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Exploring the Influence of STARA Awareness on Job Outcomes and Well Being Outcomes among University Level Teachers

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Abstract : *The rise of Industry 4.0, driven by STARA (Smart Technology, AI, Robotics, and Algorithms), has transformed business sectors, yet its impact on higher education particularly among teaching faculty in developing contexts like Nepal remains understudied. Grounded in the Job Demands-Resources (JD-R) theory, Career Planning theory and Job Insecurity theory, this study investigates how STARA awareness* influences *job outcomes* (organizational commitment, career satisfaction, turnover intentions) and *well being outcomes* (depression, cynicism). This study aims to explore the relationship between STARA Awareness on Job Outcomes and Well Being Outcomes. These relationships were assessed using multivariate technique i.e. MANOVA from the responses collected via online and physical contact from 133 university level teachers working in and in different affiliated colleges of *Tribhuvan University, Pokhara University, Purbanchal University and others. Using a quantitative survey design, data were analyzed via MANOVA, revealing a significant overall effect of STARA awareness on combined outcomes* ($p < .05$). *Follow-up ANOVA* showed STARA awareness significantly *impacted organizational commitment* ($F = 2.708$, $p < .01$) *and depression* ($F = 2.125$, $p < .05$)*, but had no significant impact on career satisfaction, turnover intentions, or cynicism. Notably, well being outcomes fully mediated* the STARA Awareness and Job Outcomes relationship. *Practical implications* highlight the need for universities to implement *STARA training programs* to reduce depression risks and strengthen organizational commitment, while policymakers should address *automation anxiety* through institutional support. By bridging *JD-R theory* with the *employee mental health* discourse, this study offers actionable insights for academia and HR professionals navigating the STARA era.

Keywords: *STARA Awareness, Job and Well Being Outcomes, Employee Mental Health, Automation Anxiety*

Introduction

The emergence of the Fourth Industrial Revolution has brought about swift progress in intelligent technologies that are progressively taking over tasks traditionally performed by human workers. Research forecasts indicate approximately 33% of current occupations may become automated (Frey & Osborne, 2017). The widespread implementation of STARA (Smart Technologies, Artificial Intelligence, Robotics, and Algorithms) across multiple sectors has created substantial transformations in social structures, daily life, and employment landscapes (Almada-Lobo, 2016; Ivanov & Webster, 2017). As these technologies enter workplaces, workers often experience apprehension about their professional futures, a phenomenon termed STARA awareness (Bankins et al., 2024). This concept refers to employees' realization that their positions could potentially be assumed by advanced technological systems, representing a precarious circumstance with negative implications for workers (Brougham & Haar, 2018).

Academic investigations have revealed that STARA awareness can impair various aspects of work-life including psychological security, dedication to organizations, job involvement, contentment with work, and performance efficiency (Kong et al., 2021; Ding, 2021), while simultaneously elevating levels of occupational exhaustion and propensity to leave jobs (Mahlasela & Chinyamurindi, 2020; Li et al., 2019), consequently adversely influencing long-term career viability. Nevertheless, contemporary research is increasingly highlighting potential beneficial outcomes of STARA awareness for professional growth (Wang et al., 2022). Specifically, studies demonstrate that when workers effectively comprehend and adjust to technological integration, they may experience improved psychological outcomes, including strengthened internal drive for their work (Liang et al., 2022). This illustrates the ambivalent characteristics of STARA awareness's influence on workers (Ding, 2021). Consequently, examining strategies to amplify the constructive aspects of STARA awareness while reducing its damaging consequences has become particularly crucial and important to be studied. Fundamentally, STARA awareness embodies the occupational anxiety and instability workers feel when confronting the possibility of technological replacement (Mahlasela & Chinyamurindi, 2020).

