Health Technology and Social Research

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Wellbeing Effects in Dementia Home Care under Caregiver Technology Burden and Behavioral Adherence

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Abstract

This study investigates the complex relationships between caregiver technology burden, behavioral adherence, and subjective wellbeing in the context of dementia home care. As digital health technologies and remote monitoring systems are increasingly deployed to support aging-in-place, informal caregivers are faced with new demands that can paradoxically exacerbate existing stress. Utilizing a cross-sectional survey design with 250 informal caregivers of people living with dementia, we proposed and tested a structural equation model to examine the direct and indirect pathways linking technology-induced burden to caregiver psychological wellbeing. The conceptual model posits that technology burden, characterized by cognitive load, system usability challenges, and technical friction, directly diminishes caregiver wellbeing while simultaneously undermining their behavioral adherence to recommended technological and care protocols. The empirical results demonstrate that higher levels of technology burden are associated with a substantial reduction in behavioral adherence, which in turn leads to a significant decline in caregiver subjective wellbeing. Furthermore, behavioral adherence was found to partially mediate the relationship between technology burden and caregiver wellbeing. These findings suggest that the clinical utility of assistive technologies in dementia care is heavily contingent upon minimizing user friction and supporting caregiver self-efficacy. The study highlights the critical need for human-centered design in healthcare informatics and provides practical recommendations for clinicians, technology developers, and healthcare policymakers.

Keywords: Dementia Care; Assistive Technology; Caregiver Burden; Behavioral Adherence; Wellbeing Effects

1. Introduction

1.1 The Landscape of Dementia Home Care and Digital Health Solutions

The global demographic transition toward an aging population has resulted in a dramatic increase in the prevalence of cognitive disorders, with dementia emerging as one of the most pressing public health challenges of the twenty-first century. Because the vast majority of individuals living with dementia prefer to remain in their own homes, the responsibility of managing their daily needs falls predominantly on informal caregivers, who are typically spouses, adult children, or other family members. While aging in place offers substantial psychological and emotional benefits for the care recipient, it imposes an extraordinary physical, emotional, and financial toll on the primary caregiver. This chronic stress environment has been extensively documented in the literature through frameworks such as the Stress Process Model [1], which details how primary stressors,

such as the care recipient's cognitive decline and behavioral disturbances, propagate secondary stressors that ultimately degrade the caregiver's physical and mental health.

In response to the growing challenges of home-based dementia care, healthcare systems and researchers have increasingly turned to digital health solutions. These technologies, collectively referred to as assistive technologies or smart home systems, encompass a wide array of devices designed to monitor the care recipient's safety, manage medical regimens, and facilitate communication with professional care providers [2]. Examples include ambient motion sensors to detect nighttime wandering, smart medication dispensers that alert caregivers when a dose is missed, global positioning system tracking devices to prevent elopement, and mobile applications designed to guide caregivers through behavioral management techniques. The fundamental premise underlying the deployment of these technologies is that they will act as a resource, reducing the active monitoring burden on caregivers, preventing adverse events, and thereby preserving or enhancing caregiver wellbeing.

1.2 The Conceptual Framework of Caregiver Burden and Adherence

Despite the theoretical benefits of digital health technologies, empirical studies have revealed a more complex reality. The introduction of digital tools into the caregiving environment is not a neutral intervention; instead, it frequently introduces a novel set of stressors that can be conceptualized as technology burden. This burden refers to the cognitive, emotional, and physical effort required to learn, configure, maintain, and troubleshoot digital health systems [3]. When technologies are poorly designed, counter-intuitive, or prone to technical malfunctions, they can generate substantial user friction, leading to heightened anxiety, frustration, and a sense of inadequacy among caregivers, many of whom may themselves be older adults with limited digital literacy.

Furthermore, the effectiveness of any technological intervention in dementia home care is strictly dependent on behavioral adherence, defined as the degree to which the caregiver consistently and correctly utilizes the technology and follows the associated care protocols [4]. Unlike clinical trials where researchers closely monitor technology usage, real-world home care environments require caregivers to self-manage these systems. High technology burden can lead to a rapid depletion of the caregiver's limited cognitive and emotional resources, prompting them to bypass system alerts, use devices incorrectly, or abandon the technology entirely [5]. Understanding the interplay between the burdens imposed by technology, the caregiver's behavioral adherence, and their ultimate psychological wellbeing is critical. To date, however, there is a paucity of research that systematically models these direct and indirect pathways [6]. This study addresses this gap by investigating how technology burden and behavioral adherence interact to shape subjective wellbeing among informal dementia caregivers.

