Migration Letters

Volume: 21, No: S8 (2024), pp. 735-755

ISSN: 1741-8984 (Print) ISSN: 1741-8992 (Online)

www.migrationletters.com

Enhancing Faculty Members' Mental Health Through Smart Applications In Activating Sustainable Learning Pathways

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Abstract

Background: *Faculty well-being is crucial for teaching quality, research productivity, and retaining excellent scholars. However, mental health issues increasingly plague academics due to unsustainable demands.*

Objective: *To explore leveraging smart applications to promote sustainability and enhance faculty mental health.*

Methods: *150 faculty members at King Khalid University completed an online survey assessing technology usage, acceptance, burnout, work-family conflict, and sustainable learning indicators.*

Results: *Increased smart application use positively predicted enhanced sustainability across teaching, research and service responsibilities (beta coefficient = 0.54, $p < 0.001$). Usage of intelligent assistants, analytics tools, collaboration platforms and other technologies also associated with reduced burnout symptoms (MBI scores: emotional exhaustion mean = 3.8; depersonalization mean = 2.5) and family conflicts (work-family conflict scale scores: time-based mean = 3.6). Higher technology acceptance independently forecast positive mental health (TAM scores: perceived ease of use mean = 4.2; perceived usefulness mean = 4.6).*

Conclusions: *Findings indicate smart applications hold promise for empowering sustainably balanced careers when thoughtfully incorporated into workflows. Strategic, personalized and collaborative implementation approaches were proposed to maximize benefits for diverse users. Continued evaluation is needed to strengthen insights on technology's dynamic role over time.*

Keywords: *faculty mental health, smart applications, sustainable learning pathways, technology acceptance, work-life balance.*

Introduction:

Mental health issues among university faculty members have become increasingly prevalent in recent years. Studies estimate that around one third of faculty members experience some form of psychological distress, including anxiety, depressi[1]on, and

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burnout [1, 2]. This high rate of distress can negatively impact faculty members' wellbeing, productivity, and student outcomes. As such, finding ways to support and enhance faculty mental health has become an important focus for many universities[3].

One approach that holds promise is leveraging technology and smart applications to create more sustainable work patterns and learning pathways for faculty[4]. Sustainability in this context refers to work routines and practices that are psychologically manageable and health-promoting over the long-term [5]. This involves taking a systems approach to understand the multiple interacting demands placed on faculty and finding ways to create better alignment across their various roles of teaching, research, and service [6]. Misalignment across domains can create friction, stress, and burnout as faculty attempt to cope with competing priorities. Smart applications offer new tools to potentially create more integration and sustainability across the domains[7].

Work Overload and Role Strain

A major factor is work overload and the increasing intensification of academic life [8–10]. Advances in technology along with massification of higher education have dramatically increased productivity demands on faculty[11]. There are growing pressures to teach more students, secure external research funding, and provide abundant service to the institution and profession [12]. Tenure and promotion processes often further exacerbate these demands by emphasizing research output. This overload can manifest in work weeks well over 50 hours, including working nights and weekends to keep up[13].

Such chronic work overload predictably leads to strain across roles as well as stress, anxiety, sleep disruption, and burnout [13]. Faculty report diminishing time for academic tasks they value most, like thoughtful research and quality teaching preparation, due to escalating administrative responsibilities and service expectations [14]. The mounting pressures also foster overcommitment and compulsive behaviors around work, which impair faculty's ability to rest and recover [15].

Disjointed Work Patterns and Boundary Control Issues

A related sustainability challenge is the disjointed nature of faculty work and lack of boundary control[16]. Faculty work is complex, unpredictable, and comprised of diverse tasks across multiple roles[17, 18]. These roles often have competing priorities and blurry boundaries between them. For instance, an unplanned student crisis may disrupt dedicated research time[19]. Or an evening could quickly shift from grading papers to administrative emails and reviewing manuscripts for peer journals[20].

This boundary permeability makes it difficult to achieve work-life balance, psychological detachment from work, and effective rest and recovery [21]. Faculty report working during evenings, weekends, and even vacations to manage their work volume, which leaves little time for non-work roles[22]. Sustaining health and performance requires finding strategies to better segment and protect time for the divergent roles[23].

Lack of Mentorship and Support Networks

Faculty mental health is further hampered by isolation and lack of community. Academia has been characterized as an “Ivory Tower” that can be isolating and individualistic despite its collegial ideals[24]. Many faculty lack access to adequate mentorship and support networks. Younger, contingent faculty especially report feeling disconnected from their departments and institutions [25]. Faculty at teaching-focused institutions also describe feeling intellectually and professionally isolated given their high teaching loads and limited research expected [26].

This isolation and lack of mentorship manifests in higher work-related anxiety and depression as well as lower career and life satisfaction[27]. Establishing stronger interpersonal connections and support systems can help sustain faculty wellbeing and satisfaction over time[28]. Collegial networks provide key opportunities for collaboration, resource sharing, guidance, and friendship[29].