The implementation of STARA technologies extends far beyond low-wage, low-skill occupations. Advanced algorithms are now performing complex tasks such as legal document analysis, the Clearwell system famously reviewed and categorized 570,000 documents within two days (Frey & Osborne, 2013), work traditionally handled by legal professionals. Similarly, automated reporting systems are becoming increasingly prevalent in business and media sectors. Meanwhile, the decreasing costs of high-precision robotic systems are making automation more accessible (Frey & Osborne, 2013). A comprehensive analysis of 702 occupations revealed significant computerization risks across various professions, including accounting, market analysis, aviation, customer service, and administrative roles (Frey & Osborne, 2013). The impact of STARA spans multiple sectors including healthcare (Bloss, 2011; Lorentziadis, 2014), education (through mass online learning platforms), transportation, and primary industries. This groundbreaking research estimated that 47% of current jobs face potential automation (Frey & Osborne, 2013), with many being well-compensated, middle-class service sector positions. This technological shift coincides with growing income inequality trends (Goos & Manning, 2007; Autor & Dorn, 2013), particularly concerning given that in New Zealand, the wealthiest 20% of households control approximately 70% of total household wealth (Statistics New Zealand, 2016), highlighting the expanding socioeconomic divide (McCammon, 2016). Even professions not directly at risk may experience secondary effects from STARA adoption in related industries. For instance, autonomous vehicle technology could eliminate demand for driving instructors, license examiners, insurance assessors, and auto body repair specialists by reducing accident rates. Furthermore, the potential for overnight autonomous travel could disrupt hospitality and airline industries (Zaldivar, 2015). As The Economist (2014) cautions, emerging technologies may permanently eliminate certain job categories without creating equivalent replacements. In Nepal**,** limited empirical research exists on how teaching faculty interpret STARA's role in their professional and psychological well being. With regard to the influence of STARA on changes in an academic setting, the objective of this study is two-fold: (a) to assess the impact of STARA awareness on job outcomes and wellbeing outcomes, and (b) to investigate the mediating effect of employee wellbeing on the relationship between STARA awareness and job outcomes.

Literature Review

Fourth Industrial Revolution, STARA in Education

The evolution of workplace dynamics has historically followed predictable patterns of transformation. In most developed economies, we've witnessed a substantial decline in primary (agricultural/mining) and secondary (manufacturing) sectors (Dennis, 1978; Charles et al., 2013), with displaced workers typically transitioning into service-oriented roles as new employment opportunities emerged (Spohrer & Maglio, 2008). Previous industrial revolutions driven by textile mechanization, steam power, transportation advances, assembly lines, labor specialization, electrification, and communication breakthroughs (Jensen, 1993) particularly manufacturing electrification significantly altered skill requirements across industries (Gray, 2013). Historically, technological displacement of lower-skilled positions often generated demand for clerical and managerial roles (Gray, 2013), but the current technological paradigm shift may differ fundamentally. The 21st century has ushered in the Fourth Industrial Revolution (Industry 4.0), a transformative era defined by the rapid digitalization of global industries (World Economic Forum, 2016; Xu et al., 2018). Far from being a temporary trend, Industry 4.0 represents a profound and disruptive shift in production and business models (Ardito et al., 2019; Buer et al., 2018; Schroeder et al., 2019). Originating with the German-coined term *"Industrie 4.0"* in 2011, this movement has since spurred governments and corporations worldwide to prioritize technological integration (Ghobakhloo, 2018; Nascimento et al., 2019). Historically, industrial progress from the 18th century mechanization to today's smart factories has grappled with a central dilemma: how to optimize output from increasingly scarce natural resources to meet rising demand, while mitigating ecological degradation and social inequities (Beier et al., 2018; Müller et al., 2018).

The integration of STARA technologies threatens to eliminate middle-tier occupations at an unprecedented scale (Feng & Graetz, 2015), with service sector positions being particularly vulnerable due to their significant contribution to operational costs. Unlike previous transitions, displaced service workers may lack an emerging "fourth" sector for immediate re-employment. Experts suggest STARA's impact on services will mirror previous industrial revolutions in magnitude, unfolding gradually over coming decades (Brynjolfsson & McAfee, 2011). Technological advancement has driven labor market polarization since the mid-20th century (Mishel et al., 2013), a phenomenon Autor and Dorn (2013) attribute to shifting consumer preferences toward product diversity combined with increasingly affordable automation of routine tasks. This research proceeds on two key premises: first, that STARA technologies are precipitating a service sector revolution; second, that widespread workforce displacement may occur imminently (Frey & Osborne, 2013). The potential consequences remain uncertain - whether new employment categories will emerge or whether middle- and lower-skilled workers will face deteriorating conditions. Prominent voices like Stephen Hawking have cautioned that current automation trends may exacerbate socioeconomic disparities (Rathi, 2015). Crucially, existing research lacks empirical data regarding workforce awareness of these impending changes and whether professionals are adapting their career trajectories accordingly. This gap in understanding informs our subsequent discussion of career planning strategies and hypothesis development.