2. Literature Review

2.1 Technology Burden in Caregiving Environments

To understand the psychological impact of digital health interventions on informal caregivers, it is essential to unpack the multi-dimensional nature of technology burden. In the field of human-computer interaction and health informatics, user friction is often evaluated through usability frameworks, but in the context of dementia care, this friction takes on a unique and acute quality [7]. Caregivers are already operating under conditions of chronic stress and cognitive overload due to the daily demands of managing memory loss, behavioral issues, and physical limitations of their loved ones. When a digital system is introduced, it imposes a cognitive learning curve that requires the caregiver to process new information, memorize procedures, and adapt their established care routines [8].

According to Cognitive Load Theory, human working memory has a limited capacity, and when information processing demands exceed this capacity, learning and performance are compromised. For an informal caregiver, the cognitive load associated with managing a technology can be divided into intrinsic load (the inherent difficulty of the care task) and extraneous load (the mental effort required by the design of the technology itself) [9]. Poorly designed user interfaces, confusing menu structures, and unclear error messages represent significant sources of extraneous cognitive load. Furthermore, many home-monitoring technologies utilize audible alerts or push notifications to warn caregivers of potential issues, such as a patient leaving a designated area or missing a medication dose. However, high rates of false positives or poorly calibrated thresholds can result in alert fatigue, where the caregiver becomes desensitized to notifications, experiencing elevated stress every time an alert sounds [10]. Technical malfunctions, connectivity issues, and the necessity of frequent battery replacements or software updates add a physical and logistical layer to the overall technology burden, turning what was intended as a supportive tool into an active source of daily frustration.

2.2 Behavioral Adherence to Home Care Protocols

In the medical and behavioral sciences, adherence has historically referred to the extent to which a patient's behavior coincides with medical or health advice [11]. In the context of technology-supported dementia home care, behavioral adherence must be conceptualized more broadly to include the caregiver's adherence to both the technological protocol (e.g., keeping devices charged, responding to prompts, entering required data) and the therapeutic protocols facilitated by that technology (e.g., executing behavioral interventions or administering medications guided by the system). Adherence is not a static behavior but a dynamic process influenced by the caregiver's motivation, perceived self-efficacy, and the perceived utility of the technology [12].

When a caregiver experiences high levels of technology burden, their capacity to maintain adherence is severely compromised. Under the strain of system configuration difficulties, recurrent false alarms, and interface confusion, caregivers often resort to coping mechanisms that undermine the technology's clinical efficacy. These coping mechanisms can range from passive non-adherence, such as ignoring notifications, to active workarounds, such as disabling sensors or turning off devices to obtain relief from constant alerts [13]. Over time, this cumulative frustration often leads to complete technology abandonment, wherein the caregiver stops using the system entirely, returning to manual, often less efficient, care methods [14]. Crucially, non-adherence does not merely represent a failure of the technology to assist; it has direct negative repercussions on the caregiving environment. When adherence fails, the risk of undetected patient wandering, medication errors, or safety hazards increases. The caregiver is then forced to return to a state of constant, hyper-vigilant manual monitoring, which directly feeds back into their subjective sense of distress and reduces their overall quality of life [15].

2.3 Impact on Informal Caregiver Wellbeing

Caregiver wellbeing is a multidimensional construct that encompasses physical health, subjective happiness, life satisfaction, and the absence of clinical psychological distress such as depression or anxiety [16]. In the literature on gerontology and family caregiving, the impact of caregiving on wellbeing is typically framed as a balance between the stressors of care and the resources available to cope with those stressors. While digital health technologies are theoretically designed to serve as a powerful coping resource, their actual impact on wellbeing is highly variable and can be double-edged.

On one hand, when technology works seamlessly and caregiver adherence is high, the system can provide significant peace of mind, reduce the need for constant physical supervision, and offer

actionable insights that make daily care management more predictable. This successful integration enhances the caregiver's sense of competence and mastery, which are key psychological buffers against burnout. On the other hand, when the technology introduces a high level of burden, the caregiver experiences a form of technostress. This technology-induced stress does not exist in a vacuum; it interacts with and amplifies the existing caregiving burden. The physical fatigue of caring for a person with dementia, combined with the mental frustration of navigating an uncooperative digital system, can accelerate the onset of emotional exhaustion and depressive symptoms. Therefore, the total effect of technology on caregiver wellbeing cannot be understood simply by looking at whether a technology is used or not. Instead, it is necessary to examine the pathway through which the burden of using that technology affects the caregiver's ability to maintain adherence to the care protocol, and how these factors jointly determine their psychological state.