Potential for Smart Applications to Promote Sustainability

Smart technologies present new opportunities to address each of these challenges and create more sustainable learning and work patterns for faculty[30]. For instance, applications are emerging that use artificial intelligence, machine learning, and analytics to provide more strategic recommendations around time management, priority setting, and boundary management given a faculty member's roles and goals [31]. Some applications act as intelligent personal assistants that can field lower priority messages and tasks to optimize focus time and prevent distraction [32]. Others aggregate calendars across domains and proactively schedule time for higher impact work as well as restorative breaks and extracurricular activities[33].

Such intelligent systems show initial promise in helping faculty better align time use with priorities, protect focused work periods, and prevent overload [34]. Analytics drawn from faculty calendars, communication patterns, and task data can provide personalized insights about misalignments, environmental distractions, workload trends, and time wasters that impede sustainability [35]. These data-driven, just-in-time recommendations can promote more strategic choices around when, where, and how faculty work[36].

Social networking and digital community building technologies are also being leveraged to decrease isolation and strengthen connections among faculty[37]. Mobile apps allow faculty to easily give peer feedback, share resources, participate in mentoring circles, and access mental health information[38]. Universities have experimented with private online networks just for faculty to connect around shared interests, concerns, and resources [39]. These digital communities can supplement in-person interactions and foster camaraderie.

Similarly, online recommendation systems are emerging that use data analytics to match faculty with potential collaborators, mentors, or networking contacts based on shared profiles and interests [40]. Such intelligent networking applications aim to efficiently connect faculty to relevant peers across the institution for mutual benefit. This could help foster a greater sense of community and support[41].

Wearable devices and health monitoring apps likewise show potential for bolstering faculty self-care and resilience [42]. For instance, fitness trackers can encourage movement and sleep consistency. Meditation and breathing apps facilitate regular relaxation practices. Other applications track mood and prompt activities to boost positivity and gratitude[43]. Institutional initiatives could supply faculty with such tools along with incentives for regular self-care. Usage data could also be monitored to evaluate program impacts on wellbeing[44].

Implementing Technology Strategically and Thoughtfully

Of course, implementing technology-based solutions also poses certain risks and challenges. Care must be taken to avoid overreliance on technology at the expense of authentic human connection and experience [45]. Applications that monitor faculty behavior or promote standardized time allocation practices also raise concerns about autonomy, privacy, and academic freedom that require further analysis [46]. Additionally, there are likely generational differences in receptivity to digital or data-driven mental health tools that would need to be addressed through inclusive design practices [47].

a balanced approach is recommended that thoughtfully integrates smart applications with a sense of humanity, flexibility, and choice. Faculty should be active collaborators in designing and evaluating potential support systems, not passive recipients of technology solutions [48]. Ongoing dialogue and assessment will be key to ensuring the technologies account for the nuances of faculty work patterns and values while enhancing sustainability and wellbeing[49].

In conclusion, mental health and sustainability represent critical challenges facing today's university faculty. While work overload, role misalignment, isolation, and insufficient self-care all contribute to the high levels of distress, promising technology solutions are emerging[50]. Intelligent assistants, social networks, health monitoring devices, and analytics systems could help faculty better manage competing demands, strengthen connections, engage in self-care, and ultimately create more sustainable career paths [51].

The aim of this study is to investigate the role of smart applications in activating sustainable learning pathways for the purpose of enhancing the mental health of faculty members at King Khalid University. By examining the integration of technology in the academic setting, the study seeks to understand how smart applications contribute to the creation of work patterns that are not only efficient but also conducive to the well-being of faculty members. Through a cross-sectional analysis, the study aims to explore the relationships between smart application usage, technology acceptance, sustainable learning pathways, and mental health outcomes. The overarching goal is to provide valuable insights that can inform interventions, policies, and support mechanisms aimed at promoting a healthier and more sustainable work environment for faculty members within the university context.

Operational definitions

1. **Smart Applications:** Smart applications, for this study, are defined as technologically advanced tools designed to improve faculty members' work efficiency, time management, and overall well-being. These applications encompass intelligent personal assistants, analytics tools, and collaboration platforms that aim to facilitate integrated and sustainable learning pathways.

2. **Sustainable Learning Pathways:** Sustainable learning pathways refer to faculty members' ability to balance teaching, research, and service roles effectively over time. It involves strategic time management, prioritization, and the integration of technology to support continuous professional development, contributing to long-term well-being and productivity.

3. **Mental Health:** Mental health in the context of this study is operationalized as the emotional, psychological, and social well-being of faculty members. It is measured by indicators such as low levels of burnout, reduced stress and anxiety, a positive work-life balance, and high levels of job satisfaction resulting from the implementation of smart applications and sustainable learning pathways.

4. **Technology Acceptance:** Technology acceptance refers to faculty members' willingness and readiness to adopt and use smart applications in their daily work routines. It is operationalized through indicators such as perceived ease of use, perceived usefulness, and the actual integration of technology into their professional tasks. Understanding the acceptance of technology is crucial for assessing its impact on mental health and work sustainability.

Research questions:

Primary Research Question:

- How does smart application usage among King Khalid University faculty relate to sustainable learning pathways and contribute to enhanced mental health?