The education sector has witnessed growing recognition of Artificial Intelligence in Education (AIED) over the past three decades (Hwang et al., 2020). AIED's capabilities have prompted discussions about potentially replacing academic roles due to its extensive automation potential (Hwang et al., 2020). Employees' willingness to adopt digital technologies significantly influences their workplace well being (Weilage & Stumpfegger, 2022). However, AI often carries negative associations, as it raises concerns about job security and future prospects, potentially harming psychological well being (Rhee & Jin, 2021; Khanyane, 2023). Pauceanu et al. (2020) predict that the Fourth Industrial Revolution will transform employment landscapes, rendering many current occupations obsolete through technological advancements. Brougham and Haar (2018) identify two primary psychological impacts of STARA technologies: feelings of hopelessness and tendencies toward vilification. While AI transforms higher education teaching environments, Popenici and Kerr (2017) emphasize that human qualities like emotional expression and natural responses remain challenging to replicate algorithmically. Higher education pedagogies and teaching methodologies are undergoing reevaluation as institutions adapt to technological changes (Popenici & Kerr, 2017). In the South African context, Oosthuizen and Mayer (2019) highlight an academic skills gap regarding STARA awareness, which may exacerbate workplace anxiety about technological integration. Many nations are working toward 2030 objectives to properly equip educators for the evolving digital workplace (Hwang et al., 2020). Moreover, most academics view STARA positively for streamlining tasks and enabling greater focus on meaningful teaching and student support, though they recognize the need for upskilling to adapt to technological changes while maintaining the irreplaceable human elements of education (Grant & Oosthuizen, 2024).

STARA and Job Outcomes

STARA awareness captures how employees perceive the impact of emerging technologies like AI, robotics, and automation on their career prospects. This concept builds upon career-planning theory (Greenhaus & Kopelman, 1981), which traditionally focused on personal skills, job opportunities, and work-life balance. However, the rapid advancement of STARA technologies necessitates an expansion of this framework, as automation may render certain careers obsolete regardless of an individual's competencies or preferences (Frey & Osborne, 2013). Modern career planning must now incorporate technological disruption as a critical factor, transforming it into a more dynamic, ongoing process (Zikic & Klehe, 2006) that accounts for the growing prevalence of boundaryless careers (Arthur & Rousseau, 2001) rather than traditional organizational career paths. Research demonstrates that career planning significantly influences work attitudes, including organizational commitment, career satisfaction, and turnover intentions (Aryee & Debrah, 1993). However, STARA awareness may undermine these outcomes by creating job insecurity and perceived threats to career progression. When employees anticipate technological displacement, they may experience reduced career satisfaction and organizational commitment, as their sense of control over their professional future diminishes (Chen et al., 2004). This aligns with findings that career-planning mismatches can increase turnover intentions (Steffy & Jones, 1988), suggesting that STARA awareness could prompt employees to seek alternative employment opportunities in response to technological disruptions in their current roles. Similarly, Hong et al. (2025) found that employees' awareness of Smart Technology, Artificial Intelligence, Robotics, and Algorithms (STARA) enhances career sustainability through increased learning motivation and reduced perceptions of resource loss based on theoretical model application of Conservation of Resources Theory. In addition to that, the study showed that when employees become aware of STARA technologies, they experience resource-related stress which activates adaptive behaviors i.e. a process that exemplifies Conservation of Resources Theory in technological work environments (Hong et al., 2025). The following section formalizes these expectations into testable propositions.

H1: STARA Awareness has a significant effect on organizational commitment.

H2: STARA awareness has a significant effect on career satisfaction.

H3: STARA awareness has a significant effect on turnover intentions.

STARA and Well Being Outcomes

STARA awareness is expected to impact not only job-related outcomes but also employee well being, as perceptions of career identity and success shape psychological health (Mirvis & Hall, 1994; Wiese et al., 2002). According to Job Insecurity Theory, the anticipation or fear of losing one's job can have detrimental effects on an individual's well being specially mental health, workplace attitudes, and overall job effectiveness i.e. job performance (Greenhalgh & Rosenblatt, 1984).When employees foresee limited career prospects due to technological disruption, their mental health may suffer, with job insecurity linked to increased stress and burnout (Dekker & Schaufeli, 1995). This uncertainty may be particularly harmful when workers lack clarity about their professional futures. Employees aware of STARA's potential threats may experience heightened anxiety, while those unaware might cope better (Chen et al., 2004). Additionally, such awareness could lead to depression (low motivation and pleasure) and workplace cynicism (detachment and negativity) as coping mechanisms (Axtell et al., 2002; Roche & Haar, 2013), suggesting STARA awareness may negatively influence both job attitudes and psychological well being. The following section reflects the above phrased reviews into testable hypothesis.

H4: STARA awareness has a significant effect on depression.

H5: STARA awareness has a significant effect on cynicism.

