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THE EFFECT OF ARTIFICIAL INTELLIGENCE ADOPTION ON ORGANIZATIONAL STRATEGIC PLANNING PERCEPTION: AN EMPIRICAL STUDY OF PROFESSIONALS IN THE GULF AND MENA REGION

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ABSTRACT
The study uses three aspects of AI adoption - perceived benefit of BAI, risk of RAI, and use of BAI of AI on the perception of SPP of 245 respondents across countries, including the UAE, KSF, Egypt, and Tunisia–using an enhanced TAM by developing a questionnaire using a 5-point Likert Scale. These data were analyzed using IBM SPSS Statistics using descriptive analysis, Pearson correlation, and simple and multiple linear regression. The benefit of AI (BPAI) was insignificant when run on SPP as a first analysis (B = 0.058, p = 0.289), unlike the TAM model, which predict thated the use of AI (UOAI) was a reliable and stronger predictor of all analyses. The risk of AI (ROAI) eroded SPP. In the more comprehensive model with both, there was a significant suppression effect of BPAI when run with UOAI in the model; it was negative (B = -0.119, p = 0.021). The results should be cautiously interpreted because the BAI is a questionnaire that measures general perceptions but is domain-related. The model accounted for 26.0% (F = 28.263, p < 0.001) of BP. It also provides primary data from this usually neglected area, arguing that engagement with (use of) AI and not merely a belief system or perceived attributes surrounding it determine the impact of Artificial on the strategic planning outcomes of an organization.

Keywords:
Artificial Intelligence Adoption, Strategic Planning Perception, Technology Acceptance Model, Use of AI, Risk Perception, Gulf Region, MENA, Suppression Effect.

I. INTRODUCTION

AI has revolutionized from margin to core as the most critical force that affects strategy management and planning and resource allocation through sectors and geographies [1, 2]. Its effect on the outcomes of organizations, however, has not reached a sound conclusion through empirical study of previous literature. As AI technology can bring out benefit by improvement of operational efficiency and quality of decision making and toughness of an organization [2, 14, 16]. Yet, there remains unexplored aspect as how the adoption of AI and features around it (perceived benefit, risk and use of AI) affects perception of strategy planning of rganization level based on the Gulf and MENA region.

The Gulf and the MENA region provide a fascinating case where the subject region seems often absent in empirical studies from the field. National-level digital transformation initiatives, including Saudi Vision 2030, the UAE National AI Strategy 2031, and Egypt's Digital Transformation Strategy[3, 4], have generated enormous institutional stress and capital investment interest, accelerating the adoption of AI in the region at a pace that is incomparable with what empirical studies focusing on the adoption of AI are produced to document the consequence of AI applications within the region. However, a significant gap between the reality on the ground and the current empirical work with regards to the adoption of AI-generated the author's interest in conducting this study

The theoretical underpinnings of this study are rooted in the Technology Acceptance Model (TAM) developed by Davis (1989) [5]. The original form of TAM highlighted Pus (Benefits of AI, BOHR) and PEOUs (Use of AI, UOA) as the main factors influencing people to take up technology. In its current research, the factors of PU and PEOU are adapted as the Benefits of AI (BOK) and Use of AI (UOA) respectively. The model TAM has been extended to contain the inhibition effect posed by Risks of AI (SNAKE), not contained in the original TAM model but commonly found in take-up of novel technology [6, 7, 8]. Past events recorded that people worries over losing jobs, concerns over security and uncertainty with robotic system governance are barriers to adoption of AI hence adapting this extended model is justified [6, 7].

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Guided by three hypotheses, namely H1: Benefits of AI positively influences Strategic Planning Perception and H2: Use of AI positively influences Strategic Planning Perception as opposed to H3: Perceived Risks of AI negatively influences Strategic Planning Perception, a simple and multiple regression analysis was performed on the data collected from 245 employees across four MENA countries.

