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RESEARCH ARTICLE

"Digital echoes: Investigating the impact of online time on happiness and well-being in abu dhabi"

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ABSTRACT

This study examines the impact of online time on well-being among Abu Dhabi residents using data from the fourth Quality-of-Life Survey. Unlike prior studies, this research explores multiple determinants: online time, happiness, subjective health, mental health, self-perceived obesity, exercise, satisfaction with family life, and social relationships. A significant path model reveals that online time adversely affects mental health, self-perceived obesity, sleep quality, and exercise, but positively correlates with happiness and subjective health. The negative effects on mental health notably influence happiness, family life satisfaction, social relationships, subjective health, and exercise. Mental health also mediates these relationships, underscoring its importance in overall well-being. Differences in online hours and well-being determinants are found across gender, age, education, nationality, and marital status. The study underscores the need for interventions to mitigate the adverse effects of excessive online time and improve well-being across demographic groups.

Keywords: Wellbeing; happiness; digital; path analysis; Abu Dhabi

1. Introduction

In an increasingly digital world, understanding the impact of online time on well-being is crucial. The pervasiveness of Internet use has profound implications for mental health, physical health, social interactions, and overall happiness[1] as recent studies have examined the connection between online time and happiness[2], health[3], obesity[4-6]; mental health[2,7], physical activity[8-10], and social relationships[11].

However, extant literature tends to focus on one or a few well-being factors, providing a limited understanding of the broader impact of online time on well-being. For instance, several studies have investigated the relationship between online time and sleep quality[12], while some other researchers have explored its effects on mental disorders[13,14]. Furthermore, while numerous studies have examined the impact

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of online time in Western contexts, only a few have been conducted in the empirical context of the Gulf Cooperation Council (GCC) region[1,15]. Several studies conducted in Abu Dhabi have explored various factors that affect well-being including self-rated health, sleep quality, mental health[16,17], but not through the lens of screen time. The dearth of research on this topic in the GCC justifies the need for providing locally relevant insights, given the unique cultural, social, and economic environment of the Emirate of Abu Dhabi, the United Arab Emirates (UAE)[18,19].

This study is unique in exploring the impact of online time on multiple well-being dimensions (including happiness, mental health, sleep quality, and life satisfaction) in the specific cultural context of Abu Dhabi. While many studies have addressed the general effects of digital engagement, our research provides region-specific insights and considers variables such as nationality, gender, and regional differences. This focus on Abu Dhabi's unique socio-economic and cultural landscape fills an important gap in the literature on digital well-being.

The motivation for this study stems from the increasing integration of digital technologies into everyday life, which has reshaped how individuals interact, communicate, and manage their well-being. While existing literature has explored the relationships between online time and well-being, most studies have been conducted in Western contexts, offering limited insights into how these dynamics unfold in culturally distinct regions such as the Gulf Cooperation Council (GCC). Abu Dhabi, as a rapidly digitizing society with a unique socio-economic and cultural landscape, offers a compelling case for examining these relationships. Understanding the nuanced effects of online time on well-being within this context can inform targeted policy interventions, promote healthier digital habits, and contribute to the global discourse on digital well-being. By identifying the interplay between online engagement and well-being indicators, this research aims to fill a critical gap in the literature and provide actionable insights for policymakers, educators, and mental health professionals in Abu Dhabi and beyond.

This present research addresses a timely and relevant issue, providing insights into how digital habits influence well-being. It aims to address the literature gap by integrating multiple well-being determinants and examining their associations with screen time. The primary objective is to elucidate the multifaceted relationships between online time and well-being through path analysis. Uncovering both direct relationships between online time and well-being indicators and the indirect effects and interdependencies among various well-being determinants, it seeks to contribute to a holistic and more nuanced understanding of how digital engagement shapes health and happiness. Furthermore, this research differentiates itself from other studies by focusing on the entire community rather than specific groups. This inclusive approach allows for a more generalized understanding of the impact of online time across various demographics. The findings of this research will be invaluable for policymakers, educators, and healthcare providers in Abu Dhabi, who will be able to develop targeted interventions and policies aimed at promoting healthier digital habits and enhancing overall quality of life.

2. Literature review

Recent studies suggest that more time spent on the Internet and social networking sites is generally linked to lower levels of happiness[20]. Although moderate social media usage sometimes is associated with higher happiness[21], increased or excessive digital media use often correlates with reduced well-being[2,22].

Recent research highlights a strong link between online time and lower subjective well-being, especially among adolescents and young adults[23]. Increased digital media use displaces activities like sleep, face-to-face interactions, and attending religious services, which are linked to higher happiness. Heavy internet users are twice as likely to be unhappy as light users[2]. Longitudinal and experimental studies show that digital media use predicts lower well-being[23,24]. Reducing screen time can improve overall well-being by allowing more beneficial activities. In Abu Dhabi, Badri et al. (2023a, 2022)[1,16] found a positive correlation between digital resources and happiness, though digital transformation also had perceived adverse effects on emotions and behavior.

Research indicates a mixed relationship between social media usage and mental health[25]. However, recent analysis shows significant effects of screen time on mental health[16]. While Coyne et al. (2020)[26] found no direct link between increased social media use and mental health issues, other studies connect social media use with symptoms of psychiatric disorders in adolescents[13]. Higher levels of depression and anxiety, especially in adolescent girls, are associated with more time on social networking sites[14]. Additionally, intense Facebook use is linked to various mental health problems and eating disorders[7]. Tandon et al. (2021)[10] found that more physical activity and less screen time correlate with better mental health in children. Different motives for social media use yield varying mental health outcomes; using it for personal contact improves mental health, while using it to reduce loneliness or for entertainment worsens it[27]. Problematic social media use is predicted by intrapersonal motives, like escaping daily life and passing time[28].