Well Being Outcomes as a Mediator on STARA Awareness and Job Outcomes

The relationship between STARA (Smart Technology, Artificial Intelligence, Robotics, and Algorithms) awareness and job-related outcomes (e.g., organizational commitment, career satisfaction, and turnover intentions) may be mediated by well being outcomes, particularly depression and cynicism. Research suggests that technological disruptions in the workplace can trigger psychological distress, which in turn influences work attitudes and behaviors (Dekker & Schaufeli, 1995; Chen et al., 2004). Employees who perceive their jobs as vulnerable to automation may experience heightened anxiety, leading to decreased motivation and increased detachment (Axtell et al., 2002; Roche & Haar, 2013). This aligns with the Job Demands-Resources (JD-R) model (Bakker & Demerouti, 2007), which posits that chronic stressors (such as job insecurity due to STARA) deplete emotional resources, resulting in burnout and reduced engagement.

Empirical studies support this mediation pathway. For instance, job insecurity has been linked to depression, which subsequently predicts lower organizational commitment and higher turnover intentions (Sverke et al., 2002). Similarly, cynicism a core dimension of burnout mediates the effects of workplace stressors on job performance and satisfaction (Maslach et al., 2001). In the context of STARA, employees who feel threatened by automation may develop depressive symptoms (e.g., hopelessness about career growth) and cynicism (e.g., disengagement from work), ultimately worsening job outcomes (Mirvis & Hall, 1994). These findings underscore the need to examine well being outcomes as a critical mediator in the STARA awareness to job outcomes relationship. Based on the review, this study identifies the need to test the following hypothesis.

H6: Well Being Outcomes mediates the relationship between STARA Awareness and Job Outcomes.

The following research frameworks for the study has been developed based on literature review to test the above mentioned hypothesis for the study and are outlined as under:

Research Framework 1

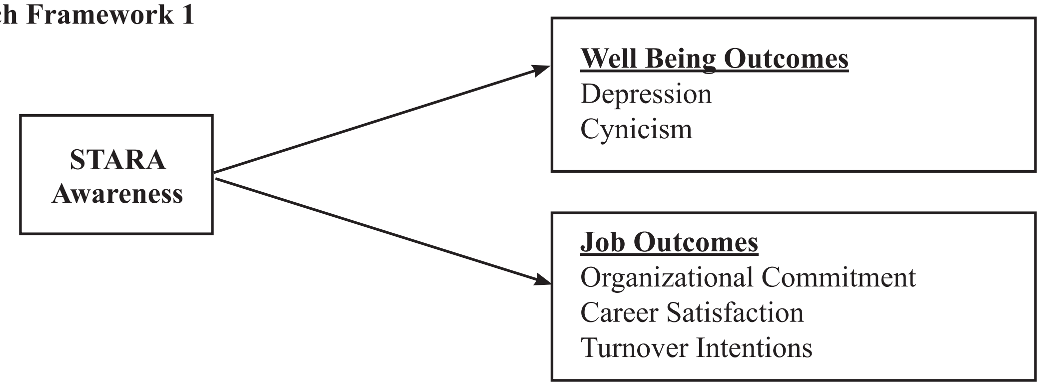

Figure 1: Research Framework 1

Source: *Adapted from Brougham and Haar (2018)*

Research Framework 2

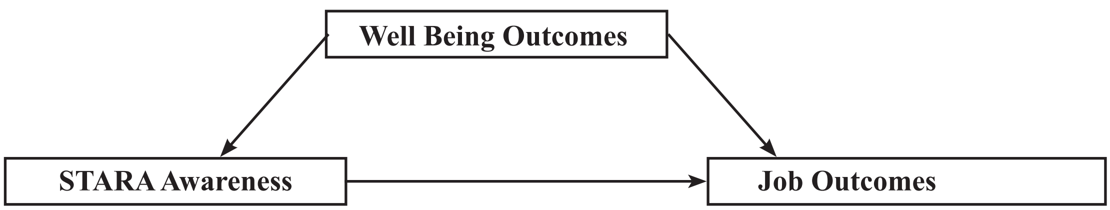

Figure 2: Research Framework 2

Source: *Adapted from Brougham and Haar (2018) and Author's own compilation (2025)*