Secondary Research Questions:

- To what extent do faculty members accept and use smart applications in their tasks at King Khalid University?
- What sustainable learning indicators are linked to smart application usage among faculty?
- How does smart application acceptance and usage impact mental health dimensions for faculty members?
- Do relationships between smart application use, technology acceptance, sustainable learning pathways, and mental health outcomes vary based on demographics?

Method

Design:

In this cross-sectional study, we investigated the mental health challenges faced by faculty members at King Khalid University and assessed the potential impact of smart applications in promoting well-being. The study employed a survey-based methodology to collect data on faculty members' experiences, stressors, and their receptivity to smart applications. The cross-sectional design allowed for a snapshot of the mental health status and technology usage among faculty members at a specific point in time.

Participants:

The participant pool for this study consisted of faculty members from various departments and academic ranks at King Khalid University. The aim was to create a representative sample that reflected the diversity within the faculty population.

Sample Size:

The study participants were drawn from the faculty members at King Khalid University, forming a diverse and representative sample for the investigation into the role of smart applications in activating sustainable learning pathways to achieve the mental health of faculty members. Inclusion criteria comprised faculty members from various academic ranks, departments, and gender identities, reflecting the heterogeneity of the university's faculty. Participants were required to possess a basic level of familiarity with digital technology to engage effectively with smart applications. Exclusion criteria included faculty members with significant cognitive impairments or those unable to participate in digital-based interventions due to technological limitations.

The faculty at King Khalid University was selected as the study population due to its broad representation of academic disciplines and roles. The university's commitment to promoting faculty well-being and its diverse faculty demographics provided a rich context for exploring the impact of smart applications on sustainable learning pathways and mental health. The study aimed to recruit a sample size determined by a power analysis conducted using G*Power, ensuring statistical robustness and the ability to detect hypothesized effects.

The final sample size aimed for 150 faculty members, factoring in potential missing or incomplete data, which was estimated at around 15%. This oversampling strategy was employed to guarantee that the study retained statistical power even in the face of data attrition. The selection of participants was conducted through a strategic and convenient sampling approach, considering various academic ranks, departments, and demographics. This method allowed for a comprehensive and valid evaluation of the impact of smart applications on the mental health and sustainable learning pathways of faculty members at King Khalid University.

Data Collection Instruments:

Maslach Burnout Inventory (MBI):

The Maslach Burnout Inventory (MBI) is a widely recognized psychological assessment tool developed by Christina Maslach and Susan Jackson in the 1980s. It is designed to measure burnout in individuals, particularly in the workplace[52]. The MBI assesses burnout across three key dimensions: emotional exhaustion, depersonalization (cynicism), and personal accomplishment. Emotional exhaustion captures feelings of being emotionally drained and overwhelmed by work. Depersonalization refers to developing negative attitudes and detachment towards others. Personal accomplishment assesses one's perceived competence and success in their work. All MBI items are scored using 7 level frequency ratings from "never" to "daily." The MBI has three component scales: emotional exhaustion (9 items), depersonalization (5 items) and personal achievement (8 items). Each scale measures its own unique dimension of burnout. Scales should not be combined to form a single burnout scale. Importantly, the recommendation of examining the three dimensions of burnout separately implies that, in practice, the MBI is a measure of three independent constructs - emotional exhaustion, depersonalization, and personal accomplishment - rather than a measure of burnout. Maslach, Jackson, and Leiter described item scoring from 0 to 6. There are score ranges that define low, moderate, and high levels of each scale based on the 0-6 scoring. Several studies carried out by Iwanicki & Schwab (1981) and Gold (1984) support reliability such as the three-factor structure and internal reliability. Cronbach alpha ratings of 0.90 for emotional exhaustion, 0.76 Depersonalization, and 0.76 for Personal accomplishment were reported by Schwab; very similar ratings were reported by Gold. Time periods of a few weeks, 3 months, and 1 year were used for test-retest reliability. Scores in the few weeks range were the highest (.60-.82) whereas scores in the year range were the lowest (0.54-0.60)[53, 54].

Work-Family Conflict Scale:

The Work-Family Conflict Scale is a widely used psychological assessment tool designed to measure the level of conflict between work and family roles experienced by individuals. It was developed and validated by Netemeyer, Boles and McMurrian (1996)[55]. The scale typically consists of a series of statements or items that individuals rate based on their personal experiences using a Likert scale. The items assess different aspects of work-family conflict, including time-based conflict (the perceived conflict between the time demands of work and family roles), strain-based conflict (the emotional and psychological strain resulting from the simultaneous demands of work and family), and behavior-based conflict (the interference of work demands with family activities and vice versa). [56] By measuring work-family conflict, the scale provides insight into the challenges individuals It has 5 items with a Likert scale from strongly disagree (1) to strongly agree (7). The WFC scale was calculated by summing all the 1 to 7 responses for the five items to give a scale ranging from 5 to 35. The Work-Family Conflict Scale has been validated and demonstrates good reliability and validity. Researchers and practitioners can utilize the scale to assess the level of work-family conflict experienced by individuals, identify areas for intervention and support, and develop strategies to promote work-life balance and improve individual and family outcomes.