Research shows a clear link between online time and adverse health outcomes[4]. Excessive screen use, especially among children and adolescents, is associated with higher body mass index, overweight, obesity[6], reduced physical activity[29], and sleep problems[3]. While some studies show no significant association between screen time and obesity[11,30], others confirm the link [5], suggesting that other factors, such as physical activity, might influence the relationship. Increased screen time can reduce participation in physical activities, increasing obesity risk[9]. Many people prefer passive, screen-based activities over outdoor exercises, detracting from overall physical activity levels[31]. Physical activity promotes health and counterbalances screen time's negative effects[32]. Social media use is also linked to lower engagement in physical activities[8], emphasizing the need to encourage outdoor exercise and sports. High physical activity levels can improve sleep patterns and physical health. Reliance on social media is linked to poor sleep quality[12,33]. Adolescents with high screen use often report poor sleep quality and daytime sleepiness[15,34]. However, the role of physical activity in mitigating the impact of screen time on sleep quality remains unclear.

Research by Subrahmanyam et al. (2000)[35] found that increased time spent online is associated with a decline in communication with family members and a shrinking social circle for Internet users. This reduction in social interaction can lead to heightened feelings of depression and loneliness. While social media can facilitate social contact to some extent, it may not provide the type of meaningful interaction desired by those using it mainly for relationship maintenance[2]. In fact, as concluded by Bonsaksen et al. (2023)[36], individuals who use social media primarily to maintain relationships tend to feel lonelier than those who spend the same amount of time on social media for other reasons. A similar study found that older adults using a variety of social media types experienced lower levels of social loneliness, while younger adults using more social media types experienced higher levels of emotional loneliness[37]. These findings highlight the complexity of the relationship between social media use and social contact, suggesting that the effects vary based on age and specific social media usage.

3. Methods and design

The study incorporated Self-Determination Theory (SDT) (Deci & Ryan, 1985)[38], which explains how digital behavior influences well-being through the fulfillment—or frustration—of autonomy, competence, and relatedness needs. When online activities satisfy these core psychological needs, individuals experience enhanced well-being. However, excessive or unbalanced engagement can disrupt these needs, leading to diminished well-being. Additionally, the study references Uses and Gratifications Theory (Katz et al., 1973)[39], which explores how individuals engage with digital platforms to fulfill specific psychological and social needs. This theory contextualizes the varied outcomes of digital engagement by highlighting how different types of online activities—such as entertainment, social communication, and the use of digital services—serve distinct personal goals and influence well-being in diverse ways.

While SDT and UGT have been widely applied in studies on digital media and well-being, this research makes several novel contributions:

1. Cultural Context: Unlike most studies rooted in Western contexts, this research applies these theories to Abu Dhabi, offering insights into how unique cultural, social, and economic factors shape the relationship between online time and well-being.
2. Integration of Well-Being Dimensions: The study extends existing models by incorporating a holistic set of well-being indicators, including mental health, happiness, subjective health, sleep quality, and social relationships, into a unified path analysis framework.
3. Focus on Demographic Moderators: This study explores how demographic factors (e.g., gender, age, nationality, education) moderate the relationships described by SDT and UGT, providing a more comprehensive understanding of individual differences in digital behaviour and its impact.
4. Indirect Effects: By using path analysis, the research investigates both direct and indirect effects of online time, particularly how mediators like mental health and sleep quality influence other well-being dimensions, thereby extending the theoretical framework.

3.1. The survey

This study used data from the 4th cycle of the Abu Dhabi Quality of Life survey (QoL-4). Utilizing various international well-being frameworks such as the OECD's Better Life Index, the World Happiness Report, the Gallup Global Well-being Survey, and the European Quality of Life Survey, QoL-4 comprehensively included subjective well-being dimensions and indicators ranging from housing, household income, employment and earnings, to health, safety, and social connections.

The QoL-4 survey was conducted online from January to June 2023, targeting residents aged 15 and above across all regions of the Emirate of Abu Dhabi. The survey was disseminated through databases maintained by various government departments and public community associations, promoted on social media platforms and during numerous events held in Abu Dhabi. Ethical approval for the survey was obtained from both the Department of Community Development and the Statistics Center Abu Dhabi.

A total of 92,576 respondents participated in the QoL-4 survey. For this paper, workers residing in workers cities and domestic workers were excluded from the analysis. To further enhance data integrity, the current study only included responses with no missing data for the variables under investigation, resulting in a final dataset of 47,638 respondents. This ensures that the analysis is based on complete information, providing robust insights into the well-being indicators among the residents of the Emirate of Abu Dhabi.

3.2. The variables

The primary objective of this study was to investigate the associations between the number of hours spent online and various well-being indicators. Based on an extensive literature review, well-being determinants assumed to be linked with online hours were chosen for analysis. These determinants represent different aspects of well-being. During the preliminary analysis, which involved correlation analysis and regression, some variables were excluded to refine the focus of the study. The final set of well-being indicators included in the analysis were happiness, satisfaction with family life, subjective health, mental health, and other determinants. These indicators were selected for their relevance and potential association with online hours, providing a comprehensive overview of the impact of screen time on different dimensions of well-being. **Table 1** details the selected indicators along with their corresponding measurement scales. The variables included in this study were selected based on an extensive review of existing literature and their relevance to the theoretical frameworks underpinning the research. Self-Determination Theory (SDT; Deci & Ryan, 1985) [38] and Uses and Gratifications Theory (UGT; Katz et al., 1973)[39] guided the selection of variables that reflect psychological needs, such as mental health, subjective health, and happiness, as well as behavioral outcomes like sleep quality and exercise. The initial set of variables was refined using correlation and regression analyses, ensuring that only the most relevant indicators with significant theoretical and empirical support were retained. The study also adapts components from models such as Valkenburg and Peter's (2013) [40] Differential Susceptibility to Media Effects Model, emphasizing demographic moderators like age, gender, and education. These modifications were tailored to the unique socio-cultural and digital landscape of Abu Dhabi, allowing for a localized examination of online time's impact on well-being.