Methodology

This study adopts a quantitative survey design to examine the relationship between STARA Awareness, Well Being Outcomes (depression and cynicism), and Job Outcomes (organizational commitment, career satisfaction, and turnover intentions). A mediation analysis is employed to assess whether Well Being Outcomes as a variable mediate the effect on the relationship between STARA Awareness and Job Outcomes. The target population consists of university level teachers of Nepal**.** A purposive sampling approach is used, with participants contacted for questionnaire distribution via professional networks (LinkedIn), social media platforms (Facebook), emailing, and personal visits. The sample size is determined using G*Power 3.1 (Faul et al., 2007), targeting a minimum of 218 respondents to ensure adequate statistical power ($\alpha = 0.05$, power = 0.95, small effect size= 0.50) where just 133 responses were collected with the response rate of 62.44%. All constructs are measured using validated Likert-scale questionnaires (5-point scales, 1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree and 5 = Strongly Agree) except for depression but with different response options i.e. 5 indicates Always, 4 indicates Often, 3 indicates Sometimes, 2 indicates Rarely and 1 indicates Never where STARA awareness has 4 items adopted from Brougham and Haar (2018), organizational commitment has 18 items adopted from Meyer et al. (1993), career satisfaction has 5 items adopted from Greenhaus et al. (1990), turnover intentions has 4 items adopted from Kelloway et al. (1999), depression has 3 items adopted from Axtell et al. (2002) and cynicism has five items adopted from Mashlach et al. (1996). All constructs has good reliability statistics with croanbach alpha of .892 for STARA awareness, .840 for OC, .928 for CS, .895 for TI, .811 for depression, .761 for cynicism and satisfies the criteria for acceptable scales for measurement i.e. $\alpha \geq .70$ indicates adequate internal consistency (Nunally et al., 1994).

Results, Discussion and Conclusions

Results

Table 1

Respondents Profile and Descriptive Statistics

Profile of Respondents with Descriptive			
Demographic Variables	***Labels***	***Frequency***	***Percentage***
Designation	Professor	6	4.5
	Assoc. Professor	17	12.8
	Asst. Professor	81	60.9
	Part Timers	29	21.8

Age	≤25	0	0
	26-35	23	17.3
	36-45	59	44.4
	46-55	42	31.6
	≥56	9	6.8
Marital Status	Married	125	94.0
	Unmarried	8	6.0
Status of the Job	Permanent	104	78.2
	Temporary	29	21.8
University	Tribhuvan University	98	73.7
	Pokhara University	23	17.3
	Purbanchal University	7	5.3
	Nepal Open University	1	.8
	Mid-West University	2	1.5
	Lumbini Buddhist University	2	1.5
Education	PhD and Above	32	24.1
	Mphil	32	24.1
	Masters	69	51.9
Gender	Male	126	94.7
	Female	7	5.3
	Others	0	0
Experience	<1	3	2.3
	1-10	49	36.8
	11-20	49	36.8
	21-30	28	21.1
	>30	4	3.0

The sample as mentioned in Table 1 comprised 133 academic professionals from Nepalese universities, predominantly male (94.7%), married (94.0%), and holding permanent positions (78.2%). Most participants were assistant professors (60.9%), aged 36-45 years (44.4%), and affiliated with Tribhuvan University (73.7%). The majority held master's degrees (51.9%) and had 1-20 years of teaching experience (73.6% combined), with equal proportions in the 1-10 year

(36.8%) and 11-20 year (36.8%) experience brackets. The sample showed limited diversity in gender representation (only 5.3% female faculty) and age distribution (82.8% aged 36-55 years), reflecting Nepal's academic workforce demographics. Notably, no respondents were under 26 years old, and only 2.3% had less than one year of teaching experience, suggesting the findings primarily reflect established faculty perspectives.

Table 2

Correlation Matrix

Correlations							
Particulars		**STARA Awareness**	**Organizational Commitment**	**Career Satisfaction**	**Turnover Intensions**	**Depression**	**Cynicism**
STARA Awareness	Pearson Correlation	1					
	Sig. (2-tailed)						
	N	133					
Organizational Commitment	Pearson Correlation	-.161	1				
	Sig. (2-tailed)	.065					
	N	133	133				
Career Satisfaction	Pearson Correlation	-.106	.568**	1			
	Sig. (2-tailed)	.223	.000				
	N	133	133	133			
Turnover Intensions	Pearson Correlation	.010	-.392**	-.208*	1		
	Sig. (2-tailed)	.905	.000	.016			
	N	133	133	133	133		
Depression	Pearson Correlation	.209*	-.360**	-.389**	.321**	1	
	Sig. (2-tailed)	.016	.000	.000	.000		
	N	133	133	133	133	133	
Cynicism	Pearson Correlation	.244**	-.335**	-.393**	.422**	.379**	1
	Sig. (2-tailed)	.005	.000	.000	.000	.000	
	N	133	133	133	133	133	133
*. Correlation is significant at the 0.05 level (2-tailed).							
**. Correlation is significant at the 0.01 level (2-tailed).							