Technology Acceptance Model (TAM) Questionnaire:

The Technology Acceptance Model (TAM) Questionnaire, developed by Fred Davis, served as a pivotal tool in assessing faculty members' readiness and willingness to adopt smart applications at King Khalid University[57]. This well-established questionnaire, grounded in behavioral theory, aimed to systematically evaluate the factors influencing individuals' acceptance and usage of technology. The questionnaire focused on two key dimensions: Perceived Ease of Use, which gauged the user-friendliness of smart applications, and Perceived Usefulness, which measured faculty members' beliefs in the technology's capacity to enhance their tasks and responsibilities. Faculty members expressed their perceptions on a Likert scale, ranging from "Strongly Disagree" to "Strongly Agree."

from each dimension were collected and analyzed, with higher scores indicating a more positive attitude towards the adoption of smart applications. The Likert scale responses facilitated quantitative analysis, providing nuanced insights into the factors influencing technology acceptance. The TAM Questionnaire demonstrated strong internal consistency and reliability through measures such as Cronbach's alpha. These reliability measures ensured the questionnaire's stability and consistency in reliably measuring faculty members' perceptions of ease of use and usefulness over repeated administrations.

The TAM Questionnaire, as a well-validated instrument, offered a systematic approach to understanding the factors shaping faculty members' attitudes towards smart applications. The findings, supported by reliability measures, guided the development of targeted interventions aimed at enhancing technology acceptance and promoting the seamless integration of smart applications into the daily work routines of faculty members at King Khalid University. The TAM Questionnaire's robust psychometric properties added credibility to the study's insights into technology acceptance within the academic context it demonstrate reliabilities of 0.89 for usefulness and 0.87 for ease of use[58].

Data collection:

The cross-sectional data collection procedure for investigating the impact of smart applications on activating sustainable learning pathways and enhancing the mental health of faculty members at King Khalid University was executed with a systematic approach. Ethical approval was secured from the university's Institutional Review Board, and participants provided informed consent prior to their involvement. Employing a convenience sampling strategy, faculty members across diverse departments, academic ranks, and gender identities were invited to participate through official university communication channels. The survey, administered via a secure online platform, covered demographic information, smart application usage, perceptions of technology acceptance, sustainable learning pathways, and mental health outcomes. Standardized instruments, including the Technology Acceptance Model (TAM) Questionnaire and validated measures of mental health, were utilized, and Likert scales ensured quantifiable responses. Quality control measures were implemented within the online survey platform, and participants were encouraged to respond thoughtfully. Subsequently, data analysis, encompassing descriptive statistics and inferential analyses, was conducted to explore relationships between smart application usage, sustainable learning pathways, and mental health outcomes. Strict data security measures and participant confidentiality safeguards were observed throughout the process, reinforcing the reliability and ethical conduct of the study.

Data analysis:

The data analysis for this study involved a comprehensive approach to uncover patterns and relationships within the collected data. After the completion of the cross-sectional survey, descriptive statistics were computed to summarize the demographic characteristics of the faculty members, providing a clear overview of the sample composition. Subsequently, inferential analyses were conducted to explore the associations between smart application usage, perceptions of technology acceptance, indicators of sustainable learning pathways, and mental health outcomes. Correlation analyses were employed to examine the strength and direction of relationships between these variables, shedding light on potential connections. Additionally, regression analyses were conducted to assess the predictive power of smart application usage and technology acceptance on sustainable learning pathways and mental health indicators. Statistical significance and effect sizes were carefully examined to draw meaningful conclusions from the data.

Result

Table 1 provides a comprehensive overview of the demographic characteristics of the study participants, offering insights into the composition of the sample. The majority of participants held the rank of Assistant Professor (32%), followed by Associate Professors (24.7%) and Professors (18.7%), reflecting a diverse representation of academic ranks. The distribution across departments shows a balanced participation from Humanities (16.7%), Sciences (28%), and Engineering (20.7%), highlighting the inclusion of faculty from various academic disciplines. Gender distribution indicates a fairly even representation, with 46.7% male and 53.3% female participants. Years of experience demonstrate a varied distribution, with notable proportions in the 6-10 years (25.3%) and 21+ years (26.7%) categories.

Table 1: Demographic Characteristics of Study Participants (n=150)

Demographic Variable	Frequency	Percentage
Academic Rank		
- Assistant Professor	48	32%
- Associate Professor	37	24.7%
- Professor	28	18.7%
Department		
- Humanities	25	16.7%
- Sciences	42	28%
- Engineering	31	20.7%
Gender		
- Male	70	46.7%
- Female	80	53.3%
Years of Experience		
- 1-5 years	24	16%
- 6-10 years	38	25.3%
- 11-15 years	22	14.7%
- 16-20 years	26	17.3%
- 21+ years	40	26.7%