Table 1. Final list of variables in the path model.

Variable	Survey item and scale
Hours online	On average how many hours do you usually spend online a day? (number of hours)
Satisfaction with family life	In general, I am satisfied with my family life. (1 strongly disagree to 5 strongly agree)
Satisfaction with social relationships	I am satisfied with my relationships with other people (1 strongly disagree to 5 strongly agree)
Subjective health	In general, how do you personally assess your current health status? (1 poor to 5 excellent)
Mental health	During the past four weeks, how much of a problem did you have with the following: feeling depressed, worry or anxiety, concentrating or remembering things, fear, loneliness, boredom, physical pain? (1 not at all - 5 to a great extent). The Cronbach Alpha for this composite was 0.940.
Self-perceived obesity	In your opinion, to what extent do you consider yourself obese? (1 not obese to 5 very obese)
Exercise and activities	How often do you do physical exercise (minimum of 30 minutes) in the last 4-6 months? (1 never to 6 daily)
Sleep quality	How do you rate the quality of your sleep at night? (1 very bad to 5 very well)
Happiness	From a scale of 0-10, how would you describe your average level of happiness as an Abu Dhabi resident?

3.3. Analysis method

This study will be clearly identified as a quantitative, cross-sectional survey that explores the relationship between online time and well-being indicators (e.g., life satisfaction, happiness, sleep quality, and mental health). A cross-sectional approach is ideal for capturing data at a single point in time to analyze current patterns in the target population's behavior and well-being. The study is composed based on three main hypotheses:

H1: Greater time spent online is associated with lower levels of life satisfaction and happiness.

H2: Individuals with higher online time report poorer sleep quality and increased mental health challenges.

H3: Nationality, gender, and other demographic variables moderate the impact of online time on well-being indicators.

The study focuses on Abu Dhabi as it provides a unique cultural and socio-economic status (SES). The rapid growth in internet penetration and digital engagement in the UAE offers an ideal environment to study the impact of online time on well-being.

Normality tests were first conducted on all indicators included in the study. In cases where the data deviated from normality assumptions, natural logarithm transformations were applied to correct these deviations. To explore the relationships between the variables considered for the model, we performed correlation and linear regression analyses. Given that the survey utilized different scales, we standardized the data to ensure consistency for path analysis. For the path analysis, we used LISREL to analyze the covariance matrix. Path analysis models are designed to determine the statistical significance of path coefficients, if any. A systematic, step-by-step approach was followed to develop the optimal path model. The capabilities of LISREL, as highlighted by Jöreskog & Sörbom (2018)[41], were instrumental in refining this model. LISREL was selected for its robust capabilities in structural equation modeling (SEM) and path analysis, which are essential for examining both direct and indirect relationships among multiple well-being determinants. Its advanced features, such as covariance-based modeling and comprehensive fit statistics, make it ideal for evaluating complex models with interconnected variables, ensuring accurate and reliable results. Additionally, LISREL's ability to handle large datasets aligns with the scale and scope of this study.

Several goodness-of-fit statistics were obtained to assess the model’s fit, including Degrees of Freedom, Maximum Likelihood Ratio Chi-Square, and the P-value for the Test of Close Fit. Additional fit statistics included the Root Mean Square Error of Approximation (RMSEA), Comparative Fit Index (CFI), Normed Fit Index (NFI), Non-Normed Fit Index (NNFI), Goodness of Fit Index (GFI), Adjusted Goodness of Fit Index (AGFI), and Root Mean Square Residual (RMR). These metrics are standard in path analysis and provide a comprehensive assessment of the model’s fit and accuracy.

The study elaborates on the demographic differences, such as gender, nationality, age, and region of residence, and explain how these factors might influence the relationship between online time and well-being. Age-related differences may affect sleep patterns and mental health, as younger individuals tend to engage more with social media platforms. Additionally, nationality-specific cultural practices might play a role in determining how online engagement impacts social connections and life satisfaction. As a result, we also performed analysis of variance (ANOVA) to identify differences in time spent online based on respondents’ gender, age, nationality, marital status, education, and region of residence. This analysis allowed us to uncover significant variations in online time across these demographic groups, providing deeper insights into the factors influencing online behavior.

4. Results

Table 2 provides a comprehensive profile of the survey respondents. The gender distribution is nearly equal, with females representing 50.5% and males 48.5% of the participants. The age group with the highest representation is 40-44 years (16.4%), followed by 15-19 years (16.0%), 35-39 years (15.8%), 30-34 years (12.5%), and 45-49 years (10.7%). In terms of educational level, 50.6% of respondents have pre-college degrees, while 49.4% have college degrees or higher. In terms of nationality, 56.6% of the respondents are Emirati nationals. Geographically, the majority of respondents are from the Abu Dhabi region (62.6%), followed by a significant portion from Al Ain region (30.9%). Marital status data indicates that 63.5% of the respondents are married, while 28.4% are single. This detailed demographic breakdown helps to understand the diverse characteristics of the survey participants, providing a solid foundation for analyzing the well-being indicators in relation to the time spent online.

Table 2. Profile of married respondents.