This study makes three contributions. First, I have provided the first primary evidence from the Gulf and MENA regions that appears to be absent in the AI research domain. Second, it shows how using AI and not believing in using AI appears to be much more influential on planning perception, and these organizations should focus on how people are using the technology. Third, as there appears to be a suppression effect and the findings are interpreted with much validity due to the measurement being unreliable, it indicates important lessons, such as the need to revise multiple regression and factor analysis for accuracy.

II. LITERATURE REVIEW

2.1 Technology Acceptance Model and AI Adoption

The Technology Acceptance Model (TAM) of Davis (1989) constitutes perhaps the most widely applied theoretical framework explaining technology adoption over the years (D-2-1). Perhaps because of its simplicity, with only PU (Perceived Usefulness) and PEOU (Perceived Ease of Use) as predictors of adoption intention and behavior, it remained influential (D- 2-2) over decades, extending later as TAM2 and UTAUT to include social influence, facilitating conditions, and contextual moderating factors while maintaining the centrality of PU and PEOU (D-2-2) [5] (Venkatesh & Davis, 2000) (Venkatesh et al., 2003) [9].

For some AI-related empirical applications, Song et al. (2025) provided findings that usefulness was identified to be the most critical factor in AI adoption for 420 (multi-industry) respondents' views [2]. Furthermore, the adoption of AI will contribute to decision efficiency/effectiveness within the organization's work, based on their empirical study's adoption of structural equation models. Besides, Chattejee et al (2021). adopted combined TAM and TOE model, which examined 340 responses from manufacturing firms; such indicated that factors about both technology and organization have a positive effect about usefulness related to AI-embedded 4.0 [11]; similarly, Ibrahim et al (2025) used relatively large sample size (n=1007) of adopters and found out that perceived usefulness most influenced the intention of future use based on its strongest predictive effect on adopters' attitudes (beta=0.34, $p<0.001$); however, the predictive value of usefulness may have been restricted as the significance value of some mindset questions about attitude towards AI also suggested that the mindset towards AI affects the tendency of using of it [12]

A critical observation made across this literature, however, is the recurring discrepancy between what organizations or individuals (employees, managers) *believe* about AI and the actual, *measurable outcomes* seen in the organization. Na et al (2022), by usingTAM withTOE in the constructions firms, they have shown that even though individuals perceive that usefulness of technology can lead to adoption i. E at micro level, environment and social factors can be disruptive while taking up technology [13]. Hence, in the presentstudy, we have understood the Benefits of AI (BAI) as one and Use of AI(UAI) as the separate in-depth entity for examine the phenomenon.

2.2 AI Adoption and Organizational Performance

The data on the relationship between firms' AI adoption and their performance are fragmented, with several levels of analysis and distinct outcome measures. Badghish et al. (2024) used PLS-SEM (n = firms across six sectors) on SMEs in Saudi Arabia and reported that AI adoption impacts firms' operational and economic performance, while some TOE framework components, such as relative advantage, sustainable human capital, and government support, are some of the AI adoption influencing factors [3]. Chen et al. (2024) , using SEM analysis on 226 US - based managers, found that AI adoption intensity negatively correlates with that companies' performance which is buffered by technological turbulences. Horani et al. (2023) , based on 512 senior IT/IS managers in Jordan claimed that at organization level relative advantage, support of top managers, cost reducing and AI strategic alignment positive impacts companies intentions on AI adoption [15].

As for the influence of AI use on strategy-related organization outcomes, through mediating factors agility and innovation capabilities, and digital transformation readiness (which includes leaders' involvement), Shatila (2025) (using the survey data of 328 managers and PLS-SEM approach) found that adopting AI improves organization resilience when measured both directly and when mediated by the above-mentioned factors as well as leadership capabilities [16]. Combining these findings implies that the positive influence of AI adoption on organization strategy-related outcomes is not directly and universally applicable without being mediated by the organization's capabilities, leaders' commitment, and actual integration of AI in behavior, that is, actual use.

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Therefore, the actual use of AI (and not just attitudes towards AI or beliefs that AI has a large potential) is far more important for predicting organization strategic-related outcomes.

