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Type 1 Diabetes Mellitus Saudi Patients' Perspective on the Adopting IoT-Enabled CGM: Validation of Critical Factors in the IAI-CGM A Framework

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***Abstract*—The increasing prevalence of diabetes, particularly in Saudi Arabia, calls for effective self-management tools to monitor blood sugar levels, such as Continuous Glucose Monitors. These are medical devices that can be used to track the glucose levels of people without a fingerstick blood sample. However, the adoption of IoT-enabled Continuous Glucose Monitors (IoT-CGM) can be challenging due to the use of new technology. This study proposes the Intention to Adopt IoT-enabled Continuous Glucose Monitors (IAI-CGM) a framework, which incorporates practical, technological, and user behaviour considerations based on the Technology Acceptance Model (TAM). The study defines 8 hypotheses that are analysed using structural equation modelling. Data was collected; from 873 type 1 diabetes patients (T1DM) from Saudi Arabia. The model predicts the significant impact of all factors on adoption intent except technology -related self-efficacy (TRSE), enabling the assessment of Saudi T1DM patients for IoT-CGM readiness. Furthermore, the framework's novelty may serve as inspiration for developing comparable frameworks for wearable or attached health monitoring devices in patients with other illnesses and in other geographical locations.**

***Index Terms*—IAI-CGM, TIDM, Internet of Things, Continuous Glucose Monitors, Adoption Intention, Technology Acceptance Model.**

I. INTRODUCTION

THE RISING prevalence of diabetes in Saudi Arabia can be attributed to the Westernized food and sedentary lifestyle prevalent in the country. A quarter of Saudi adults are expected to develop diabetes by 2030, with over half of Saudis over the age of 30 having diabetes or being at risk [1]. The solution to this issue lies in patients taking control of their healthcare and self-managing their blood sugar levels [2]. However, patients often lack the ability to follow physicians' advice on self-care management, necessitating the use of sophisticated technology. The emergence of innovative wearable technology has created an opportunity for the creation of a wireless body area network that could monitor healthcare delivery, including diabetes self-management [3]. To standardize IoT-enabled Continuous Glucose Monitoring (CGM) devices in Saudi Arabian primary care institutions, the country must undertake an in-depth analysis and publication on IoT in its healthcare system.

This study aims to measure patient preparation and willingness to use a CGM in primary diabetes care settings in Saudi Arabia to promote patient autonomy. The research will involve conducting a literature review to determine the extent to which intelligent technologies have permeated the Saudi healthcare system. It will also use the Technology Acceptance Model (TAM) to measure patient autonomy readiness towards IoT adoption by surveying people with type-1 diabetes. The study's scope and objectives include a quantitative analysis of diabetic patients in Saudi Arabia regarding their preparedness for autonomy. With resource constraints and significant health management risks facing emerging nations, research in this field is vital. In addition, the study aims to fill a research gap by examining Saudi Arabia's digital transformation efforts and readiness for IoT in healthcare [4]. The study's results will contribute to advancing IoT-enabled CGM adoption and primary diabetes self-management in Saudi Arabia, helping the country meet its digital transformation goals by 2030 [5].

II. THEORETICAL BACKGROUND

A. Role of CGM in T1DM Primary Care

Continuous Glucose Monitoring (CGM) is crucial for primary care in managing Type 1 diabetes. It enables patients to respond to their readings and maintain safe blood sugar levels, leading to increased self-management care [6]. CGMs provide continual feedback on blood sugar levels, encouraging patients to take their medication as recommended, thereby improving glucose levels.

However, in Saudi Arabia, poor drug compliance is a significant issue, with inadequate education and urban lifestyles being the main factors [7].

To improve technology tolerance among low-income and urban patients, IoT-CGM deployment requires patient health literacy improvement [8]. When primary care institutions provide self-management instruction and follow-up, it can help reduce patients' blood glucose levels. Self-management increases patients' health-related motivation, autonomy, and competence, but its effectiveness requires educating patients about their responsibilities in controlling T1DM. Encouraging patient autonomy helps doctors regulate blood glucose levels. This implies that with the help of health education provided to the patients could increase the sense of responsibilities to control T1DM disease themselves with self-empowerment [9]. The study concludes that IoT-CGMs might improve patient autonomy, but their adoption is uncertain, and adoption issues need to be addressed [10].