Gender	Number	Percent
Male	23,598	48.5%
Female	24,040	50.5%
Age		
15-19	7,621	16.0%
20-24	1,649	3.5%
25-29	3,293	6.9%
30-34	5,959	12.5%
35-39	7,534	15.8%
40-44	7,832	16.4%
45-49	5,099	10.7%
50-54	3,378	7.1%
55-59	1,719	3.6%
60+	3,554	7.5%
Education		
Pre-college	24,116	50.6%
College degree	16,841	35.4%
Postgraduate	6,681	14.0%
Nationality		
Emirati	26,944	56.6%
Non-Emirati	20,694	43.4%
Region of residence		
Abu Dhabi	29,798	62.6%
Al Ain	14,709	30.9%
Al Dhafra	3,131	6.60%
Marital status		
Single	13,541	28.4%
Married	30,234	63.5%
Divorced	2,429	5.1%
Separated	359	0.6%
Widow/widower	1,075	2,3%

Table 3 presents the covariance matrix for the determinants used in the study. The values in the covariance matrix indicate how two variables change in relation to each other. Positive covariance values suggest that the variables tend to increase or decrease together, implying a direct relationship. Conversely, negative covariance values indicate that as one variable increases, the other decreases, reflecting an inverse relationship. These covariance values are essential in path analysis, as they provide insights into the strength and direction of the relationships between variables. This information is critical for accurately estimating the path coefficients and understanding the interconnectedness of the determinants within the model.

Table 3. Covariance matrix.

	SQ	SH	OB	MH	EA	FS	FR	HP	OO
Sleep quality (SQ)	-1.001								
Subjective health (SH)	0.275	0.775							
Self-perceived obesity (OB)	-0.101	-0.165	1.047						
Mental health (MH)	-0.401	-0.285	0.151	0.806					
Exercise and Activity (EA)	0.161	0.176	-0.161	-0.155	0.853				
Satisfaction with family life (FS)	0.347	0.265	-0.059	-0.407	0.119	1.028			
Sa. with social relationships (FR)	0.289	0.225	-0.065	-0.335	0.115	0.508	0.892		
Happiness (HP)	0.298	0.241	-0.045	-0.347	0.067	0.435	0.342	0.897	
Hours online (OO)	-0.074	-0.013	0.058	0.106	-0.057	-0.052	-0.040	-0.013	0.587

A highly significant path model was developed based on final statistical measurements. Figure 1 illustrates the final path model, with model accuracy indicators and parameter values shown in **Table 4**, confirming that the derived model structures are acceptable. The most used model measurement statistics are the CFI and the RMSEA. The CFI equals the discrepancy function adjusted for sample size and ranges from 0 to 1, with higher values indicating a better model fit. A CFI value of 0.90 or greater is considered acceptable. In this study, the CFI is 0.999, indicating an excellent model fit. The RMSEA measures the residuals in the model, with values also ranging from 0 to 1. Lower RMSEA values signify a better model fit, with values of 0.06 or less considered acceptable. The RMSEA for the current model is 0.0189, which is well within the acceptable range. All other measurements shown in **Table 4** further support the conclusion that the overall model is acceptable.

Table 4. Goodness-of-fit statistics.

Measurement statistics	Measurement results
Degrees of Freedom	7
Maximum Likelihood Ratio Chi-Square	2.889 (P-0.221)
Root Mean Square Error of Approximation (RMSEA)	0.0189
Normed Fit Index (NFI)	0.999
Non-Normed Fit Index (NNFI)	0.992
Comparative Fit Index (CFI)	0.999
Incremental Fit Index (IFI)	0.999
Root Mean Square Residual (RMR)	0.00558
Standardized RMR	0.00578
Goodness of Fit Index (GFI)	1.00
Adjusted Goodness of Fit Index (AGFI)	0.996

When interpreting the results of the path analysis, it is essential to concentrate on the variable of interest - hours online - and its associations with various outcome measures such as happiness, subjective health, and mental health. By examining both direct and indirect effects, we gain a deeper understanding of the complex interplay between these determinants. Direct effects show the immediate impact of hours spent online on each outcome measure, while indirect effects reveal the influence of online hours through intermediary variables. Furthermore, attention should be given to the strength and significance of these effects, as well as any potential mediating or moderating factors that might influence the observed relationships. This approach helps elucidate how online hours impact individual well-being. Additionally, before examining the path coefficients, it is crucial to understand the positive and negative scales for each path, as some scales are negatively worded (e.g., obesity, mental health). To highlight these differences, all adverse effects are presented in bold in **Figure 1**.

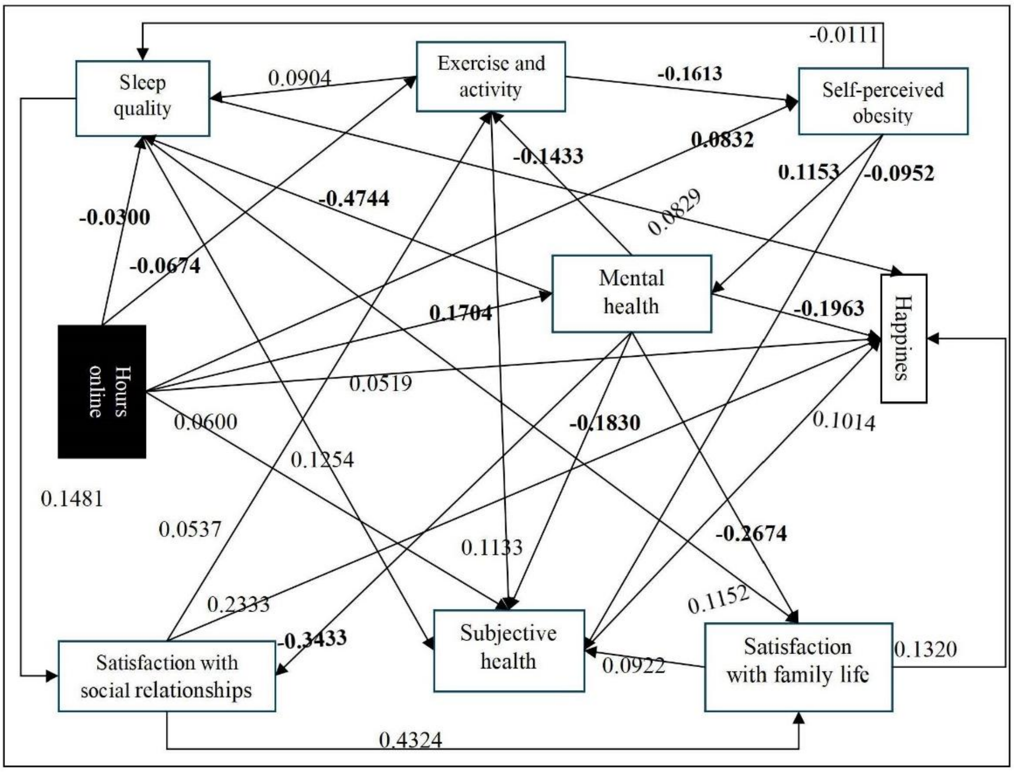

Figure 1. The final path model.