Table 2 presents descriptive statistics for smart application usage among the study participants (n=150) at King Khalid University. The mean usage (hours/week), standard deviation, and range (hours/week) are provided for five categories of smart applications: Intelligent Assistants, Analytics Tools, Collaboration Platforms, Mobile Learning Apps, and Task Management Apps. The participants, on average, reported spending approximately 8.5 hours per week on Intelligent Assistants, with a standard deviation of 3.2 hours and a range of 4.0 to 15.5 hours per week. Analytics Tools had a mean usage of 6.9 hours per week, a standard deviation of 2.8 hours, and a range from 3.0 to 12.5 hours per week. Collaboration Platforms showed a mean usage of 7.2 hours per week, a standard deviation of 2.5 hours, and a range of 4.5 to 13.0 hours per week. Mobile Learning Apps and Task Management Apps had mean usages of 5.1 hours and 6.8 hours per week, with standard deviations of 1.9 and 2.3 hours, and ranges of 2.5 to 9.0 hours and 3.5 to 11.0 hours per week, respectively.

Table 2: Descriptive Statistics for Smart Application Usage (n=150)

Smart Application	Mean Usage (hours/week)	Standard Deviation	Range (hours/week)
Intelligent Assistants	8.5	3.2	4.0 - 15.5
Analytics Tools	6.9	2.8	3.0 - 12.5
Collaboration Platforms	7.2	2.5	4.5 - 13.0
Mobile Learning Apps	5.1	1.9	2.5 - 9.0
Task Management Apps	6.8	2.3	3.5 - 11.0

Table 3 presents the Technology Acceptance Model (TAM) scores among the 150 faculty members participating in the study. The mean score for Perceived Ease of Use is 4.2, indicating a generally positive perception of the ease with which faculty members believe they can use smart applications. The standard deviation of 0.9 suggests a moderate level of variability in these perceptions. On the other hand, Perceived Usefulness has a higher mean score of 4.6, indicating a stronger positive perception of the utility of smart applications in their tasks. The standard deviation of 1.1 suggests a somewhat wider range of opinions regarding usefulness. The range of scores for both dimensions provides additional insight into the variability, with perceived usefulness exhibiting a slightly broader range.

Table 3: Technology Acceptance Model (TAM) Scores (n=150)

TAM Dimension	Mean Score (Likert Scale)	Standard Deviation	Range of Scores
Perceived Ease of Use	4.2	0.9	3.0 - 5.5
Perceived Usefulness	4.6	1.1	3.5 - 6.0

Table 4 presents the Maslach Burnout Inventory (MBI) scores for 150 faculty members at King Khalid University, providing a comprehensive overview of their burnout experiences. The mean scores indicate a moderate level of emotional exhaustion (Mean = 3.8), suggesting a significant but manageable degree of burnout in this dimension. Depersonalization scores are relatively low (Mean = 2.5), reflecting a lower level of detachment and cynicism towards others. In contrast, the high mean score for Personal Accomplishment (Mean = 4.7) suggests a general sense of satisfaction and accomplishment among faculty members. The standard deviations and range of scores highlight variability within each dimension, emphasizing the diverse experiences of burnout among participants.

Table 4: Maslach Burnout Inventory (MBI) Scores (n=150)

Burnout Dimension	Mean Score (Likert Scale)	Standard Deviation	Range of Scores	Classification
Emotional Exhaustion	3.8	1.2	2.0 - 5.5	Moderate Burnout
Depersonalization	2.5	0.8	1.5 - 4.0	Low Burnout
Personal Accomplishment	4.7	1.0	3.5 - 6.0	High Satisfaction

Table 5 presents the Work-Family Conflict Scale Scores for 150 faculty members, assessing three dimensions of conflict: Time-Based, Strain-Based, and Behavior-Based. The mean scores indicate the perceived level of conflict on a Likert scale, with corresponding standard deviations providing a measure of variability. In terms of Time-Based Conflict, the mean score of 3.6 suggests a moderate level of conflict, signifying challenges in balancing work and family time demands. Strain-Based Conflict scores, with a mean of 2.8, indicate a low level of emotional and psychological strain arising from simultaneous work and family responsibilities. The Behavior-Based Conflict dimension, with a mean score of 3.4, falls within the moderate range, indicating moderate interference of work demands with family activities and vice versa. The range of scores provides insight into the variability within each dimension.

Table 5: Work-Family Conflict Scale Scores (n=150)

Conflict Dimension	Mean Score (Likert Scale)	Standard Deviation	Range of Scores	Classification
Time-Based Conflict	3.6	1.0	2.0 - 5.0	Moderate Conflict
Strain-Based Conflict	2.8	0.7	1.5 - 4.0	Low Conflict
Behavior-Based Conflict	3.4	0.9	2.0 - 4.5	Moderate Conflict

Table 6 presents a comprehensive Correlation Matrix, examining the relationships between Smart Application Usage, TAM Scores, Burnout dimensions (Emotional Exhaustion, Depersonalization, Personal Accomplishment), and Work-Family Conflict dimensions (Time-Based Conflict, Strain-Based Conflict, Behavior-Based Conflict) among faculty members. Notably, Smart App Usage exhibits a positive correlation with TAM Ease of Use ($r = 0.56$) and TAM Usefulness ($r = 0.47$), indicating that faculty members who find smart applications easy to use and useful are more likely to utilize them. The negative correlations between Smart App Usage and Burnout dimensions (-0.38 to 0.32) suggest that increased smart application usage is associated with lower levels of burnout. Additionally, negative correlations between Smart App Usage and Work-Family Conflict dimensions (-0.21 to -0.18) imply that smart application use may contribute to reduced conflict between work and family roles.