B. IoT-CGM Adoption Concerns

The use of Internet of Things continuous glucose monitoring (IoT-CGM) devices has been shown to provide numerous benefits to diabetics, such as improved long-term complication management [11]. However, despite the advancements in accuracy and dependability, these devices have not been widely adopted, with most diabetics still relying on the traditional method of drawing blood from a fingertip to measure their blood glucose levels. The slow uptake of IoT-CGM can be attributed to various factors, such as initial concerns about the devices' lack of accuracy [12], patients' unawareness of the advantages they offer, and sociopsychological and economic barriers to adoption.

Studies have shown that proper use of CGM devices, advice from medical professionals, and acting on CGM alarms can significantly reduce long-term difficulties in diabetic patients [13], [14]. The study by Gia et al. [15] provided evidence that proper guidance from health professional can help to reduce the long-term complications from 75 percent to 40 percent in the accuracy of CGM.

However, without a technology acceptance model (TAM) study, it is difficult to determine whether patients nationwide will adhere to the recommendations and continue to benefit from long-term complication management. Furthermore, wearable smart gadgets, including IoT-CGM, are still in their infancy, and persuading developing nations to adopt them will require work.

However, according to Rodbard [16], still there are only 8 percent to 17 percent of T1DM patients using CGM devices. Although, it is evidenced by the study [17], that the overall size of IoT healthcare sector expected to reach up as a 2 trillion US dollar industry by 2025. Despite this prediction fancy prediction still the adoption rate is very low.

Another study by Ayanlande et al. [18] elaborates that acceptability of CMG devices is also hinge on the patient’s socio-psychological aspect, along with the affordability of patients and the healthcare system of the region where they reside. Another study provides that the availability is dependent on the scope of the service to meet minimum requirements [19]. Furthermore, another study [20], discussed the development of HIT enabled patient care that empowers patient and provides them with self-management capabilities, with the end goal that health matters such as diabetes patient care does not go poorly managed.

Saudi Arabia, a wealthy nation with an unequal income distribution, has only recently started using IoT-CGM. Its patient population is diverse, including those who have already adopted IoT-CGM, those who have heard of it but are hesitant to use it, and those who have never heard of it. Therefore, research on IoT-CGM adoption in Saudi Arabia includes many controversies.

To address the slow uptake of IoT-CGM, a new paradigm for adoption using the theoretical foundations of the technology acceptance model is proposed. The TAM considers factors such as sociopsychological, economic, and healthcare infrastructure determinants of acceptance, affordability, accessibility, and satisfaction with the service's breadth. However, there is a dearth of knowledge on the usage of healthcare technology that is unique to type 1 diabetes mellitus (T1DM), which is a health issue that should not be handled carelessly [21].

Making IoT-CGM more widely used in Saudi Arabia and other nations is a major issue, and the first stage in achieving the criteria set for improving healthcare quality in Saudi Arabia is understanding the viability of adoption. The literature on continuous glucose monitoring for diabetes with the Internet of Things is voluminous, but most studies have focused on the advantages of self-management, its effectiveness, and an analysis of the variables that influence the slow uptake of medical technology.

Therefore, determining the adoption characteristics of T1DM patients and providing a framework for adoption specific to them constitute the initial stages. Wearable smart devices offer the most appropriate solutions, but patients are not required to utilize them, and health factors and technological adoption scales are not always taken into consideration. Thus, providing a framework for IoT-CGM adoption that is specific to T1DM patients is crucial. The proposed structure provides theoretical underpinnings for this framework and a clear picture of a nation's present adaptability.

The authors proposed the Intention to Adopt IoT-enabled Continuous Glucose Monitors (IAI-CGM) framework in [4]. Based on this framework, the study aims to identify factors affecting adoption to analyse the readiness and willingness of primary diabetes T1DM patients, particularly in Saudi Arabia, to use (IoT-CGM) technology. The framework has strong predictive capabilities for assessing the adoption of Internet of Things-enabled Continuous Glucose Monitors (IoT-CGMs) used for monitoring blood glucose levels. The factors of the proposed framework include Perceived Reliability (PR), Perceived Usefulness (PU), Ease of Use (EU), Information Overload (IO), Technology Related Self-Efficacy (TRSE), Attitude (AT), Intention to Use (IT), and

Visibility of Body Change (VBC) as designed by Borges and Kubiak's [22].