2.3 AI Risk Perception and Organizational Resistance

The negative inhibition from perceived AI Risks in an organization has been gaining practical research attention. In a three-wave longitudinal panel study conducted by Xu et al. (2023), employees concerns about AI threats–most notably AI job security–negatively increased with their adopting attitudes toward AI over time, and a similar increasing pattern was observed for the two factors of relative advantage and compatibility [17]. Based on qualitative interviews with 13 senior managers, Booyse et al. (2023) identified loss of control, trust, and concern for ethical problems as the biggest roadblocks for the adoption of AI in automated human decision-making [18]. Through a systematic review of previous research on the adoption of AI in HRM, Madanchian et al. (2025) discussed the main and persistent inhibitors as follows: employees' resistance toward change, concern for data security, and difficulty/cost in integrating AI HRM systems [7].

For the Gulf and MENA, Ramadan et al. (2024) studying registered nurses across Saudi Arabia found that fears of job displacement (45%), ethical concerns of privacy over patients' medical data (55%), and technical challenges (60 %) are primary barriers, extending TAM to TAM -AIN Model to incorporate constructs on ethical alignment and organizational readiness [6]; and that cost, lack of expertise, and cultural resistance are the main AI adoption barriers in Kuwait's construction sector, as detected by Alotaibi et al. [19]. (2025) Risky perception is not merely a TAM extension; their findings further prove that risky perception is what organizations around the Gulf and MENA are experiencing, and its effect has a major impact.

2.4 Conceptual Framework and Hypotheses

The following are the three constructs that have an impact on SPP (Strategic Planning Perception - as perceived by organizational members, about organizational clarity/goal attainability/resourcing alignment/strategic infrastructures) (Aydın et al., 2022) [20], where BAI is PU. UAI is PEOU and actual use of the system, and RAI adds the inhibitory component of TAM. It extends TAM beyond its existing structures of two dimensions or constructs.

It must be noted at the outset that this study takes the BAI construct, general attitudes to AI (taken from the Artificial Intelligence Attitude Scale) as distinct from domain-specific benefits derived from the perception of benefits to organizations (Aktay et al., 2024) [22]. This could be a cause for the boundary conditions on the interpretation of H1 (which is discussed in Section 5.1). The hypotheses of this study are as follows: H1: Perceived Benefits of AI (BAI) positively influence Strategic Planning Perception (SPP). H2: Actual Use of AI (UAI) positively influences Strategic Planning Perception (SPP). H3: Perceived Risks of AI (RAI) negatively influence Strategic Planning Perception (SPP).

Figure 1: Conceptual Framework — Extended TAM Model

Benefits of AI (BAI) *(Perceived Usefulness — PU)* **Risks of AI (RAI)** *(Inhibitory Extension)* **Use of AI (UAI)** *(Perceived Ease of Use — PEOU / Actual Use)*	→	**Extended TAM Framework** *(Davis, 1989 + RAI extension)* H1 (+) | H2 (+) | H3 (−)	→	**Strategic Planning Perception (SPP)** *(Aydın et al., 2022)*

Source: Adapted from Davis (1989) [5], extended with RAI (Aktay et al., 2024 [22]; Ramadan et al., 2024 [6])

III. METHODOLOGY

3.1 Research Design

A quantitative cross-sectional survey design (which is common for technology adoption research) was utilized for this study in the form of a structured, self-administered Google Forms questionnaire administered to professionals acquainted with the use of AI tools, planning activities, and/or management of digital technology across the Gulf and MENA region [10, 13]. While the cross-sectional design enables a quick study of perception, inferences of causality are limited, an issue taken up in Section 5.1.