It is noteworthy that screen time has significant adverse effects on several well-being indicators: mental health, sleep quality, exercise and activity, and self-perceived obesity, with coefficients of -0.1704, -0.0300, -0.0674, and -0.0832, respectively. These negative impacts underline the detrimental consequences of excessive online time on these aspects of well-being. Conversely, online time shows significant positive effects on happiness and subjective health, with coefficients of 0.0519 and 0.0600, respectively. These positive effects suggest that some aspects of online engagement can enhance these particular aspects of well-being. However, it is also important to note that online time does not exhibit direct associations with satisfaction in family life and satisfaction with social relationships. This indicates that while online time influences certain personal health and happiness metrics, it does not directly affect social relationships indicators.

The determinant with the most significant number of connections, both incoming and outgoing, is mental health, which has eight paths associated with it. Additionally, these paths involving mental health exhibit high magnitudes. Mental health exerts direct negative impacts on several well-being indicators. Specifically, it negatively affects sleep quality (-0.4744), satisfaction with social relationships (-0.3433), satisfaction in family life (-0.2674), happiness (-0.1963), subjective health (-0.1830), and exercise and activity (-0.1433). These substantial negative impacts highlight the critical role mental health plays in influencing a wide range of well-being aspects. On the other hand, mental health itself is directly and negatively influenced by other determinants. Obesity has a negative effect on mental health, with a coefficient of 0.1153, and hours spent online significantly impact mental health negatively, with a coefficient of 0.1704. These findings underscore the central position of mental health in the network of well-being indicators, demonstrating both its broad influence on other aspects and its susceptibility to negative influences from obesity and excessive online time.

Table 5 provides the details on the final outcomes of the path model, including the value of estimates, their t-values, and significance levels. The coefficients for 28 associations are displayed, highlighting the interconnections between various well-being indicators. As mentioned above, both hours spent online and mental health exhibit six significant associations with other indicators. The data also reveal that satisfaction with family life has a strong influence on happiness (0.1320) and subjective health (0.0922). Furthermore, satisfaction with social relationships significantly impacts both satisfaction with family life (0.4324) and happiness (0.2333). Sleep quality exerts a significant effect on satisfaction with social relationships (0.1481), satisfaction with family life (0.1152), and subjective health (0.1254). This highlights the crucial role of good sleep in maintaining positive social interactions and overall health. Obesity has the most significant effect on mental health, indicating that higher levels of obesity are associated with poorer mental health. Exercise and activities show the most substantial impact on self-perceived obesity (-0.1613), emphasizing the importance of physical activity in managing weight. Lastly, subjective health has its most crucial effect on happiness (0.1014), highlighting that better perceived health is strongly linked to greater happiness. These detailed associations from **Table 5** illustrate the complex interplay between different well-being indicators and emphasize the importance of addressing multiple facets of health and lifestyle to improve overall well-being.

Table 5. The significant paths in the model and their significance.

From	To	Estimate	z-value	Sig.
Hours online	Happiness	0.0519	10.004	0.001
Hours online	Subjective health	0.0600	12.621	0.001
Hours online	Mental health	0.1704	32.364	0.001
Hours online	Self-perceived obesity	0.0832	13.763	0.001
Hours online	Exercise and activities	-0.0674	-12.293	0.001
Hours online	Sleep quality	-0.0300	-5.5582	0.001
Mental health	Satisfaction with family life	-0.2674	-55.340	0.001
Mental health	Happiness	-0.1963	-38.621	0.001
Mental health	Exercise and activities	-0.1433	-27.629	0.001
Mental health	Sleep quality	-0.4744	-100.64	0.001
Mental health	Subjective health	-0.1830	-37.164	0.001
Mental health	Satisfaction with social relationships	-0.3433	-69.349	0.001
Satisfaction with family life	Happiness	0.1320	55.340	0.001
Satisfaction with family life	Subjective health	0.0922	20.864	0.001
Satisfaction with social relationships	Satisfaction with family life	0.4324	99.427	0.001
Satisfaction with social relationships	Happiness	0.2333	21.902	0.001
Satisfaction with social relationships	Exercise and activities	0.0537	10.962	0.001
Sleep quality	Satisfaction with social relationships	0.1481	33.539	0.001
Sleep quality	Subjective health	0.1254	30.477	0.001
Sleep quality	Satisfaction with family life	0.1152	27.259	0.001
Sleep quality	Happiness	0.0829	19.602	0.001

From	To	Estimate	z-value	Sig.
Self-perceived obesity	Sleep quality	-0.0111	-6.889	0.001
Self-perceived obesity	Subjective health	-0.0952	-26.454	0.001
Self-perceived obesity	Mental health	0.1153	28.639	0.001
Exercise and activities	Subjective health	0.1133	27.961	0.001
Exercise and activities	Self-perceived obesity	-0.1613	-31.597	0.001
Exercise and activities	Sleep quality	0.0904	19.640	0.001
Subjective health	Happiness	0.1014	21.902	0.001

Table 5. (*Continued*)

Table 6 details the path model's direct, indirect, and total effects, offering a comprehensive view of the relationships among the studied variables. As anticipated, mental health exhibits the highest total effects. Focusing on hours online, the most substantial total effects are observed on sleep quality and mental health. The determinants of social connections, specifically satisfaction with family life and social relationships, yield the highest total effects on happiness. This finding reinforces the importance of strong social relationships in enhancing individual happiness. Additionally, the most pronounced total effects of exercise and sports are evident on subjective health and self-perceived obesity. These results emphasize the vital role of physical activity in promoting perceived health and managing weight. **Table 6** again illustrates the complex interplay of these determinants and their cumulative impact on various aspects of well-being, highlighting the importance of a holistic approach to health and lifestyle interventions.