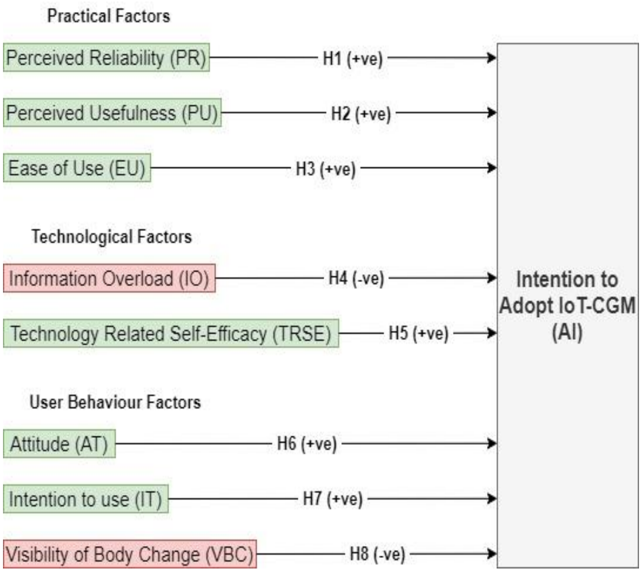

Fig 1: Proposed IAI-CGM Framework [4]

II. RESEARCH METHODOLOGY

This study aims to investigate the factors that influence the adoption of IoT-CGM devices by T1DM patients in Saudi Arabia. The study used an online survey to collect quantitative data from participants. Qualtrics was used for survey creation and administration, while Microsoft OneDrive was utilized for data storage. In addition, IBM SPSS was used for data analysis.

The survey questions were grounded in the theoretical framework of the study, which identified usability, technology, and user behaviour as the primary drivers of adoption intention. The study sample size was calculated based on a confidence level of 95% and a confidence interval of 5%; the total population is 11,662 of T1DM, and based on the statistics provided by [2], at least 372 responses we are required. Therefore, an accurate total sample of 873 was collected from the T1DM patients from King Khalid Hospital Saudi Arabia and Najran region.

There are three categories of human factors that influence patients' decisions to embrace continuous glucose monitoring devices that are enabled by the Internet of Things: those that are purely theoretical, those that pertain to technology, and those that pertain to user behaviour. Perceived reliability, perceived utility, and simplicity of use are three of the metrics used to assess the practical factors of a product's performance. The technological factors are measured by the innovation orientation and the technology-related self-efficacy measures, while the user behavioural factors are measured by the attitude, intention to use, and the visibility of body change factors.

The study took ethical measures to protect the interests of all those involved, making sure participants knew that taking the survey was completely optional and that they could stop at any time without consequences or explanations. Participants were also made aware that their data would not be sold or otherwise distributed to outside parties and were assured complete privacy. The study did not seek individual information in the questionnaires, and participants were instructed not to provide any identifying information in the survey. In the case of a participant's comment warranting a quotation, a unique numeric identity would be issued instead. Data collection methods and research instruments were approved by Institutional Review Board (IRB) in Saudi Arabia, Ministry of Health; King Khaled Najran Hospital (KKNH) by assigning IRB registration number with KACST, KSA: H-11-N-081; IRB Log Number 2022-01E.

The survey questionnaire was developed based on the findings of a previous study [22]. The theoretical framework of this study provides the foundation for the survey. The survey consists of questions that allow for assigning values to each variable. This is done using a 5-point Likert scale system, where 1 indicates "Strongly disagree", and 5 indicates "strongly agree".

IV. RESULTS

In a quantitative study, selecting an appropriate sample size is critical to ensure reliable and transferable results while eliminating bias. The sampling strategy employed in this study followed scientific principles and focused on patients with Type 1 diabetes at King Khaled Najran Hospital and the Najran region in Saudi Arabia. The survey was administered online using Qualtrics, with data immediately entered into a database. Outliers are exceptional data points that fall outside of the norm and can result from typos, poor wording of questionnaires, or data input errors. Univariate outliers stand out in only one way, while multivariate outliers have multiple scores that deviate from the norm [23]. The frequency distribution test and other normality tests can help detect outliers [24]. The research variables in this study had z-scores of less than 3.29 and a standard deviation range of 0.708 to 1.302, indicating no extreme values among the outliers.

