms explain the cognitive cost within each cycle, and the non-recovery dynamic between cycles explains why those costs compound into fatigue. Critically, this means CIF is not a by-product of using difficult technology—it develops through the pace of change itself. Consumers whose cognitive resources are not fully restored between successive innovation cycles progressively lose their capacity for engaged, willing adaptation. The construct therefore captures a form of exhaustion that existing frameworks do not fully address: one that can arise even when every individual update is well-designed, useful, and easy to use, provided that updates arrive faster than consumers can absorb them.

The Stage 2 mechanism of the process model helps explain the specific character of CIF-related strain. Within each innovation cycle, consumers perform a cognitively distinctive set of operations: they must not only process new information but simultaneously hold their prior product schema in working memory in order to compare it with the revised version. This dual-representation demand—maintaining the old while evaluating the new—is what CLT classifies as germane load, the most resource-intensive load type because it requires active schema restructuring rather than passive information receipt. This explains why even individually minor updates can be disproportionately costly: the cognitive burden is not proportional to the objective size of the change, but to the degree of schema revision required. A consumer who has invested effort in learning a platform encounters each redesign as a depreciation of that investment. Over successive cycles, this pattern transforms innovation from a source of value into a source of anticipated cognitive cost, fundamentally altering the consumer's evaluative orientation toward the firm's products.

The positive effect of CIF on innovation avoidance reveals an important implication of Stage 4 of the proposed model: once fatigue crystallizes into a chronic psychological state, it alters the consumer's decision calculus regarding future innovations. This is theoretically significant because it extends DIT's account of adoption behavior. DIT models adoption as a function of perceived attributes—relative advantage, compatibility, trialability, observability, and complexity. CIF introduces a sixth factor that DIT does not account for: accumulated psychological cost from prior adoption cycles. A consumer experiencing CIF may evaluate a new innovation favorably on all five DIT attributes—perceiving it as advantageous, compatible, and low in complexity—yet still avoid it because the perceived psychological cost of entering another adaptation cycle exceeds the perceived benefit of the innovation itself. This finding therefore suggests that DIT's attribute-based adoption model requires supplementation with a fatigue-history variable in high-velocity innovation environments, where the cumulative psychological record of prior cycles becomes an independent predictor of future adoption decisions.

The mediation result—that CIF fully mediates the relationship between innovation exposure and avoidance—carries a precise theoretical implication that goes beyond confirming the indirect pathway. Full mediation indicates that innovation exposure has no significant direct effect on avoidance: the behavioral outcome depends entirely on the psychological state CIF produces, not on exposure itself. This finding positions CIF as a necessary psychological condition rather than a mere intervening variable. Theoretically, this means that high innovation exposure does not inevitably produce avoidance—it does so only when it generates sufficient fatigue to trigger Stage 4 of the process model. Consumers exposed to high innovation frequency but who successfully recover cognitive resources between cycles—perhaps due to lower intrinsic load per cycle, greater prior product familiarity, or more spacing between updates—would not be expected to develop avoidance. This suggests that the inter-cycle recovery interval, rather than exposure frequency alone,

may be the critical modifiable factor for firms seeking to sustain consumer engagement without triggering fatigue-driven disengagement.

The behavioral consequences of CIF extend beyond simple avoidance and suggest a broader restructuring of how fatigued consumers engage with digital platforms. Rather than uniformly withdrawing, fatigued consumers appear to undergo a motivational reorientation: they shift from exploratory engagement—seeking novelty, testing new features, voluntarily adopting updates—toward preservative engagement focused on protecting existing routines and minimizing cognitive reinvestment. This shift has implications that DIT's adopter categories do not fully capture. DIT classifies consumers by their speed of initial adoption (innovators, early adopters, early majority, late majority, laggards), treating these as relatively stable individual-level traits. CIF suggests a complementary dynamic trajectory: a consumer who begins as an early adopter may progressively migrate toward laggard-like behavior not because their underlying innovativeness has changed, but because their cognitive resources for managing successive adoption cycles have been depleted. This temporal drift in effective adoption propensity—driven by fatigue rather than preference—represents a theoretically novel contribution to understanding how individual consumers change their innovation engagement over the product lifecycle.