3. Methodology and Analytical Framework

3.1 Study Design and Participant Selection

To empirically investigate the relationships between caregiver technology burden, behavioral adherence, and subjective wellbeing, we implemented a quantitative, cross-sectional survey design [17]. The primary objective was to test a structural model where technology burden exerts both a direct negative effect on wellbeing and an indirect effect mediated by behavioral adherence. The target population consisted of informal, unpaid family caregivers who were actively providing care for a relative living with a clinical diagnosis of dementia and residing in a community-dwelling setting.

Participants were recruited using a purposive sampling strategy through several channels, including outpatient memory clinics, community-based caregiver support groups, and regional dementia advocacy organizations [18]. To ensure that participants had sufficient exposure to the technology under evaluation, specific inclusion criteria were established: the caregiver must have been providing a minimum of 20 hours of care per week, and they must have been utilizing at least one home-based monitoring, safety, or care management technology for at least three consecutive months prior to enrollment. Eligible technologies included smart medication dispensers, ambient sensor networks, wearable GPS tracking devices, and interactive mobile health applications designed specifically for dementia care. Caregivers who met these criteria were provided with either a paper-based or secure online questionnaire, which took approximately twenty-five minutes to complete. Ethical approval for the study was secured from the Institutional Review Board, and all participants provided written informed consent prior to data collection [19]. A total of 250 completed questionnaires were collected and retained for the final analysis.

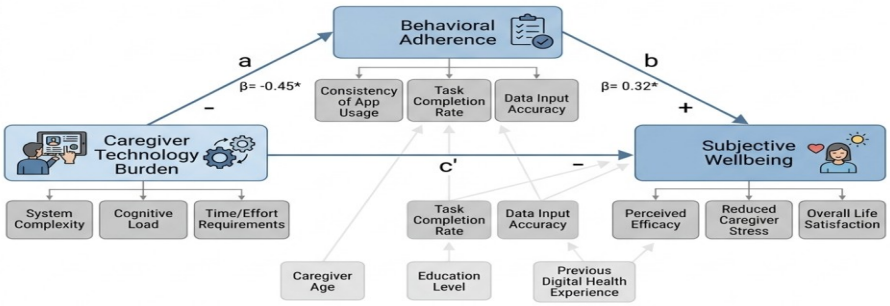

Figure 1: Conceptual Path Model Linking Caregiver Technology Burden, Behavioral Adherence, and Subjective Wellbeing

3.2 Measurement Instruments and Variables

The survey instrument comprised several validated scales adapted to the specific context of technology-supported dementia care. The primary independent variable, caregiver technology burden, was measured using a newly constructed composite scale that combined items from the System Usability Scale and the Technostress Creators Scale [20]. This 8-item instrument assessed the caregiver's perception of the complexity of the technology, the frequency of technical difficulties, the cognitive effort required to operate the system, and the stress associated with false alarms or system notifications. Responses were recorded on a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree), with higher scores indicating a greater technology burden.

Behavioral adherence was measured using a 6-item scale adapted from standard treatment adherence and digital health engagement measures [21]. This scale evaluated the frequency and consistency with which caregivers engaged with the technology as prescribed, including keeping devices charged, responding to system notifications, entering required behavioral logs, and following the system's therapeutic recommendations. Items were scored on a 5-point frequency scale ranging from 1 (never) to 5 (always), with higher scores reflecting superior behavioral adherence. The primary dependent variable, subjective wellbeing, was assessed using the five-item World Health Organization Five Well-Being Index (WHO-5), a widely accepted instrument for measuring positive psychological wellbeing. Caregivers rated their feelings over the past two weeks on a scale from 0 (at no time) to 5 (all of the time). Additionally, to control for confounding variables that might influence caregiver wellbeing, we collected demographic information (caregiver age, gender, education level, and relationship to the patient) and assessed general caregiver burden using the Zarit Burden Interview (ZBI-12) to isolate the specific effects of technology-induced stress from general caregiving strain.