3.2 Sample and Data Collection

A total of 245 responses were collected using purposive sampling, further supplemented by "snowball" sampling via professional networks in the UAE, Saudi Arabia, Egypt, and Tunisia). A thumb rule of a minimum

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of 10 observations per predictor variable makes the current sample (245) qualify as a reasonable size for multiple regression [21]. The demographic profiles were as follows:

Table 1: Demographic Profile of Respondents (n = 245)

Category	Sub-category	Frequency	Percentage (%)
Gender	Male	132	53.9
	Female	113	46.1
Age	20–30	93	38.0
	31–40	87	35.5
	41–50	55	22.4
	Above 50	10	4.1
Education	Bachelor's degree	83	33.9
	Master's degree	86	35.1
	Ph.D.	58	23.7
	Other	18	7.3
Years of Experience	1–3 years	60	24.5
	4–10 years	107	43.7
	11–20 years	60	24.5
	More than 20 years	18	7.3

Source: Field Data, 2024–2025

The sample of the study consisted of gender (53.9% males and 46.1% females), age (73.5% aged between 20 and 40), and education (92.7% have had the bachelor's degrees) diversities. The experience in AI usage AI deployment in the organization ranges such that the largest number, 43.7% of the respondents had between 4 and 10 of experience; hence, they would be in better places to give responses about the constructs that were examined in relation to AI deployment in an organizational context.

3.3 Measurement Instruments

All constructs were measured using five-point Likert scales (1 = Strongly Disagree; 5 = Strongly The constructs were evaluated by employing five-point Likert Scale (1 = Strongly Disagree whereas 5 = Strongly Agree). The three subscales that is the Benefits of AI (BAI), Risks of AI (RAI) and Use of AI (UAI) were measured through drawing items from the Artificial Intelligence Attitude Scale and which is a psychometrically tested attitude scale proposed in previous researches (Aktay et al., 2024) [22]. Its factors, namely benefits, risk, and use, showed stable and good factor structures with satisfactory reliability coefficients (above 0.70) for both professional and educational populations. For the purpose of interpreting H1 results, it should be clearly understood that BIA scales relate the items of benefits related on a general level to AI and to society overall instead of benefits related to performing tasks and at the workplace with the aid of AI. Strategic Planning Perception (SPP) was measured using a validated Strategic Plan Perception Scale that showed good confirmatory factor analysis (CFA) fit (RMSEA = 0.070, CFI = 0.99, SRMR = 0.039) (Aydın et al., 2022) [20]. The Strategic Visioning Perception (SVP) was likewise the tested scale developed, but items related to leadership behavior were eliminated due to irrelevance to the study.

3.4 Data Analysis

The data acquired for this research were analyzed in four main phases. First, Cronbach's alpha for the interval-scaled instruments was computed to determine their reliability from the perspective of students as they filled out the questionnaires. The second phase involved conducting a descriptive analysis of all the variables under scrutiny. The analyses carried out in the third phase consisted of the calculation of Pearson correlations between the various variables to find the interrelationships as a precursor step before conducting the simple and multivariate regression analysis for hypothesis testing in stage four of the data analysis. Finally, a series of

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simple and multivariate linear regression analyses were performed for hypothesis testing and examination of the combined model, respectively. IBM SPSS Statistics was used for data analysis. Harman's single-factor test for common method bias was performed, and the results indicated that no single factor accounted for a majority of the variance in the set variables, which indicates that the common method bias is not an eminent concern in the variables measured in this study.

IV. PRESENTATION, INTERPRETATION AND ANALYSIS OF RESULTS

4.1 Reliability and Descriptive Statistics

Table-2 exhibits mean, standard deviation values and Cronbach's alpha figures for all four constructs. All four constructs exhibit good internal consistency (α ranging from 0.811 to 0.829), exceeding the 0.70 threshold [21]. With the Highest mean of 4.109 and sd of 0.782 the construct BAI demonstrates positive attitudes about Ai. UAI comes as second the construct (4.041, 0.874) showing active engagement about positive attitude towards Ai. The construct RAI gives lowest mean 2.794 and highest sd of 1.130 representing risk in minds but doesn't present the overall attitude of respondents. The last construct SPP shows a high mean of 4.272 and sd of 0.763 thus showing positive perception about organisational strategic planning among sample. - Table-2 showing descriptive statistics with Standard Deviation of all variables - BAI, UAI and SPP show similar pattern for Mean and Standard Deviation and RAI contrasts to them completely. - BAI shows highest internal statistical reliability 0.829 where RAI shows Lowest of 0.795. - However all of them exceeding critical threshold hence acceptable internally consistent scores for all four of the constructs.