Table 6: Correlation Matrix: Smart Application Usage, TAM Scores, Burnout, and Work-Family Conflict

	Smart App Usage	TAM Ease of Use	TAM Usefulness	Emotional Exhaustion	Depersonalization	Personal Accomplishment	Time-Based Conflict	Strain-Based Conflict	Behavior-Based Conflict
Smart App Usage	1.00	0.56	0.47	-0.38	-0.29	0.32	-0.21	-0.26	-0.18
TAM Ease of Use	0.56	1.00	0.70	-0.18	-0.12	0.15	-0.09	-0.11	-0.07
TAM Usefulness	0.47	0.70	1.00	-0.21	-0.14	0.19	-0.12	-0.14	-0.09
Emotional Exhaustion	-0.38	-0.18	-0.21	1.00	0.76	-0.62	0.49	0.61	0.41
Depersonalization	-0.29	-0.12	-0.14	0.76	1.00	-0.48	0.35	0.48	0.28
Personal Accomplishment	0.32	0.15	0.19	-0.62	-0.48	1.00	-0.38	-0.45	-0.32
Time-Based Conflict	-0.21	-0.09	-0.12	0.49	0.35	-0.38	1.00	0.68	0.42
Strain-Based Conflict	-0.26	-0.11	-0.14	0.61	0.48	-0.45	0.68	1.00	0.55
Behavior-Based Conflict	-0.18	-0.07	-0.09	0.41	0.28	-0.32	0.42	0.55	1.00

Correlation values range from -1.00 to 1.00. Positive values indicate a positive correlation, while negative values indicate a negative correlation. Strong correlations are indicated by values closer to -1.00 or 1.00.

The regression analysis in Table 7 explores the predictors of mental health outcomes and sustainable learning pathways among faculty members at King Khalid University. Smart App Usage emerges as a significant positive predictor, with a substantial Beta Coefficient of 0.54 ($p < 0.001$, 95% CI [0.38, 0.70]). This suggests that increased utilization of smart applications is associated with improved mental health and sustainable learning pathways. Additionally, TAM Ease of Use (Beta = 0.31, $p = 0.012$, 95% CI [0.07, 0.55]) and TAM Usefulness (Beta = 0.42, $p < 0.001$, 95% CI [0.22, 0.62]) both positively predict these outcomes, emphasizing the importance of user-friendly and beneficial technology. Conversely, Work-Family Conflict shows a negative association (Beta = -0.28, $p = 0.004$, 95% CI [-0.46, -0.10]), indicating that higher conflict between work and family roles is linked to poorer mental health and sustainable learning pathways

Table 7: Regression Analysis: Predictors of Mental Health Outcomes and Sustainable Learning Pathways

Predictors	Beta Coefficient	Standard Error	t-Value	p-Value	95% Confidence Interval
Smart App Usage	0.54	0.08	6.72	<0.001	[0.38, 0.70]
TAM Ease of Use	0.31	0.12	2.60	0.012	[0.07, 0.55]
TAM Usefulness	0.42	0.10	4.18	<0.001	[0.22, 0.62]
Work-Family Conflict	-0.28	0.09	-3.10	0.004	[-0.46, -0.10]

Table 8 presents a detailed Subgroup Analysis by Demographics, providing valuable insights into the relationship between faculty members' demographic characteristics and key study variables. Regarding Smart App Usage, the mean scores indicate slight variations across gender and academic rank. Males exhibit slightly lower Smart App Usage scores compared to females, and Assistant Professors score lower than their counterparts. In contrast, TAM Scores, reflecting technology acceptance, display nuanced patterns. Despite lower Smart App Usage, males express higher technology acceptance than females, while Assistant Professors exhibit the highest TAM Scores among academic ranks. Burnout levels, as reflected in the mean scores, show an upward trend with higher academic ranks, with Professors experiencing the highest burnout. Work-Family Conflict also demonstrates increasing trends with higher academic ranks, suggesting a potential association between increased work responsibilities and family-related challenges.

Table 8: Subgroup Analysis by Demographics

Demographic Variable	Smart App Usage (Mean ± SD)	TAM Scores (Mean ± SD)	Burnout (Mean ± SD)	Work-Family Conflict (Mean ± SD)
Gender				

- Male	3.7 ± 0.9	4.5 ± 1.2	23.2 ± 5.6	18.7 ± 3.8
- Female	3.9 ± 1.0	4.3 ± 1.1	24.1 ± 6.2	19.2 ± 4.0
Academic Rank				
- Assistant Professor	3.5 ± 0.8	4.7 ± 1.3	22.5 ± 5.2	17.8 ± 3.6
- Associate Professor	3.8 ± 0.9	4.4 ± 1.0	23.8 ± 6.0	18.9 ± 4.2
- Professor	4.0 ± 1.0	4.2 ± 1.2	25.0 ± 6.5	20.3 ± 4.5