A. Data Analysis and Confirmatory Factor Analysis (CFA)

Confirming the theoretical structure of variables is a crucial part of CFA analysis. It involves conducting one-dimensionality, reliability, divergent, and convergent validity tests. Researchers can determine whether to adopt a theory based on these results. To establish relationships in SEM, researchers should perform CFA on all latent variables, with a minimum latent concept loading of 0.60 for the assessment items measured by one-dimensionality [25]. CFA findings are founded on nine different latent constructs. A few examples of these constructs are technology-related self-efficacy (TRSE), information overload (IO), perceived reliability (PR), perceived usefulness (PU), ease of use (EU), attitude (AT), intention to use (IT), visibility of body change (VBC), and intention to adopt (AI).

TABLE I
RELIABILITY AND CONSTRUCT VALIDITY

Constructs	Cronbach (above 0.7)	CR	AVE	MSV
TRSE	.756	0.763	0.521	0.274
IO	.772	0.776	0.537	0.383
PR	.842	0.844	0.643	0.127
PU	.821	0.848	0.652	0.475
EU	.821	0.835	0.629	0.241
AT	.773	0.785	0.553	0.441
IT	.786	0.790	0.557	0.475
VBC	.856	.0.868	0.623	0.397

B. *Measures of the Model Validity*

To ensure construct validity and composite reliability, Cronbach's alpha and Composite Reliability (C.R.) values were used before hypothesis testing. The present study used Cronbach's alpha with a cut-off value of 0.70, and another study suggests cut-off values of 0.60 for C.R. and 0.70 for Cronbach's alpha [26]. The reliability scores in Table I are greater than 0.70. Both Cronbach's alpha and C.R. were used to examine internal consistency, showing the convergent and discriminant validity and reliability of findings and comparing it with cut-off-points [27]. The results indicate that all variables are free from measurement error. Assessment for consistency refers to measurements on the same point on two different scales, assuming that an instrument can assess a similar context over time. Cronbach's alpha is considered the initial step to ensure reliability. The present study uses Cronbach's alpha and Composite reliability to test instrument reliability. The study used average variance extracted (AVE) to identify variation in latent variables caused by random measurement errors, with a cut-off value of 0.50 or greater. AVE values were between 0.537 to 0.644. Discriminant validity was achieved through the maximum shared squared variance (MSV), Fornell-Larcker test, and average shared squared variance (ASV), with AVE for each construct higher than MSV [28]. The CFA assessment of the model showed that both convergent and discriminant validity met the fitness criteria.

TABLE II
DESCRIPTIVE ANALYSIS AND FACTORS LOADINGS FOR ITEMS

Measure	**Chi-square (CMIN) / Degrees of freedom (D.F.)**	**Comparative fit index (CFI)**	**Standardized root mean square residual (SRMR)**	**Root mean square error of approximation (RMSEA)**	**Normed Fit Index (NFI)**
Estimate	4.380	0.913	0.054	0.062	0.901
Threshold	Between 1 and 5	> 0.90	< 0.08	< 0.08	> 0.90
Interpretation	Good fit	Good fit	Good fit	Good fit	Good fit

C. Model Good Fit

The study involved 873 participants, and the observed results for the fitness of the model indicated that all observed statistical values were under the cut-off threshold as given (CMIN/DF = 4.380, CFI = 0.913, SRMR = 0.054, RMSEA = 0.062, NFI = 0.901). Therefore, no issue was observed about the good fit of the model. The results are shown in Table II.

D. Discriminant Validity

Table III illustrated that there were no problems regarding discriminant validity, as the square roots of the AVEs' "diagonal line" showed values greater than the values below the diagonal, as demonstrated below. The findings suggest that the CFA model's evaluation was valid with respect to both convergent and discriminant validity criteria.