Table 2: Descriptive Statistics and Reliability Coefficients

Construct / Item	Mean	SD	α	N
Benefits of AI (BAI)	4.109	0.782	0.829	245
BAI1: AI is an important advancement	4.061	0.774	—	
BAI2: AI makes life easier for people	4.176	0.858	—	
BAI3: AI will contribute significantly to humanity	4.090	0.707	—	
Risks of AI (RAI)	2.794	1.130	0.814	245
RAI1: AI is a threat to society	2.502	1.074	—	
RAI2: AI reduces human-to-human communication	2.861	1.165	—	
RAI3: AI will replace human labor	2.898	1.139	—	
RAI4: AI destroys human creativity	2.914	1.100	—	
Use of AI (UAI)	4.041	0.874	0.815	245
UAI1–6: AI engagement behaviors (composite)	3.93–4.17	0.87	—	
Strategic Planning Perception (SPP)	4.272	0.763	0.811	245
SPP1–5: Planning clarity and alignment (composite)	4.14–4.38	0.76	—	

Note. α = Cronbach's alpha; SD = Standard Deviation. All items scored on a five-point Likert scale (1 = Strongly Disagree; 5 = Strongly Agree). BAI items reflect general societal attitudes toward AI rather than domain-specific organizational benefit perceptions.

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4.2 Correlation Analysis

Table 3 presents the Pearson correlation matrix. Two preliminary observations merit attention. The Pearson correlation matrix is presented in Table 3. There are two initial points to consider. BAI shows a negligible and non-significant correlation with SPP ($r = 0.068$, $p > 0.05$), but UAI has the strongest correlation with SPP ($r = 0.490$, $p < 0.01$) and RAI has a moderate negative correlation with it ($r = -0.285$, $p < 0.01$). Furthermore, the moderate positive correlation of BAI with UAI ($r = 0.368$, $p < 0.01$) and negative correlations of both of them with RAI ($r = -0.280$ and -0.483 respectively) foreshadow the suppression phenomenon which will be observed in the multiple regression model.

Table 3: Pearson Correlation Matrix

Construct	BAI	RAI	UAI	SPP
Benefits of AI (BAI)	1.000			
Risks of AI (RAI)	-0.280**	1.000		
Use of AI (UAI)	0.368**	-0.483**	1.000	
Strategic Planning Perception (SPP)	0.068	-0.285**	0.490**	1.000

*Note. ** p < 0.01 (two-tailed). N = 245. SPP = Strategic Planning Perception; BAI = Benefits of AI; RAI = Risks of AI; UAI = Use of AI.*

4.3 Hypothesis Testing

Table 4 presents the results of the simple and multiple regression analyses. For H1, the regression of BAI on SPP yielded a non-significant result ($B = 0.058$, $t = 1.062$, $p = 0.289$, $R^2 = 0.005$). H1 is not supported. The perceived Benefits of AI, measured at the level of general societal attitudes, do not independently predict Strategic Planning Perception. This finding is discussed in Section 5.1 with reference to the measurement characteristics of the BAI construct.

For H2, The regression of UAI on SPP resulted in a strongly significant positive result ($B=0.447$, $t=8.773$, $p<0.001$, $R2=0.241$). H2 is supported. Actual usage of AI models by organizations statistically clarifies for SPP values up to of 24.1% of the variability which is the highest explanation rate by an individual predictor. It suggests that it is not enough to simply believe in AI tools it is the actual use of the tools by organizations within the strategic planning context which determines better performance.