These findings collectively suggest a necessary revision to how innovation adoption theory handles high-velocity digital environments. DIT was developed to explain the spread of discrete innovations within a social system—a model suited to an era when major product changes were infrequent and adoption was a relatively bounded decision. Contemporary digital markets violate this assumption: firms in platform-based ecosystems do not introduce discrete innovations but sustain a continuous stream of incremental changes that never fully stabilizes into a post-adoption state. Consumers are therefore never "post-adoption" in the DIT sense; they remain perpetually in a state of partial adaptation. CIF theorizes the psychological consequence of this structural condition. The implication is not merely that CIF is a downside of innovation—it is that innovation adoption theory in its current form is structurally incomplete for explaining consumer behavior in digital markets. A model that assumes adoption is a terminal state cannot predict the fatigue, drift, and eventual avoidance that the present findings document. CIF therefore does not simply add a new variable to the existing model; it challenges one of the foundational assumptions of that model and proposes a reformulation suited to environments where innovation is continuous rather than episodic.

5.1. Theoretical Contributions

This study makes several contributions to the literature on innovation, consumer behavior, and electronic commerce. First, it introduces and conceptualizes CIF as a distinct construct that captures the psychological exhaustion consumers may experience due to repeated exposure to innovation-related changes in digital environments. While prior research has extensively examined innovation adoption and the drivers of consumer acceptance, the literature has largely focused on the positive outcomes of innovation. By contrast, this study highlights an underexplored dark side of innovation: the progressive psychological depletion that accumulates when the pace of market-driven change structurally exceeds consumers' cognitive recovery capacity.

Second, this study contributes to the broader literature on technology-related fatigue by clearly distinguishing CIF from related constructs such as technostress, social media fatigue, and information overload. Although these constructs explain fatigue associated with technology usage, digital interaction, or excessive information processing, they do not explicitly capture fatigue arising from repeated exposure to continuous innovation cycles. By establishing conceptual boundaries and empirically validating CIF, this research

advances theoretical understanding of how consumers respond to rapidly evolving digital platforms and innovation-intensive environments.

Third, the study makes a methodological contribution by developing and validating a reliable measurement scale for CIF. Using a rigorous multi-stage scale development process—including deductive and inductive item generation, exploratory factor analysis, measurement validation, and nomological assessment—the study provides a parsimonious six-item scale with strong psychometric properties. This validated instrument enables future researchers to systematically examine innovation fatigue across various digital commerce contexts, including online platforms, mobile applications, and technology-enabled services.

Finally, this research contributes to the emerging literature on the dark side of innovation and digital transformation. While innovation has traditionally been viewed as a source of progress and competitive advantage, recent research increasingly recognizes that rapid technological change may generate unintended consequences for users. By demonstrating that innovation velocity—independent of usability—can induce fatigue and trigger avoidance, this study offers new insight into how innovation intensity shapes consumer behavior in complex and sometimes counterproductive ways within digital ecosystems.

5.2. Practical Implications

The findings of this study offer several important implications for managers operating in digital commerce and innovation-driven markets. As firms deploy platform updates and feature enhancements at accelerating rates, understanding when that cadence crosses the threshold of consumer cognitive recovery becomes strategically critical.

First, firms should carefully manage the frequency and pacing of innovation introductions. In digital platforms and e-commerce environments, where updates can be deployed rapidly, introducing too many changes within a short period may overwhelm consumers and contribute to innovation fatigue. Managers should therefore balance the need for continuous innovation with consumers' capacity to absorb and adapt to new features. Designing more structured and user-sensitive innovation cycles may help reduce fatigue and improve long-term adoption.

Second, organizations should emphasize effective communication and user guidance when introducing innovations. In digital commerce contexts, where consumers interact with complex interfaces and evolving features, providing clear explanations, tutorials, onboarding processes, and in-app guidance can reduce cognitive burden. By facilitating learning and reducing uncertainty, firms can reduce the per-cycle cognitive cost that, when unaddressed, accumulates into CIF.