TABLE III
DISCRIMINANT VALIDITY

	TRSE	IO	PR	PU	EU	AT	IT	VBC	AI
TRSE	**0.722**								
IO	-0.249	**0.733**							
PR	-0.066	0.356	**0.802**						
PU	0.523	-0.294	-0.034	**0.807**					
EU	0.270	-0.400	-0.230	0.375	**0.793**				
AT	0.430	-0.274	0.023	0.664	0.377	**0.744**			
IT	0.429	-0.431	-0.062	0.689	0.458	0.617	**0.747**		
VBC	-0.350	0.619	0.313	-0.494	-0.491	-0.428	-0.610	**0.789**	
AI	0.421	-0.584	0.059	0.713	0.484	0.669	0.725	-0.630	**0.725**

E. Structural Equation Model

In order to test the hypotheses of the study Structural Equation Modelling (SEM) was used to investigate the interrelationship between latent and observed variables via the software AMOS version 28. The SEM approach is widely used in various research fields, such as psychology, behaviour al studies and education. In order to ensure the accuracy of the data, a confirmatory factor analysis was conducted to assess the validity of the collected data. The SEM model includes both structural and measurement models. Therefore, the AVE score in the convergent validity test should be greater than 0.5, indicating a good model fit [27].

All factors caused a significant change in the dependent factors except hypothesis 5, where TRSE does not have a significant effect on the intention to adopt IoT-CGM. The present study discusses critical factors related to the intention to adopt IoT-CGM.

Results clearly indicate significant differences from previous findings, which may be attributable to regional or cultural differences in corporate climate or at the individual level. After getting empirical evidence based on structural equation modelling, it was observed in Table IV that Perceived Reliability (PR) has a significant positive influence on intention to adopt IoT-CGM ($\beta = 0.154$ along with p-value < 0.001). Similarly, perceived usefulness (PU) has a significant positive influence on the intention to adopt IoT-CGM ($\beta = 0.251$ along with p-value < 0.001). Next, it was observed that Ease of Use (EU) has a significant positive influence on intention to adopt IoT-CGM ($\beta = 0.077$ along with p-value < 0.001). Similarly, information overload (IO) has a significant negative influence on the intention to adopt

TABLE IV
REGRESSION WEIGHTS FOR PATH COEFFICIENTS AND ITS SIGNIFICANCE

Structural Relation			Regression Weight	Standard Error (S.E.)	Critical ratio (C.R.)	P value	Result
AI	<---	TRSE	-0.017	0.035	-0.484	> 0.629	Rejected
AI	<---	IO	-0.128	0.032	-3.986	< .001***	Supported
AI	<---	PR	0.154	0.024	6.433	< .001***	Supported
AI	<---	PU	0.251	0.050	5.045	< .001***	Supported
AI	<---	EU	0.077	0.028	2.737	< 0.006**	Supported
AI	<---	AT	0.194	0.049	3.929	< .001***	Supported
AI	<---	VBC	-0.153	0.036	-4.209	< .001***	Supported
AI	<---	IT	0.171	0.058	2.928	<0.003**	Supported

IoT-CGM (β = -0.128, along with $p < 0.001$). On the one hand, Technology Related Self-Efficacy (TRSE) does not have a significant influence on the intention to adopt IoT-CGM (beta = -0.017 along with p-value > 0.05). Furthermore, attitude (AT) positively influences Adoption Intention (AI), β value =.194 along with $p < 0.05$). Next, results show that intention to use (IT) positively influences intention to adopt IoT-CGM, with β value = 0.171 along with $p < 0.05$). Results further indicate that visibility of body change (VBC) has a significant negative impact on intention to adopt IoT-CGM along with β = -0.153 and p-value < 0.05. Based on overall results, it is observed that all independent variables cause a significant change in intention to adopt IoT-CGM except TRSE, as it did not cause a significant change in the intention to adopt IoT-CGM. One reason could be the mistrust that makes people reject IoT-CGM. So, the intention to not use IoT-CGM is correlated with a lack of knowledge, little desire to learn and doubt related to the technology or its adoption.

F. *Descriptive Statistics*

Descriptive results Table V shows that in the survey, there were 440 Male (50.4%), and 433 females (49.6%). 36.7% of participants were within the age group of 18-25, 37.1 % of participants were within the age group 26-35, participants from the age group of 36 to 45 were 22.0 %; and participants from the age group of 46 to 60 were only 3.9 %, and there were only 3 participants or (0.30 %) older than 60. The majority, 43.5%, were reported to have a bachelor's degree, 29.1% had secondary school education and Ph.D. degree holders only accounted for 0.5%. Furthermore, only 2.1% had only completed primary school, while 18.3% had diplomas, 2.7% had master's degrees, and 3.8% had only completed elementary school education.