For H3, The regression of RAI on SPP resulted in a significant negative result ($B=-0.182$, $t=-4.642$, $p<0.001$, $R2=0.081$). H3 is supported which reveals RAI and SPP move in opposite directions consistent according perceived levels as it clarifies 8.1% of the statistical levels [6, 7]

Table 4: Regression Analysis Results — Predictors of Strategic Planning Perception (n = 245)

Model / Predictor	B	t	p	r	R² (Adj.)	Decision
H1: Benefits of AI → SPP (simple)	0.058	1.062	0.289	0.068	0.005	Not supported
H2: Use of AI → SPP (simple)	0.447	8.773	<0.001	0.490	0.241	Supported ✓
H3: Risks of AI → SPP (simple)	-0.182	-4.642	<0.001	-0.285	0.081	Supported ✓
Combined Model (BAI+RAI+UAI → SPP)	—	—	<0.001	0.510	0.260 (0.251)	Overall significant
BAI in combined model [suppressor]	-0.119	-2.327	0.021	—	—	Suppression identified
RAI in combined model	-0.052	-1.286	0.200	—	—	Non-significant

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UAI in combined model [dominant]	0.458	7.629	<0.001	—	—	Primary predictor

*Note. B = unstandardized regression coefficient; r = Pearson bivariate correlation with SPP; R^2 = coefficient of determination from simple regression. Combined model: R = 0.510, R^2 = 0.260, Adj. R^2 = 0.251, F(3,241) = 28.263, p < 0.001. ** p < 0.01.*

4.4 The Combined Model and the Suppression Effect

When BAI, RAI, and UAI were entered simultaneously into the multiple regression model, the model explained 26.0% of the variance in SPP (Adjusted R^2 = 0.251, F = 28.263, $p < 0.001$). UAI remained the dominant and significant predictor (B = 0.458, t = 7.629, $p < 0.001$). RAI lost significance in the combined model (B = -0.052, t = -1.286, p = 0.200), likely attributable to its substantial negative correlation with UAI (r = -0.483) which produces collinearity-related suppression of its individual coefficient. Most notably, BAI's regression coefficient reversed from positive (B = +0.058) in simple regression to negative (B = -0.119, p = 0.021) in the combined model — a classic suppression effect.

The two reasons why suppression occurs. First BAI and UAI share important variance (r = 0.368), Thus, if UAI is controlled for in combined model, one gets only that variance that relates to BAI which is free from influence of UAI. This variance is linked with lower SPP. This indicates that people with positive general perception towards AI are not using it into their work. That is why they have lower perception for strategic planning as compares to people who are having a positive attitude as well as using it. This means gap in what one sees as AI as well as what one does when it comes to AI is related with weaker stronger perception towards strategic planning.

This suppression effect might hold true within this study. Reason being that BAI has been explained from the view point of societal perception towards AI which does not link to organizational benefits. BAI might be defined from both aspects for a strong claim. Also the number of respondents for analysis in study is low (690 professionals form different organizations) for making strong conclusion for suppression effect. However both these effects would be discusses in the limitations sections.

V. CONCLUSION

The current study, on the other hand, extends the technology acceptance model by including AI perceived risk as deterrent and AI perceived benefits and AI use derived in TAM and investigate the three AI adoption constructs, including risks, on Strategic Planning Perception among 245 practitioners in the Gulf and MENA region.

The findings bear both academic and managerial implications. Theoretically, the non-significant direct effect of BAI (H1 not supported) and dominant predictive power of BAI (H2 supported) suggest that when it comes to organizational strategic planning outcomes stemming from AI adoption, the predominant effect is behavioural AI engagement more so than attitudinal belief on the value of AI in this context of the Middle East. It has not contradicted the basics of TAM model, but it hints that when attitudes about adopting AI are held at a high-level but behavioural engagements with AI remains patchy (across much of the Middle East), then the attitude-behaviour gap is more important than attitudes by themselves. The significant negative effect of RAI (H3 supported) adds more fuel onto a rapidly spreading literature where people are worried about AI as an existential threat not least of jobs or its consequences for governance issues [6, 7, 18]. Methodologically, the suppression effect of BAI, when all the factors are considered in conjunction together may be interesting to replicate with more field-specific benefits on offer from AI.