Table 1: Demographic Characteristics of Participants

Variable	Category	Frequency	Percentage
Caregiver Age	Under 50 years	52	20.8
Caregiver Age	50 to 65 years	138	55.2
Caregiver Age	Over 65 years	60	24.0
Caregiver Gender	Female	168	67.2
Caregiver Gender	Male	82	32.8

Variable	Category	Frequency	Percentage
Relationship to Patient	Spouse	98	39.2
Relationship to Patient	Adult Child	124	49.6
Relationship to Patient	Other Relative	28	11.2
Years of Caregiving	Less than 1 year	34	13.6
Years of Caregiving	1 to 3 years	142	56.8
Years of Caregiving	More than 3 years	74	29.6

The descriptive characteristics of the sample presented in Table 1 indicate a diverse representation of caregivers. The majority of the respondents were female, representing approximately two-thirds of the sample, which is highly consistent with national and international caregiving demographics. Furthermore, more than half of the sample fell within the 50 to 65 age bracket, suggesting a mid-life population that may be balancing caregiving with occupational responsibilities. Spouse caregivers and adult child caregivers made up the vast majority of the sample, representing the primary familial relationships involved in home-based dementia care. The duration of caregiving was also substantial, with the majority of caregivers having provided support for one to three years, suggesting they had established clear routines and had significant experience with the demands of dementia care.

4. Empirical Results and Data Interpretation

4.1 Descriptive Analysis of Burden and Adherence

Prior to executing the primary structural analyses, a preliminary descriptive assessment was conducted to evaluate the distribution, central tendencies, and correlations among the core study variables. The mean score for the Caregiver Technology Burden scale was 3.12 (standard deviation = 0.84), which indicates a moderate-to-high level of technology-induced stress and usability difficulty among the participants [22]. Behavioral Adherence yielded a mean score of 3.45 (standard deviation = 0.72), suggesting that while most caregivers attempted to utilize the technologies, they encountered notable consistency challenges in their daily routines. Subjective Wellbeing, as measured by the WHO-5, had a mean score of 52.4 out of 100 (standard deviation = 18.6), reflecting a relatively low level of positive mental health, which is characteristic of dementia caregivers experiencing chronic strain.

Bivariate correlation analyses revealed highly significant relationships in the hypothesized directions. Caregiver technology burden was strongly and negatively correlated with behavioral adherence ($r = -0.48$, $p < 0.01$) and moderately and negatively correlated with subjective wellbeing ($r = -0.38$, $p < 0.01$). Conversely, behavioral adherence was moderately and positively correlated with subjective wellbeing ($r = 0.42$, $p < 0.01$). To ensure the validity of these relationships and to rule out potential statistical artifacts, collinearity diagnostics were performed [23]. The Variance Inflation Factors (VIF) for all predictor variables ranged between 1.15 and 1.42, which are well below the conservative threshold of 5.0, thereby indicating that multicollinearity did not pose a threat to the integrity of the subsequent structural equation modeling.

4.2 Mediation Analysis and Path Models

To test the hypothesized direct and indirect relationships, we utilized Covariance-Based Structural Equation Modeling (CB-SEM). This analytical approach allows for the simultaneous estimation of multiple regression equations and is ideal for evaluating complex mediation models. The measurement model was first assessed using Confirmatory Factor Analysis (CFA) to confirm the construct validity and reliability of the latent variables. All standardized factor loadings were above the acceptable threshold of 0.50, and composite reliability values for each latent construct exceeded 0.70, establishing robust measurement properties.

The structural model was then estimated, incorporating general caregiver burden and patient functional status as control variables to ensure that the observed technology effects were distinct from the broader background stress of caregiving. The structural model demonstrated an excellent fit to the empirical data [24]. The chi-square to degrees of freedom ratio was 1.58, which is well below the recommended limit of 3.0. Additional fit indices further confirmed the model's strength, with the Comparative Fit Index (CFI) at 0.96, the Tucker-Lewis Index (TLI) at 0.95, the Root Mean Square Error of Approximation (RMSEA) at 0.048, and the Standardized Root Mean Square Residual (SRMR) at 0.042.