In the Table 2, the Pearson correlation matrix revealed several significant relationships among the variables where STARA Awareness showed a positive correlation with Depression (r=.209*, p =.016) and Cynicism (r =.244**, p=.005), suggesting that higher STARA awareness is associated with slightly higher levels of depression and cynicism. Furthermore, no significant correlations with Organizational Commitment (r= -0.161, p = .065), Career Satisfaction (r= -0.106, p =.223), or Turnover Intentions (r = .010, p = .905). Similarly, Organizational Commitment has been strongly positively correlated with Career Satisfaction (r = .568**, p< .001), indicating that employees with higher commitment also reported greater career satisfaction and negatively correlated with Turnover Intentions (r= -0.392**, p< .001), Depression (r = -0..360**, p < .001), and Cynicism (r = -0.335**, p < .001), suggesting that committed employees are less likely to leave, experience depression, or exhibit cynicism. Moreover, Career Satisfaction demonstrated negative relationships with Turnover Intentions (r = -0.208*, p = .016), Depression (r = -0.389**, p < .001), and Cynicism (r = -0.393**, p < .001), implying that satisfied employees are less prone to quitting, depressive feelings, or cynical attitudes. In addition to that, Turnover Intentions is positively associated with Depression (r = 0.321**, p < .001) and Cynicism (r = 0.422**, p < .001), indicating that employees considering leaving their jobs reported higher distress and negativity. Lastly, Depression and Cynicism were moderately positively correlated (r = 0.379**, p < .001), aligning with expectations that emotional exhaustion and negative attitudes coexist.

Table 3

MANOVA Analysis

Multivariate Tests						
Effect		Value	F	Hypothesis df	Error df	Sig.
Intercept	Pillai's Trace	.981	1164.460[b]	5.000	113.000	.000
	Wilks' Lambda	.019	1164.460[b]	5.000	113.000	.000
	Hotelling's Trace	51.525	1164.460[b]	5.000	113.000	.000
	Roy's Largest Root	51.525	1164.460[b]	5.000	113.000	.000
STARA Awareness	Pillai's Trace	.759	1.396	75.000	585.000	.020
	Wilks' Lambda	.420	1.443	75.000	545.469	.012
	Hotelling's Trace	1.000	1.486	75.000	557.000	.007
	Roy's Largest Root	.466	3.633[c]	15.000	117.000	.000

Table 4

ANOVA Analysis between Subjects Effects

Tests of Between-Subjects Effects						
Source	Dependent Variable	Type III Sum of Squares	Df	Mean Square	F	Sig.
Corrected Model	Organizational Commitment	10.862[a]	15	.724	2.708	.001
	Career Satisfaction	13.029[b]	15	.869	1.290	.219
	Turnover Intensions	12.986[c]	15	.866	.776	.702
	Depression	22.987[d]	15	1.532	2.125	.013
	Cynicism	14.671[e]	15	.978	1.712	.058
Intercept	Organizational Commitment	644.449	1	644.449	2410.267	.000
	Career Satisfaction	734.850	1	734.850	1091.399	.000
	Turnover Intentions	221.852	1	221.852	198.743	.000
	Depression	227.646	1	227.646	315.613	.000
	Cynicism	261.445	1	261.445	457.650	.000
STARA Awareness	Organizational Commitment	10.862	15	.724	2.708	.001
	Career Satisfaction	13.029	15	.869	1.290	.219
	Turnover Intentions	12.986	15	.866	.776	.702
	Depression	22.987	15	1.532	2.125	.013
	Cynicism	14.671	15	.978	1.712	.058
Error	Organizational Commitment	31.283	117	.267		
	Career Satisfaction	78.777	117	.673		
	Turnover Intentions	130.604	117	1.116		
	Depression	84.390	117	.721		
	Cynicism	66.840	117	.571		
Total	Organizational Commitment	1775.278	133			
	Career Satisfaction	1917.760	133			
	Turnover Intentions	727.813	133			
	Depression	703.889	133			
	Cynicism	752.800	133			
Corrected Total	Organizational Commitment	42.145	132			
	Career Satisfaction	91.806	132			
	Turnover Intentions	143.590	132			
	Depression	107.377	132			
	Cynicism	81.511	132			
a. R Squared = .258 (Adjusted R Squared = .163)						
b. R Squared = .142 (Adjusted R Squared = .032)						
c. R Squared = .090 (Adjusted R Squared = -.026)						
d. R Squared = .214 (Adjusted R Squared = .113)						
e. R Squared = .180 (Adjusted R Squared = .075)						