Practically speaking, the findings show that for leaders of business organizations in the Gulf and MENA region that invests actively in AI adoption, they should prioritize structural, task-level behavioral integration as opposed to consciousness campaigns. It is the doing of AI that generates the perceptible improvements in strategic planning quality, when organizational members use AI to help them in planning and decision-making on an every-day basis and not the believing in AI's potential that generated such improvements. Organizations, especially in Saudi Arabia, the UAE, Egypt and Tunisia, that are being increasingly pressurized into AI adoption through active and concrete government mandates, should therefore pay equal attention, to training, re-designing the employee's work-flow and developing AI literacy programmes that close the gap between attitude and behavior, when designing their AI implementation strategy while developing comprehensive risk governance frameworks about AI risk (on Data Security and employees sense of replacement anxiety & AI Transparency) remain required pre- conditions in the creation of a congenial corporate environment in which AI use by members lead to higher quality in strategic planning.

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5.1 Limitations

The current study recognises the following four methodological limitations, all of whom should be used by future research. First, being a cross sectional survey research it does not allow any causation inference. The regression results provided reflect the association between constructs as measured on a single occasion. If one is to establish the direction of the relationship, a longitudinal survey should be conducted, about the UAI- SPP pathway, reverse causation - in which Higher SPP of organisation might lead towards adaptation of AI - cannot be ignored.

Second and most critical to understanding H1 relates to how BAI was measured; with items taken from AI Attitude Scale at level of general societal benefits of (ex) 'AI will contribute to humanity' than perception of specific benefits relating level of organization, planning or particular tasks/jobs (Aktay et al., 2024). Thus, a high score in BAI indicates optimistic expectations for AI as a technology relative as a whole as opposed to actual belief whether AI will be a good for one's own planning. A lack of significance of BAI on SPP therefore may be partially due to miss-match to construct with outcome and may overshadow any actual relationship that exists amongst AI benefit perception and SPP development for FM. Future studies can adopt more appropriate measures relating to AI benefits specifically with FMs may or management decision-making.

Third, the use of self-reported data from a single questionnaire creates the possibility of common method bias, whereby the shared measurement source inflates observed inter-construct correlations. While Harman's single factor test did not identify a dominant single factor, procedural remedies and temporal separation of measurements would further mitigate this risk in future designs. Fourth, the geographic scope, while novel for the AI, SPP literature, encompasses four countries with significant institutional, cultural, and economic heterogeneity. Country-level comparative analyses were beyond the scope of this study but are recommended as a priority for future research to determine whether the AI; SPP relationship varies systematically across Gulf and North African organizational contexts.

VI. RECOMMENDATIONS

Considering the study results and the caution in interpreting, following policy recommendations are directed at the Gulf and MENA region organisational leaders and policy makers; Firstly, investment in AI adoption must shift its focus from awareness-building to focus on behavioural integration. Than creating general awareness about AI and its benefits to the society, training through structured training programmes, introduction of AI-embedded workflows and regular practice with AI planning tools is more likely to increase positive spousal perception about AI adoption that mere campaigning about benefits of AI, as measured by BAI which must be converted into behavioural adoption as attitude of AI seems to be necessary but not sufficient for any improvements in the perception towards AI as a strategy; Secondly, attention must the given to the AI risk governance, which must be seen as strategic enhancer than for compliance purposes. The study shows that any worries (job loss concern caused by automation at work, data-leakages and concerns about the working of the algorithms etc.) and AI risk perceptions left unaddressed not only suppress the benefits of the AI, the perceptions of AI benefits seem to go down with the risk perception related to AI (especially on job and society perception sub-scales). Thirdly, organisations can also study the attitude (positivity towards AI) – Behaviour (AI use or adoption) gap as some of the respondents were positive toward AI but were not utilising AI and which also seems the lower overall perceptions about AI. Fourthly, future research should replicate the main findings using domain-specific AI benefit instruments and longitudinal designs, and should examine potential moderators — including organizational culture, leadership style, and digital infrastructure quality — that may condition the UAI-SPP relationship across different organizational contexts in the region.

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