TABLE V
SAMPLE CHARACTERISTICS (N = 873)

		Frequency	Percentage			Frequency	Percentage
Gender	**Male**	440	50.4%	**Education level**	**Primary School**	18	2.1%
	Female	433	49.6%		**Elementary School**	33	3.8%
Ages	**18-25**	320	36.7%		**Secondary school or less**	254	29.1%
	26-35	324	37.1%		**Diploma**	160	18.3%
	36-45	192	22.0%		**Bachelor degree**	380	43.5%
	46-60	34	3.9%		**Master degree**	24	2.7%
	60+	3	0.3%		**Doctorate degree**	4	0.5%

V. DISCUSSION

The study provided an updated framework based on empirical findings on Internet of Things-enabled Continuous Glucose Monitoring (IoT-CGM), which empowers type 1 diabetics. The results from Table IV. The approach illustrated how several factors affect patients' inclinations to use internet-enabled continuous glucose monitoring. The dimensions of human factors that affect the patients' intentions to adopt IoT-enabled continuous glucose monitoring devices are grouped into three factors.

Practical factors: These are the first set of factors that influences the adoption of IoT-CGM.

The study found that perceived reliability was a significant factor that affected the adoption of IoT-CGM [29]. Similarly, empirical results from the present study show that perceived reliability (PR) has a significant positive influence on intention to adopt IoT-CGM along with β = 0.154 and p-value < 0.001. Therefore, there are 0.154 units of positive change in IAI-CGM when PR changes by 1 unit. Another study revealed that customers' feelings regarding new technology were positively correlated with their faith in the gadget's accuracy [30]. Trust was found to be the most crucial attribute while communicating with doctors.

The perceived usefulness of IoT-CGMs improves behavioural intention. User satisfaction with continuous glucose monitors (CGMs) may be affected by aspects, including the availability of trend and graph glucose readings and the ability of CGMs to compensate automatically for glucose level swings in real-time [31]. The present study also observed that perceived usefulness (PU) is a significant factor that positively influences intention to adopt IoT-CGM along β = 0.251 and p-value < 0.001. Furthermore, it shows 0.251 units change in IAI-CGM due to PU.

Ease of use (EU) is an essential practical factor in the practical factor when adopting a product. Furthermore, the simplicity of use is a critical factor that influences early computer adopters' behavioural intentions [31]. Similarly, the present study also observes that Ease of Use (EU) has a significant positive influence on IAI-CGM with β = 0.077 along with a p-value < 0.001. However, there is a positive influence of the EU on IAI-CGM.

Technological factors: These are the second set of factors that affects the adoption of IoT-CGM.

Information overload is one of the critical technological factors. Tansey et al. [31] have suggested that an excessive number of features in CGMs can lead to information overload for users. Although real-time glucose readings in IoT-CGMs may be an attractive feature but a constant influx of information can also be burdensome for users, potentially resulting in a negative response to the technology. Similarly, it was observed in the empirical results that information overload (IO) has a significant negative influence on intention to adopt IoT-CGM along with β = -0.128 and $p < 0.001$. However, the presence of an overload feature in IAI-CGM can have a negative impact on user adoption, as users may become overwhelmed by the excess information provided.

Technological self-efficacy [4] is characterized as type 1 diabetes patients' perception of their capability to utilize IoT-enabled continuous glucose monitors and their ability to trust new technology. Apart from expectations and the ability to trust, there could also be the issue of technology and the lack of knowledge and know-how to use the technology, which might be the reason for the low adoption rate causing the insignificant relationship of TRSE with the intention to adopt [32] Similarly, results show that Technology Related Self-Efficacy (TRSE) does not have a significant influence on the intention to adopt IoT-CGM beta = - 0.017 along with p-value > 0.05.

User behavioural factors: These are the third set of factors that affects the adoption of IoT-CGM.