Several determinants did not exhibit direct connections with other variables. **Table 7** offers a detailed examination of these indicators that lack direct links to specific variables. While the path model does not display a direct connection between hours online and satisfaction with family life, it reveals an indirect association with a coefficient of 0.0583, mediated by mental health. Similarly, mental health serves as a mediator between hours online and satisfaction with social relationships, with an indirect effect of 0.0457. Additionally, the relationship between exercise and activities and happiness is mediated through sleep quality (with a coefficient of 0.0075) and subjective health (0.0114). Furthermore, the indirect associations between self-perceived obesity and happiness, satisfaction with social relationships, and satisfaction with family life should also be noted. This indicates that we must not overlook the indirect effects when analyzing the determinants of well-being, as they can provide valuable insights into the underlying mechanisms at play.

Table 6. Direct, indirect, and full effects.

Path from	Path to	Direct effect	Indirect effect	Full effect
Mental health	Happiness	-0.1960	0.1031	0.2991
Mental health	Subjective health	-0.1830	0.1003	0.2833
Mental health	Satisfaction with social relationships	-0.3430	0.0721	0.4151
Mental health	Satisfaction with family life	-0.2690	0.0545	-0.3235
Mental health	Exercise and activities	-0.1430	0.0184	0.1614
Subjective health	Happiness	0.1012	0.0104	0.1116
Self-perceived obesity	Subjective health	-0.0952	0.0241	0.1193
Self-perceived obesity	Mental health	0.1152	---------	0.1152
Self-perceived obesity	Sleep quality	-0.0111	---------	0.0111

Path from	Path to	Direct effect	Indirect effect	Full effect
Hours online	Happiness	0.0519	0.0419	0.0938
Hours online	Subjective health	0.0600	0.0393	0.0993
Hours online	Self-perceived obesity	0.0832	0.0109	0.0921
Hours online	Sleep quality	-0.0674	0.0884	0.1558
Hours online	Exercise and activities	-0.0674	0.0244	0.0918
Hours online	Mental health	0.1704	0.0015	0.1716
Satisfaction with social relationships	Satisfaction with family life	0.4321	---------	0.4321
Satisfaction with social relationships	Exercise and activities	0.0537	---------	0.0537
Satisfaction with social relationships	Happiness	0.1322	0.1068	0.2390
Satisfaction with family life	Happiness	0.2333	0.0093	0.2426
Satisfaction with family life	Subjective health	0.0922	---------	0.0922
Sleep quality	Satisfaction with social relationships	0.1482	---------	0.1482
Sleep quality	Satisfaction with family life	0.1154	---------	0.1154
Sleep quality	Happiness	0.0829	0.1055	0.1884
Sleep quality	Subjective health	0.1254	0.0973	0.2227
Exercise and activities	Subjective health	0.1133	0.0266	0.1399
Exercise and activities	Self-perceived obesity	-0.1611	---------	0.1611

Table 6. (*Continued*)

Table 7. Indicators with only (indirect associations) with other indicators.

Indirect path from	Mediating indicator(s)	Path to	Resulted coefficient
Hours online	Metal health	Satisfaction with family life	0.0583
Hours online	Mental health	Satisfaction with social relationships	0.0457
Exercise and activities	Sleep quality	Happiness	0.0075
Exercise and activities	Subjective health	Happiness	0.0114
Exercise and activities	Sleep quality	Satisfaction with family life	0.0104
Self-perceived obesity	Sleep quality	Happiness	0.0009
Self-perceived obesity	Subjective health	Happiness	0.0126
Self-perceived obesity	Mental health	Satisfaction with family life	0.0309
Self-perceived obesity	Mental health	Satisfaction with social relationships	0.0395

It is also essential to explore the differences in these well-being indicators among different demographic groups of respondents. These groups are categorized by gender, age, education, nationality, and marital status. **Table 8** presents the ANOVA scores and the mean values for each group in relation to the selected determinants. This analysis helps to understand how demographic factors influence online behavior and well-being, providing deeper insights into the diverse experiences of the respondents. Notably, females spend considerably more time online, averaging 7.093 hours compared to 5.597 hours for males. In terms of happiness, females also report higher scores, with an average of 7.807 compared to 7.498 for males. Male respondents exhibit better outcomes in terms of mental health, subjective health, and sleep quality.

Examining the data by age, younger respondents spend significantly more time online than their older counterparts. However, happiness scores are the highest for both the youngest and the oldest groups, with scores of 8.071 and 8.444, respectively. The youngest respondents reported the worst mental health, with an average score of 2.520, in contrast to the oldest respondents, who recorded the most positive mental health with a score of 1.742. This trend extends to sleep quality as well, with older individuals faring better. Nevertheless, the youngest respondents reported the highest subjective health scores.

Individuals with college degrees spent the most time online, averaging 6.055 hours, whereas those with pre-university qualifications spent significantly less time online, averaging 3.878 hours. Despite spending less time online, those with pre-college degrees reported the highest levels of happiness and mental health.

Table 8. Means and ANOVA of well-being determinants in the model, by demographic category.