The Table 3 tests whether the independent variable (STARA Awareness) has a significant effect on the combined set of dependent variables (Organizational Commitment, Career Satisfaction, Turnover Intentions, Depression, Cynicism i.e. Job Outcomes and Well Being Outcomes). The key findings state that all multivariate test statistics (Pillai's Trace, Wilks' Lambda, Hotelling's Trace, Roy's Largest Root) are highly significant ($p < .001$), indicating that the intercept-only model explains a substantial portion of the variance. Since the MANOVA is significant, we examine the univariate ANOVAs in Table 4 for each dependent variable to see which specific outcomes are affected by STARA Awareness and follows as mentioned below:

Table 5

Hypothesis Testing (H1:H5)

Dependent Variable	**F-statistic**	**p-value**	**Effect Size (R^2)**	**Adjusted R^2**	**Conclusion**
Organizational Commitment	$F(15,117) = 2.708$	.001	0.258	0.163	**H1 Significant**
Career Satisfaction	$F(15,117) = 1.290$	.219	0.142	0.032	H2 Not Significant
Turnover Intentions	$F(15,117) = 0.776$	.702	0.090	-0.026	H3 Not Significant
Depression	$F(15,117) = 2.125$	.013	0.214	0.113	**H4 Significant**
Cynicism	$F(15,117) = 1.712$	.058	0.180	0.075	H5 Marginal (ns)

The Table 5 explains the significant effects of STARA Awareness on Organizational Commitment ($p < .05$) i.e. STARA Awareness has a significant effect ($p = .001$). **$R^2 = 0.258$ →** ~25.8% of variance explained (adjusted $R^2 = 0.163$). Similarly, significant effects of STARA Awareness on Depression ($p < .05$) i.e. STARA Awareness has a significant effect ($p = .013$). **$R^2 = 0.214$** → ~21.4% of variance explained (adjusted $R^2 = 0.113$). In addition to that, the table 5 also shows non-significant effects ($p > .05$) of STARA Awareness on Career Satisfaction ($p = .219$) having no effect, on Turnover Intentions ($p = .702$) having no effect and finally on Cynicism ($p = .058$) having marginally non-significant (trend). In overall, Multivariate Analysis (MANOVA) confirms that STARA Awareness has a statistically significant overall effect on the combined dependent variables. The Follow-up ANOVAs reveal that this effect is primarily driven by Organizational Commitment and Depression Levels. Similarly, no significant effects were found for Customer Satisfaction, Turnover Intentions, or Cynicism (though Cynicism showed a marginal trend).

Table 6

Mediation Analysis of Well Being Outcomes on the Relationship between STARA Awareness and Job Outcomes

Variable Relationship (Path)	Coeff (β)	SE	t	P	95% CI (LL, UL)
Total Effect (c)	-0.0823	0.0421	-1.9538	0.0529	[-0.1657, 0.0010]
Direct Effect (c')	-0.0380	0.0416	-0.9119	0.3635	[-0.1204, 0.0444]
Indirect Effect (a×b)	-0.0443	0.0208	-	-	[-0.0927, -0.0121]
Path a (X → M)	0.2083	0.0637	3.2692	0.0014	[0.0823, 0.3344]
Path b (M → Y)	-0.2128	0.0549	-3.8773	0.0002	[-0.3214, -0.1042]

Note. X = STARA Awareness, M = Well Being Outcomes, Y = Job Outcomes. N = 133. Confidence intervals for indirect effect are bias-corrected bootstrap CIs based on 5,000 samples. All coefficients are unstandardized.

The author examined whether Well Being Outcomes mediated the relationship between STARA Awareness and Job Outcomes using Hayes' PROCESS Macro (Model 4) with 5,000 bootstrap samples and is presented in Table 6. The analysis revealed a significant indirect effect, suggesting mediation. The key findings based on total effect model depicts that STARA Awareness showed a marginally significant negative relationship with Job Outcomes (B = -0.0823, SE = 0.0421, p = 0.0529, 95% CI -0.1657, 0.0010]). Similarly, based on mediation pathways Path a (X→M) STARA Awareness significantly predicted Well Being Outcomes (B = 0.2083, SE = 0.0637, p = 0.0014, 95% CI [0.0823, 0.3344]) and Path b (M→Y) Well Being Outcomes negatively predicted Job Outcomes (B = -0.2128, SE = 0.0549, p = 0.0002, 95% CI [-0.3214, -0.1042]).Moreover, based on direct and Indirect effects, the direct effect became non-significant when including the mediator (B = -0.0380, SE = 0.0416, p = 0.3635, 95% CI [-0.1204, 0.0444]) and the indirect effect was significant (B = -0.0443, SE = 0.0208, 95% CI [-0.0927, -0.0121]). Furthermore, the results indicate full mediation, as the total effect was marginally significant, the indirect effect through Well Being Outcomes was significant and the direct effect became non-significant when accounting for the mediator. The negative coefficient for Path b suggests that higher Well Being Outcomes is associated with poorer Job Outcomes in the sample, which may warrant for further investigation. In overall, the results indicate that Well Being Outcomes fully mediates the relationship between STARA Awareness and Job Outcomes hence stating the acceptance of hypothesis H6.