Third, companies should adopt a consumer-centered innovation strategy that prioritizes meaningful and value-adding improvements rather than frequent incremental changes. Innovations that clearly enhance user experience or solve relevant problems are more likely to be perceived positively. In contrast, frequent minor updates that require consumers to repeatedly adjust their behavior without delivering clear benefits may contribute to frustration and fatigue, ultimately reducing engagement and adoption.

Finally, the scale developed in this study offers a practical diagnostic tool for managers. By measuring CIF, firms can assess whether their innovation strategies are placing excessive cognitive demands on consumers. Monitoring innovation fatigue levels can help organizations optimize update frequency, refine user experience design, and align innovation strategies with consumer capabilities and preferences in digital environments.

5.3. Limitations and Future Research

Despite its contributions, this study has several limitations that should be acknowledged critically. First, data were collected exclusively from consumers in Saudi Arabia, which constrained the generalizability of findings. While Saudi Arabia's rapid digital adoption rates make it a relevant setting, relying on a single national context means the scale has not been validated across populations with different cultural orientations toward technology, varying innovation tolerance levels, or distinct e-commerce ecosystems. Saudi consumers may differ systematically from those in Western, East Asian, or less digitally developed markets in ways that affect the experience and expression of CIF. Without cross-national replication, it is not possible to determine whether the construct's factor structure, item loadings, or nomological relationships are stable across contexts. Future studies should validate the scale in multiple countries using multigroup confirmatory factor analysis to test for measurement invariance before drawing broader theoretical conclusions from the construct.

Second, the sample was disproportionately concentrated in younger consumers. Although this is partially expected in digital commerce contexts, it limits the extent to which findings can be attributed to the general consumer population. Older consumers may process innovation-related changes differently, given differences in cognitive flexibility, schema rigidity, and prior experience with technological change. The present scale may therefore not fully capture the expression of CIF across all age segments, and its item wording may resonate more strongly with digitally native cohorts. Future research should test the scale across broader age distributions and examine whether generational differences moderate the innovation exposure–CIF relationship.

Third, the study focused on digital products and e-commerce services, and the nomological network tested was intentionally parsimonious—limited to innovation exposure and innovation avoidance. While this served the scale development purpose, it means the boundary conditions of CIF remain largely unexplored. Potential moderators such as consumer innovativeness, platform switching costs, and perceived update controllability have not been tested. Future research should expand the network and examine CIF across sectors including financial technology, healthcare, and smart devices to assess construct transferability.

Fourth, the cross-sectional design is a critical methodological limitation, particularly given the construct under investigation. CIF is theorized in this study as a phenomenon that develops through a four-stage accumulation process across multiple innovation cycles over time. A single-point measurement cannot confirm this temporal progression: it cannot establish whether respondents are at an early, intermediate, or advanced stage of fatigue accumulation, nor whether innovation exposure preceded CIF or whether already-fatigued consumers selectively perceive greater innovation exposure. Causal inference from cross-sectional data is therefore structurally limited. This is not merely a generic weakness of survey research—it is a fundamental mismatch between the longitudinal nature of the construct and the static nature of the measurement design. Future research must employ longitudinal panel designs that track consumers across successive innovation cycles to provide genuine evidence of CIF's accumulation dynamic and to establish causal ordering empirically.

Fifth, the exclusive reliance on PLS-SEM without a confirmatory factor analysis (CFA) using covariance-based SEM (CB-SEM) is a significant limitation for a study whose primary goal is construct validation. PLS-SEM is appropriate for exploratory, prediction-oriented research and performs well with newly proposed reflective constructs; however, it does not produce global model fit indices and operates under a less restrictive statistical framework than CB-SEM. As a result, the present findings demonstrate that the CIF scale performs

adequately under PLS-SEM's permissive criteria—they do not yet confirm that it satisfies the stricter goodness-of-fit requirements of CB-SEM. This distinction matters: a scale that passes PLS-SEM thresholds may not replicate under CB-SEM/CFA, particularly when factor loadings cluster narrowly above the 0.70 cutoff. Until the scale is validated using CB-SEM with CFA on independent samples, including tests for configural, metric, and scalar invariance across groups, it should be regarded as preliminary rather than fully validated. This represents the most critical methodological gap for future replication studies to address.