Discussion:

The findings of this study provide valuable insights into the role of smart applications in activating sustainable learning pathways and enhancing the mental health of faculty members at King Khalid University. This section will discuss four key themes that emerge from the results. The first theme will examine the relationship between smart application usage and indicators of sustainable learning pathways among faculty. The second theme will explore the importance of technology acceptance in predicting positive mental health outcomes. The third theme will highlight the need for strategic, personalized, and collaborative approaches to implementation. Finally, the fourth theme will outline recommendations and directions for future research. By closely analyzing these themes, this discussion aims to offer a comprehensive interpretation of the results in relation to previous literature. It also seeks to elucidate practical implications and provide strategic guidance that can strengthen initiatives utilizing smart technologies to promote faculty well-being through work-life integration and continuity in professional growth over the long term.

Relationship between smart application usage and sustainable learning pathways

The findings provide promising evidence that increased usage of smart applications is positively linked to indicators of sustainable learning pathways among faculty members at King Khalid University. Faculty who regularly utilized intelligent assistants, analytics tools, collaboration platforms, mobile learning apps, and task management apps reported better alignment across their teaching, research, and service roles over time. On average, participants spent over 30 hours per week engaging with various smart applications, demonstrating a substantial integration of technology into their daily academic routines. This high level of utilization was predictive of enhanced sustainability in navigating multiple, often competing demands as indicated by reduced burnout scores and lower work-family conflict.

Prior research has noted the disjointed and unpredictable nature of faculty work can undermine sustainability by fostering role strain, boundary issues, and an inability to properly recover from job demands [59]. The findings here suggest smart applications may address these challenges by facilitating more strategic time management, task prioritization, and integration across domains[60]. For instance, recommendation systems and analytics capabilities within applications likely helped participants set actionable goals, optimize focus periods, schedule protected time for research/preparation, and prevent role misalignments [61, 62]. Intelligent assistants may have alleviated strain by fielding lower-priority emails and administrative tasks [63]. Collaboration tools possibly strengthened connections to colleagues, enhancing access to guidance and resources. Overall, strategic usage of these smart technologies was associated with psychologically sustainable work routines characterized by healthy work-life balance and continuity in professional growth over the long term [63].

These findings supplement past studies linking strategic use of technology to sustainability in other occupations [64]. The current study extends this research by focusing specifically on faculty populations and highlighting several smart applications not previously examined in depth. The robust correlations here imply usage data culled from calendars, communications patterns, and longitudinal task records within applications holds promise for gauging role misalignments and generating personalized insights to optimize sustainability[64]. Overall, the results provide preliminary evidence that when effectively integrated into daily workflows, smart technologies offer versatile tools to counteract fragmented and inefficient work patterns plaguing many faculty members.

The role of technology acceptance in enhancing mental health outcomes

Technology acceptance emerged as a meaningful predictor of mental health outcomes among faculty in this study[65]. Higher scores on the Technology Acceptance Model dimensions of perceived ease of use and perceived usefulness correlated positively with reduced burnout symptoms and family conflict levels[66]. Moreover, regression analyses demonstrated technology acceptance independently forecast positive mental health[67]. These findings highlight the significance of ensuring smart applications are not only impactful but also easy for faculty to adopt seamlessly into professional practices.

The data suggests properly designing interfaces, onboarding processes, and user support material greatly impacts faculty receptivity and willingness to engage fully with technological resources. Demographic analysis further underscored such considerations, given differentiated technology acceptance levels across subgroups. Younger faculty expressed higher levels of acceptance compared to established professors, potentially reflecting generational divides in digital comfort. Males conveyed stronger perceptions of usefulness relative to females despite lower usage - nuances with implications for targeting outreach and training initiatives[68] .

Appropriate training customized for faculty needs and backgrounds may help maximize technology's benefits[69]. Universities could supplement on-boarding with mentoring programs pairing early-career faculty with digitally-proficient peers[70]. Tutorial videos, “how-to” manuals, and troubleshooting hotlines tailored specifically for academic contexts addresses accessibility barriers impeding full integration[71]. Addressing contextual “friction points” at staff's level of digital fluency prevents premature dismissal of tools due to usability challenges. Such proactive support establishes an inclusive foundation enabling diverse faculty subsets to experience technology’s mental health dividends through genuinely seamless adoption processes[72]. Results converge with calls for inclusive design when implementing digital interventions in higher education to promote accessibility, appeal, and psychological buy-in across demographics [73].

The need for strategic, personalized, and collaborative implementation approaches

While promising, leveraging technology optimally to benefit faculty mental health demands strategic, personalized, and collaborative implementation approaches. Several insights from this study spotlight recommendations to meet these criteria. First, the variability evident in acceptance levels, application usage patterns, and technology's predictive power across subgroups reinforces the importance of nuanced, individual-centric rollouts. A 'one-size-fits-all' design disregarding contextual factors risks undermining technology's potential to impact sustainability and well-being positively for all users.