Discussion

The study examined the relationships between STARA Awareness, Well Being Outcomes, and Job Outcomes among Nepalese academic professionals. The MANOVA results revealed significant multivariate effects of STARA awareness on the combined dependent variables (p

$< .001$). Follow-up ANOVAs demonstrated that STARA Awareness significantly predicted organizational commitment ($p = .001$, $R^2 = 0.26$) and depression levels ($p = .013$, $R^2 = 0.21$), but not career satisfaction, turnover intentions, or cynicism. These findings suggest that STARA Awareness primarily affects work-related attitudes and mental health outcomes rather than job satisfaction or turnover-related variables in this population. The mediation analysis yielded important insights, revealing that Well Being Outcomes fully mediated the relationship between STARA Awareness and Job Outcomes (indirect effect: B = -0.0443, 95% CI [-0.0927, -0.0121]). The negative association between Well Being Outcomes and Job Outcomes was unexpected and warrants further investigation. This counterintuitive finding may reflect measurement issues or unique cultural aspects of the Nepalese academic context where higher well being could correlate with reduced work focus or productivity. The predominantly male (94.7%), married (94.0%), and permanent (78.2%) sample composition suggests these findings may be most applicable to established faculty members in similar cultural contexts. The underrepresentation of female faculty (5.3%) limits generalizability to more gender-balanced academic populations.

In addition to the above discussion, the findings of this study exactly matches with the similar type of study undertaken by Brougham and Haar (2018) in New Zealand among employees working in service sector where STARA Awareness negatively correlates with organizational commitment and career satisfaction and positively correlates with turnover intentions, depression and cynicism. Moreover, as the research findings in this area is very limited in number global studies with similar variables and variable association with each other is difficult to find. Therefore, this study would be a foundational work for other researchers to undertake similar study in different contexts. The study's findings indicate that greater employee awareness of STARA (Smart Technology, Artificial Intelligence, Robotics, and Algorithms) and its relevance to their roles correlates with reduced organizational commitment and career satisfaction. This aligns with Aryee and Debrah's (1993) career-planning model, which posits that effective career planning fosters a positive feedback loop, enhancing career satisfaction and workplace self-esteem. The rise of STARA, however, may disrupt this process, undermining career planning success and exacerbating the instability associated with boundaryless careers a trend likely to intensify with advancing technology. Additionally, employees who perceive STARA as more impactful report stronger negative outcomes, including increased turnover intentions, depression, and cynicism. These results are consistent with prior research, such as Virtanen et al. (2003), which found that unfulfilled career growth expectations are linked to stress, burnout, and intentions to leave an organization. The study's conclusions thus reflect broader concerns about technology driven workplace transformations and their psychological toll on employees. Additionally, the study conducted by Başer et al. (2025) identified the negative effects of STARA awareness on job outcomes among hotel employees i.e. STARA awareness negatively affected the psychological relationship between individuals and organizations which matches with the study findings of this research where increase in STARA awareness leads to increase in turnover intentions, depression and cynicism.

Conclusion

This study makes several important contributions to understanding STARA Awareness effects in higher education where STARA Awareness significantly impacts organizational commitment and depression levels among faculty, secondly, well being outcomes fully mediates the STARA Awareness-Job Outcomes relationship and the unexpected negative Well Being-Job Outcomes association highlights potential cultural specificities in how technology adoption affects academic work. The findings suggest that universities implementing STARA technologies should develop targeted interventions to maintain organizational commitment, provide mental health support to mitigate depression risks and further investigate the Well Being-Job Outcomes relationship in local contexts. Moreover, policymakers should develop institutional support mechanisms to cope up with anxiety created out of automation as automation and sophisticated technology creates fear for job insecurity resulting into adverse impact on job performance and psychological well being. Lastly, limitations include the cross-sectional design, gender imbalance, and single-country focus. Future research should employ longitudinal designs across more diverse populations to better understand causal relationships and cultural moderators. The unexpected findings regarding Well Being and Job Outcomes particularly merit qualitative investigation to understand the underlying mechanisms in this context.

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