Table 2: Path Coefficient Estimates of the Structural Equation Model

Path	Standardized Estimate	Standard Error	Critical Ratio	p-value
Technology Burden to Behavioral Adherence	-0.42	0.06	-7.00	Less than 0.001
Behavioral Adherence to Subjective Wellbeing	0.35	0.05	7.00	Less than 0.001
Technology Burden to Subjective Wellbeing	-0.28	0.07	-4.00	Less than 0.001
General Caregiver Burden to Subjective Wellbeing	-0.19	0.04	-4.75	Less than 0.001
Patient Functional Status to Behavioral Adherence	0.12	0.03	4.00	Less than 0.001

The standardized path coefficients, standard errors, critical ratios, and significance values for the structural model are detailed in Table 2. The path from Technology Burden to Behavioral Adherence was negative and highly significant, indicating that an increase in technology-induced friction strongly impairs the caregiver's ability to adhere to the care protocols. The path from Behavioral Adherence to Subjective Wellbeing was positive and highly significant, suggesting that successful, consistent engagement with technology is associated with better caregiver psychological health. Crucially, the direct path from Technology Burden to Subjective Wellbeing remained negative and statistically significant, confirming that technology burden also exerts a direct toll on wellbeing, independent of adherence levels.

To formally test the mediation hypothesis, we employed the bootstrapping method with 5,000 resamples to compute the standardized indirect effect and its associated 95 percent bias-corrected confidence intervals [25]. The results indicated that the standardized indirect effect of technology burden on subjective wellbeing, mediated through behavioral adherence, was -0.147, with a 95 percent confidence interval ranging from -0.214 to -0.092. Because the confidence interval did not include zero, we can conclude that behavioral adherence statistically mediates the relationship between technology burden and caregiver wellbeing. Since both the direct and indirect paths were statistically significant, behavioral adherence acts as a partial mediator, explaining a substantial portion of the negative impact that technology-related strain exerts on caregiver mental health.

5. Discussion and Implications

5.1 Synthesis of Findings and Theoretical Contributions

The empirical findings of this study provide a nuanced understanding of how digital health technologies operate within the fragile ecology of home-based dementia care. By shifting the scholarly focus from simple technology adoption to the post-adoption phenomena of user burden and behavioral adherence, this research offers several key theoretical insights. First, the results expand Pearlin’s Stress Process Model by demonstrating that digital assistive technologies, which

are traditionally categorized as external coping resources, can paradoxically manifest as active secondary stressors [26]. When a digital tool is difficult to operate, prone to false alarms, or poorly aligned with the caregiver's daily routines, it creates a unique form of technostress that directly degrades subjective wellbeing, independent of the primary stress associated with the patient's dementia progression.

Second, this study identifies behavioral adherence as a critical behavioral mechanism that explains how technology burden translates into psychological outcomes [27]. The confirmation of partial mediation suggests that the negative impact of technology burden is not merely a psychological reaction to frustration; it has behavioral consequences that directly disrupt the caregiving process. When technology burden is high, caregivers are driven to ignore alerts, disable features, or abandon the system, which compromises the safety and predictability of the care environment. This lack of adherence ultimately results in a loss of the very benefits that the technology was intended to provide, forcing caregivers back into a state of hyper-vigilance and exacerbating their emotional distress. This highlights a critical loop: usability is not just a commercial convenience but a fundamental determinant of clinical safety and caregiver mental health.

5.2 Practical Recommendations and Future Directions

The practical implications of these findings are highly relevant for technology designers, healthcare providers, and policy makers. For software developers and engineers, the results emphasize the necessity of adopting human-centered design principles that prioritize the cognitive limitations and stress levels of the end-user [28]. Interfaces for dementia care technologies must be simplified, utilizing large targets, clear visual hierarchies, and minimal text to reduce extraneous cognitive load. Crucially, alert systems must incorporate intelligent, adaptive algorithms to minimize false alarms and prevent alert fatigue. Designers should also build proactive troubleshooting assistance into devices, such as simple, interactive visual guides, to reduce the frustration associated with minor technical malfunctions.

For clinicians and community care organizations, these findings suggest that technology should not be prescribed without a thorough baseline assessment of the caregiver’s digital literacy and psychological readiness. Standard training protocols should be developed to guide caregivers through the initial adoption phase, and ongoing technical support should be integrated into clinical home care programs [29]. Finally, while this study provides strong evidence of these relationships, its cross-sectional design limits our ability to make definitive causal claims. Future research should employ longitudinal designs to track how technology burden and behavioral adherence evolve over the course of the dementia care trajectory. Additionally, investigating these dynamics across diverse socioeconomic and cultural groups would help determine the generalizability of the model and ensure that digital health solutions do not inadvertently widen health disparities.

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