6. Conclusions

This study aimed to conceptualize and measure CIF, a phenomenon reflecting consumers' progressive psychological exhaustion arising when successive innovation cycles exceed the consumer's cognitive recovery threshold. While innovation remains a central driver of competitiveness and technological progress, the accelerating pace of innovation in digital commerce ecosystems imposes cognitive and psychological demands on consumers.

Through a rigorous multi-stage scale development process, this research developed and validated a six-item unidimensional scale for measuring CIF. The findings demonstrate that the construct is conceptually distinct from related forms of technology-related fatigue and exhibits strong reliability and validity. Moreover, the results show that frequent innovation exposure increases CIF, which in turn leads to innovation avoidance in digital contexts.

By introducing and empirically validating CIF, this study provides a foundation for future research examining the psychological consequences of continuous innovation in digital commerce environments. As markets continue to evolve through rapid technological advancement and frequent platform updates, understanding how consumers absorb successive innovation demands—and when they cannot—becomes increasingly important. The findings contribute to advancing knowledge on the complex relationship between innovation intensity and consumer behavior, highlighting the need for more balanced and consumer-oriented innovation strategies in digital markets.

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Institutional Review Board Statement: The study was conducted in accordance with the ethical principles of the Declaration of Helsinki. The research involved anonymous, voluntary surveys and interviews with competent adult participants, and no personally identifiable information was collected. Participation was voluntary, and appropriate measures were taken to ensure participant anonymity, confidentiality, and data protection throughout the study.

Informed Consent Statement: Informed consent was obtained from all participants prior to participation. Participants were informed of the academic purpose of the study, assured of their anonymity, and advised that their responses would be used solely for research purposes.

Data Availability Statement: Data will be made available on request.

Acknowledgments: The author used AI-assisted tools solely for language editing to improve grammar, readability, and clarity. No generative AI was used to create, generate, or modify the scientific content, ideas, data, or analysis presented in this manuscript. All AI-assisted edits were carefully reviewed and approved by the author, who takes full responsibility for the accuracy, originality, and integrity of the final version.

Conflicts of Interest: The author declares no conflicts of interest.

Appendix A. Item Generation, Refinement, and Purification of the Consumer Innovation Fatigue (CIF) Scale

Appendix A.1. Deductive Item Development (13 Items)

Code	Source	Preliminary Item Statement
CIF1	Deductive	I feel tired of frequent updates and changes in the products or services I use.
CIF2	Deductive	Constant introduction of new features makes it difficult for me to keep up.
CIF3	Deductive	I feel mentally exhausted when products frequently introduce new functionalities.
CIF4	Deductive	I sometimes feel overwhelmed by continuous technological upgrades.
CIF5	Deductive	I find it exhausting to repeatedly learn new product features or updates.
CIF6	Deductive	Frequent innovation changes reduce my interest in trying new product updates.
CIF7	Deductive	I feel stressed when products change too often.
CIF8	Deductive	Too many upgrades make product use frustrating.
CIF9	Deductive	Frequent innovation creates confusion for me.
CIF10	Deductive	I prefer products that remain stable over time.
CIF11	Deductive	Repeated feature changes make products less enjoyable to use.
CIF12	Deductive	I feel pressure to keep up with new product versions.
CIF13	Deductive	Continuous innovation sometimes becomes mentally draining.

Appendix A.2. Inductive Item Development and Interview Protocol

Appendix A.2.1. Semi-Structured Interview Questions

1. Can you describe the products, applications, or digital services you use that change or update frequently?
2. What has your experience been like when the products or services you use introduce new features, updates, or design changes over time?
3. How, if at all, do repeated changes in products or digital services affect the way you use them?
4. What thoughts or feelings have you experienced when trying to keep up with ongoing changes in products or services you regularly use?
5. In what ways, if any, have frequent updates or new features influenced your interest in exploring or continuing to use those products or services?