	Hours online	Happiness	Mental health	Subjective health	Sleep quality
Gender					
ANOVA	1125 (0.001)	172.9 (0.001)	1171 (0.001)	18.73 (0.001)	71.97 (0.001)
Male	5.597	7.498	2.111	3.486	3.433
Female	7.093	7.807	2.413	3.441	3.324
Age					
ANOVA	532.8 (0.001)	107.7 (0.001)	281.3 (0.001)	203.2 (0.001)	68.85 (0.001)
15-19	8.906	8.071	2.520	3.758	3.227
20-24	7.965	7.753	2.407	3.756	3.378
25-29	7.264	7.440	2.437	3.680	3.224
30-34	6.618	7.263	2.400	3.518	3.266
35-39	6.237	7.297	2.321	3.416	3.298
40-44	5.918	7.477	2.243	3.380	3.363
45-49	5.463	7.592	2.178	3.347	3.502
50-54	5.089	7.804	2.011	3.357	3.592
55-59	4.668	8.101	1.853	3.347	3.723
60+	3.320	8.444	1.742	2.967	3.870
Education					
ANOVA	216.8 (0.001)	35.29 (0.001)	87.93 (0.001)	132.7 (0.001)	8.944 (0.001)
Pre-University	3.878	8.223	1.974	2.863	3.653
College degree	6.055	7.536	2.527	3.484	3.894
Maser degree	5.723	7.431	2.183	3.441	3.423
Doctorate degree	5.342	7.829	2.008	3.582	3.531
Nationality					
ANOVA	694.1 (0.001)	1.136 (0.285)	39.61 (0.001)	68.41 (0.732)	376.2 (0.001)
Emirati	6.869	7.642	2.288	3.414	3.264
Non-Emirati	5.677	7.668	2.232	3.503	3.503
Marital status					
ANOVA	678.1 (0.001)	47.59 (0.001)	350.9 (0.001)	206.4 (0.001)	21.56 (0.001)
Single	8.271	7.789	2.496	3.643	3.273

	Hours online	Happiness	Mental health	Subjective health	Sleep quality
Married	5.519	7.635	2.128	3.424	3.424
Divorced	6.742	7.129	2.598	3.211	3.253
Separated	6.655	6.934	2.587	3.243	3.291
Widow	3.953	8.203	2.101	2.782	3.442

Table 8. (*Continued*)

In terms of differences by nationality, Emiratis reported higher online hours compared to non-Emiratis, with averages of 6.869 hours and 5.677 hours, respectively. However, there was no significant difference in happiness scores between the two groups, nor in subjective health scores. Non-Emiratis reported more positive mental health and sleep quality outcomes. Marital status also plays a role in online activity and well-being. Single individuals recorded the highest online hours at 8.271, while widowed individuals recorded the lowest at 3.953 hours. On the happiness scale, the widowed reported the highest score of 8.203, while separated individuals reported the lowest at 6.934. Singles scored the highest in subjective health with an average of 3.643, whereas the widowed scored the lowest at 2.782.

5. Discussions

The path model developed in this study emphasizes the connections and interactions among various well-being factors, such as subjective health, mental health, social relations, exercise and activities, particularly in relation to happiness and online hours. In general, the results of the model align with findings from various research that illustrate the effects of screen time or digital device usage on specific well-being factors such as happiness[23], mental health[13], subjective health[4], social relations[35,36], sleep quality[12], obesity[5] , and physical activity and sport[32].

The results indicate that increased online time negatively impacts mental health, consistent with numerous studies[14]. Excessive online use can lead to social isolation, anxiety, reduced self-esteem, cyberbullying, and exposure to harmful content, adversely affecting mental well-being. Contrasting with Coyne et al. (2020)[26], our findings show a correlation between prolonged online time and mental health issues, particularly among females in Abu Dhabi. Gender differences in digital media use and its implications are notable; females focus more on emotional bonding and social interactions, while males engage more in online gaming[41,42]. Females also struggle more with regulating social media use, leading to higher rates of depression and anxiety[2,43]. Our study supports the need to consider social context, individual differences, and motives for online activity to understand the complex relationship between online time and mental health[27,28].

Our results show a positive correlation between online hours and happiness, contradicting mainstream literature that often reports negative associations [23]. While digital media can displace beneficial activities like family time, Abu Dhabi's digital transformation may elevate residents' happiness through increased digital services and resources [1]. The focus should be on mitigating adverse effects like cyberbullying rather than solely reducing screen time to enhance well-being. Additionally, our study indicates that the online hours-happiness relationship varies across demographic groups; younger individuals might derive more happiness from online interactions than older counterparts. These nuanced findings underscore the complexity of the online activity-happiness relationship and present challenges for policymakers.

Similarly, a positive association between hours spent online and subjective health is confirmed by this study, which contrasts with several studies that have reported a clear link between increased online time and various adverse health outcomes[3,4]. There are several possible explanations for this discrepancy. First, the distinction between subjective health and more objective health outcomes such as body mass index should be made. Second, the positive correlation between hours spent online and subjective health is likely mediated by age. Adolescents in Abu Dhabi, while reported the longest online time, also rated highly their physical health. Third, online engagement provides individuals with access to health-related information, wellness resources and support, thereby enhancing their perception of health.

Our study reveals a negative association between self-perceived obesity and online hours, aligning with research linking excessive screen time to higher body mass index and obesity, especially among children and adolescents[6]. This underscores the impact of sedentary behaviors associated with prolonged online activity, contributing to unhealthy weight gain[32]. Additionally, there is a negative relationship between online hours and physical activity[29]. Online hours are also negatively associated with sleep quality, consistent with research showing that screen time before bed disrupts sleep by suppressing melatonin production[12]. These findings highlight the need for policymakers to consider the multifaceted impacts of online activity on health. While online engagement can enhance subjective health, it poses risks to body weight management, physical activity, and sleep quality, all significant predictors of well-being in Abu Dhabi[1,16].