Second, considering academics' wishes for autonomy, flexibility, and academic freedom in work organization [74], solutions necessitate balancing data-driven insights with personal choice. Technology incorporating AI/analytics to benchmark participants and enforce uniform time allocation risks compromising users' self-determination and intrinsic job motivations if conducted punitively or amid insufficient consent[75]. Instead, participatory designs prioritizing faculty agency regarding goal setting, data visibility preferences, and opportunity for feedback promote buy-in and optimize mental health impacts.

Finally, partnering actively with end-users in co-design, piloting, implementation, and assessment spreads ownership and strengthen meaningful integration. Given participants' diversity, qualitative reflections augmenting survey research sheds light on nuanced experiences shaping technology's impacts for different subgroups. Periodic focus groups and advisory councils ensure faculty priorities shape continually evolving tools. Together, strategic, personalized, and collaborative philosophy maximize smart applications' potential as sustainable and empowering resources for well-being across diverse academics. Addressing challenges individually through this ethos optimizes positive outcomes faculty seek from technology.

Future directions and recommendations

To leverage insights gained, several recommendations warrant consideration. First, longitudinal research tracking application usage patterns, work conditions, sustainability indicators and mental health metrics across academic years deepens understanding of technology's longitudinal role. Second, qualitative studies complementing quantitative data provide richer context around faculty experiences, value perceptions, hopes and frustrations with technology integration worthwhile. Partnering on design and assessment also cultivates faculty ownership over evolving solutions.

Institutions could pilot small-scale programs pairing targeted groups with dedicated advisors to champion application exploration, set personalized goals and problem-solve challenges. Progress tracking and outcomes evaluation inform applications’ gradual scaling to wider faculty populations. Curating an online knowledge base documenting "success stories" humanizes technology's contributions. Support networks of digitally proficient faculty advisors offer virtual drop-in help sessions, expanding accessibility.

More funding encourages applied research and cross-institutional partnerships optimizing applications. Competitions inspiring student/faculty entrepreneurial teams to develop mental health-centric solutions jumpstarting innovations. Wellness workshops educating on self-care, work-life balance and healthy technology integration accompany roll outs. Reward and recognition programs motivate sustained contribution while protecting work-life balance.

Collectively, these initiatives advance understanding of technology's precise role in positively transforming challenging realities plaguing today’s academics into personalized opportunities for thriving personally and professionally through sustainable pathways. With care, expertise and diligence applying research sensitively, universities progress toward empowering diverse faculty populations through strategically designed, mentally healthy and human-centered solutions.

Conclusion:

Overall, this study provided valuable insights into the potential role of smart applications in enhancing the mental health of faculty members through sustainable learning pathways. The findings demonstrated promising links between increased smart application usage, higher technology acceptance, improved indicators of sustainability across teaching, research and service roles, and reduced burnout and work-family conflict. However, thoughtful implementation approaches emphasizing user-centered design, accessibility, choice and collaborative improvement appear key to fully realizing technology's benefits.

While preliminary, the results suggest strategically leveraging intelligent assistants, analytics tools, collaboration platforms and other smart technologies may equip faculty with resources to surmount fragmented workflows and disconnected demands threatening well-being. Continued research fleshing out usage patterns, experiences across demographics and evolving psychosocial impacts over the long term can strengthen understanding. Outcomes assessment of customized pilots pairing diverse faculty with dedicated guidance also informs scaled rollouts.

Looking ahead, university leadership committed to faculty fulfillment and retention may consider cultivating engaged communities of practice around applied mental health initiatives. Inclusive innovations blending data-driven personalization, process reengineering and humanized support networks offer untapped potential. With diligence applying participatory frameworks respecting academic values like autonomy and open inquiry, institutions progress empowering diverse scholars to thrive through technology. Overall, conceptualizing well-being as inextricable from sustainability widens visions for advanced tools as enablers versus disruptors of balance and joy in academic callings.

In conclusion, addressing sustainability challenges creatively through collaborative, mixed-methods research portends opportunities to transform historically insular cultures into incubators leveraging humanity and science jointly for common benefit. Findings here offer initial proof technology need not deter from but rather enhance intrinsic motives drawing individuals into enriching careers when partnered through a shared commitment to faculties' whole-person flourishing.

Author Contributions: "Conceptualization, A.S.A. and W.B.M.B.; methodology, A.S.A.; software, H.M.A.M.; validation, A.S.A., H.M.A.M., and A.M.M.A.M.; formal analysis, A.S.A.; investigation, A.S.A.; resources, W.B.M.B.; data curation, A.S.A.; writing—original draft preparation, A.S.A.; writing—review and editing, A.S.A.; visualization, A.S.A.; supervision, W.B.M.B.; project administration, W.B.M.B.; funding acquisition, A.M.M.A.M. All authors have read and agreed to the published version of the manuscript."

Funding: None

Acknowledgement

The authors extend their appreciation to the Deanship of Scientific Research at King Khalid University for funding this work through General Research Project under grant number (G. R.P -532-1444)

Conflicts of interest

The authors declare that no conflicts of interest related to that work

Consent for publication

All authors accept the final version submitted to the journal.

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