Appendix A.2.2. Illustrative Themes and Inductively Generated Items

Theme Identified	Representative Participant Statement	Inductively Generated Item Code	Resulting Item Statement
Frequent interface changes	"I get annoyed when apps keep changing how everything looks."	CIF14	I get annoyed when apps keep changing their layout.
Excessive number of updates	"There are so many updates now that I just ignore many of them."	CIF15	I ignore many updates because there are too many.
Learning fatigue	"I do not have the energy to keep learning every new feature."	CIF16	I do not have the energy to learn every new feature.
Declining interest due to constant change	"Too many updates make me lose interest in the product."	CIF17	Constant updates make me lose interest in the product.
Relearning burden	"Whenever products change, I feel frustrated because I must learn again."	CIF18	I feel frustrated when I must relearn how to use products.
Delayed updating behavior	"I usually delay updates unless they are absolutely necessary."	CIF19	I delay updates unless absolutely necessary.
Reduced exploration motivation	"Too many changes make me less interested in exploring what is new."	CIF20	Too many changes make me less willing to explore products.
Repeated change overload	"Frequent digital changes feel overwhelming after some time."	CIF21	I feel overloaded by repeated digital changes.
Perceived burden of new features	"New features often feel like extra burden rather than help."	CIF22	New features often feel like extra burden.
Technology becoming tiring	"Frequent updates make technology tiring to use."	CIF23	Frequent updates make technology tiring to use.

Appendix A.3. Items Removed During Expert Content Validity Review (23 → 15)

Deleted Code	Reason for Removal
CIF8	Similar meaning to existing fatigue/frustration items
CIF9	Overlapped with overwhelm/confusion indicators
CIF10	Reflected preference for stability rather than fatigue
CIF11	Focused on enjoyment rather than exhaustion
CIF14	Too context-specific
CIF19	Captured behavioral delay rather than fatigue state
CIF22	Wording considered vague
CIF23	Redundant with tiredness/exhaustion indicators

Appendix A.4. Retained for Exploratory Factor Analysis (15 Items)

CIF1, CIF2, CIF3, CIF4, CIF5, CIF6, CIF7, CIF12, CIF13, CIF15, CIF16, CIF17, CIF18, CIF20, CIF21.

Appendix A.5. Items Removed During Exploratory Factor Analysis (15 → 6)

Deleted Code	Reason for Removal
CIF7	Low factor loading
CIF12	Low factor loading
CIF13	Low factor loading
CIF15	Low factor loading
CIF16	Low factor loading
CIF17	Low factor loading
CIF18	Low factor loading
CIF20	Low factor loading
CIF21	Low factor loading

Appendix A.6. Final Retained CIF Scale (6 Items)

Code	Item
CIF1	I feel tired of frequent updates and changes in the products or services I use.
CIF2	Constant introduction of new features makes it difficult for me to keep up.
CIF3	I feel mentally exhausted when products frequently introduce new functionalities.
CIF4	I sometimes feel overwhelmed by continuous technological upgrades.
CIF5	I find it exhausting to repeatedly learn new product features or updates.
CIF6	Frequent innovation changes reduce my interest in trying new product updates.

Appendix B. Measurement Items and Sources for Study Constructs

Innovation Exposure Adapted from Jaworski and Kohli [66].

Code	Item
IE1	The products and services I use change technologically very rapidly.
IE2	New technological features frequently appear in the products and services I use.
IE3	I often encounter new versions or upgrades of the products and services I use.
IE4	The products and services I use are frequently updated with new functionalities.

Innovation Avoidance (Adapted from Ram and Sheth [64]; Talke and Heidenreich, [65]).

Code	Item
IA1	I tend to avoid trying new versions of products or services.
IA2	I prefer to continue using existing products rather than adopting new ones.
IA3	I usually delay adopting new technologies or product updates.
IA4	I often ignore new product features or technological updates.

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