A notable finding from the Abu Dhabi study is that the final path model did not show substantial direct associations between hours online and satisfaction with either family life or social relationships. This suggests that simply spending more time online does not directly impact individual's assessment of the quality of these social relationships. However, the study identified significant indirect negative associations, mediated by factors such as mental health and sleep quality. This means that prolonged online hours can negatively affect mental health and sleep quality, which could reduce one's ability to maintain positive and healthy interactions with family and friends and in turn harm family and social relationships. By addressing the mediating factors like mental health and sleep quality, it is possible to mitigate the negative impacts of excessive online time on social relationships.

Besides gender differences, the study highlights the significance of individual characteristics in the relationship between online hours and well-being. Age is critical, with the highest online hours among 15-24-year-olds, who heavily rely on digital platforms for social interaction, information, and entertainment. However, this increased online time can harm their mental and physical health, necessitating age-appropriate guidelines and interventions. College graduates reported the highest online hours, likely due to the use of digital tools for academics and professional development. While digital literacy is vital, balancing online and offline activities is crucial to prevent adverse health outcomes. Nationality also influenced online behavior, with Emiratis reporting higher online hours than non-Emiratis, possibly due to cultural or socio-economic factors. Understanding these nuances is essential for developing effective public health strategies tailored to the specific needs and habits of different national groups.

Taken together, these findings underscore the multifaceted impacts of excessive online engagement and highlight the need for balanced Internet use. Understanding these variations is crucial for creating policies that leverage the positive aspects of online engagement while mitigating potential negative impacts on mental health and well-being. Policymakers and health professionals should consider these associations when developing guidelines and interventions aiming to balance the benefits of online engagement with strategies to encourage physical activity and healthy behaviors to mitigate potential adverse health outcomes.

The study is conducted in Abu Dhabi, a region that has undergone rapid digital transformation and exhibits unique cultural, social, and economic characteristics. Research focused on how online time affects well-being within this specific context is limited, offering new insights into the relationship between digital behavior and well-being in a non-Western setting. While previous studies have focused on one or two aspects of well-being (such as mental health or life satisfaction), this study takes a holistic approach, examining a range of well-being determinants—including happiness, sleep quality, social engagement, and mental health—within a single framework. This broader analysis provides a more nuanced understanding of the interplay between online time and well-being outcomes. The inclusion of demographic variables such as gender, nationality, and region of residence allows the study to explore variations in the impact of online engagement across different population groups. This segmentation offers unique insights into how digital behavior influences well-being in diverse socio-cultural contexts, filling a gap in the literature

6. Conclusions

The use of path analysis in this study represents a significant advancement in understanding the complex interplay between online time and various well-being determinants among Abu Dhabi residents. By employing this sophisticated statistical technique, the research provides a comprehensive and detailed examination of both direct and indirect relationships among the key variables. This complexity poses significant challenges for social policymakers, who must navigate these nuanced relationships to creating policies that effectively promote the benefits of online engagement and at the same time address the negative implications of increased screen time in the digital age.

While the digital age offers numerous benefits, this study emphasizes the need for mindful and balanced online behavior to enhance overall well-being. Particularly notable are the adverse effects on mental health, which serve as a critical mediator, influencing other aspects of well-being such as happiness and satisfaction with family life. Given the substantial negative impacts of excessive online time on mental health and the subsequent effects on overall well-being, policymakers, educators, and health professionals should collaboratively work towards creating supportive environments that foster healthy digital habits and address the mental health challenges posed by excessive online engagement.

Interventions could include digital wellness programs, promoting balanced online and offline activities, and enhancing mental health support systems, particularly for high-risk groups identified in this study. Targeted programs could be developed for younger adults to encourage physical activities and social interactions outside the digital realm. Educational institutions could integrate digital wellness education into their curricula to help students manage their online time effectively. Moreover, public health campaigns could be designed to raise awareness about the potential negative impacts of excessive online time, particularly among high-usage groups like females, young adults, and singles. These campaigns could promote healthy online habits, such as regular breaks, setting time limits, and engaging in offline activities, and educate the public about the potential risks of excessive screen time. In areas like education, social relations, and community interactions, a one-size-fits-all approach may not be effective. Policymakers must consider these diverse factors to develop strategies that address the specific needs and circumstances of different demographic groups. For instance, gender-specific approaches may be necessary to address the impact of online time on health and well-being in Abu Dhabi.

The findings on the negative impact of excessive online time on mental health, sleep quality, and life satisfaction can guide the development of policies and public awareness campaigns promoting healthy digital habits. Policymakers can use this evidence to design initiatives encouraging screen time balance, mental health support, and media literacy programs in schools and communities. Schools can benefit from these results by integrating digital well-being strategies into their curricula. The study highlights important correlations between online engagement and mental health outcomes, providing mental health professionals with a better understanding of the potential risks associated with digital overuse. These insights can inform interventions targeting anxiety, depression, and sleep disorders linked to excessive screen time. Parents can benefit from these insights to monitor and guide their children's online behavior. Community leaders can also organize youth programs or activities aimed at promoting offline socialization and engagement to enhance well-being.

Future studies should try to distinguish between different types of online activities—such as digital services (e.g., accessing government services, online banking, or education platforms); entertainment (e.g., streaming videos, gaming, or browsing recreational content); and social communication (e.g., interactions on social media or messaging apps). Such consideration would inevitably differ, and the contribution of the research would be greater. In addition, future research should assist in developing and evaluating targeted strategies to mitigate these adverse outcomes. Moreover, longitudinal studies are recommended to further explore the causality and long-term effects of online time on well-being. Expanding the scope to include other potentially influential factors, such as the quality and type of online activities, will also provide deeper insights into how digital engagement shapes well-being.

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Conflict of interest

The authors declare no conflict of interest.

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