Users' views on technology are measured in this factor. Technology perception is also reflected in consumers' mental processes, which shows intention to use [33]. Empirical results also show that intention to use positively influences IAI-CGM, β value =.171, along with $p < 0.05$. Patients' perspectives of how others view them also influences their technology choices. The patients' scheduled activities were based on their attitudes and personal values [34]. A person's behavioural intention also depend on how much they value their own attitudes and the societal norms around them. Similarly, empirical results show that attitude (AT) positively influences Adoption Intention (AI), β value =.194 along with $p < 0.05$. Furthermore, visibility of body change (VBC) is found to have negative influence on the Adoption Intention (AI), β value =-.153 along with $p < 0.05$.

The present study discusses critical factors related to intention to adopt IoT-CGM. Empirical findings with some differences may be attributable to regional or cultural perspectives. However, adoption of IAI-CGM framework may subject to cultural and individual differences that need to be addressed before adopting this framework.

The Updated framework that is presented below In Fig.2, that can be used to determine the adoption intention of IoT-CGMs and has been termed the Intention to Adopt IoT-enabled CGM (IAI-CGM) framework. This framework has been proposed to determine the adoption intention based on the practical factors of using IoT-CGMs, the technological factors of using IoT-CGMs, and factors regarding user behavioural factors. PR, PU, and EU are all practical factors that increases the adoption intention among users. IO and TRSE are technological factors. IO decreases adoption intention, and TRSE has an insignificant effect on adoption intention. User behavioural factors are AT, IT, and VBC. AT and IT factors increase adoption intention, while VBC decreases adoption intention.

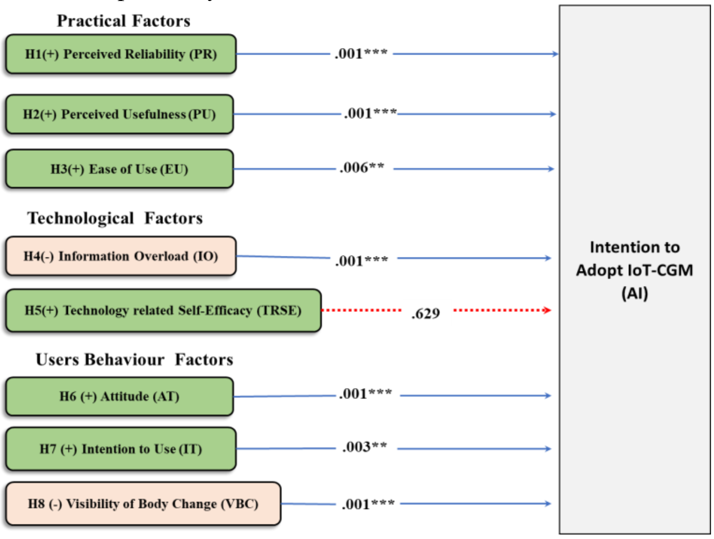

Fig2: The Updated IAI-CGM Framework

A. *Implications*

This study analyzed the factors affecting the adoption of Internet of things-enabled continuous glucose monitors among Saudi users. The authors used an integrated research methodology that incorporated the TAM and other factors to examine the perceived reliability and utility of the monitors, as well as user behavioural and technological factors (see Fig 2 The Updated IAI-CGM Framework). The study found that an individual's perceived reliability of continuous glucose monitoring and its utility were the most important factors affecting adoption. Physical changes in the body negatively impacted adoption, and technology-related self-efficacy did not affect adoption intention. The study also revealed that Saudi Arabians were skeptical of government hospitals and their ability to train them in wearable technologies. This study provides valuable insights into the adoption of IoT-enabled continuous glucose monitors and can aid in future research in this area.

VI. CONCLUSION

In this study, we constructed the Updated framework (IAI-CGM) to identify critical factors that influence the adoption of (IoT-CGM). We present the theoretical background by way of a literature review that outlines previous empirical findings related to type 1 diabetic patients using IoT-CGM from King Khalid Hospital Saudi Arabia and the Najran region. Then, our updated framework (IAI-CGM) is based on investigating three main categories of factors, including practical factors, technological factors, and user behavioural factors.

Among the practical factors, PR, PU, and EU are identified as drivers that increase adoption intention among users. However, with the technological factors, only IO influenced adoption intention, while TRSE was found to have an insignificant impact on adoption intention. Finally, user behavioural factors AT, IT, and VBC are also relevant. Both AT and IT increase adoption intention, while VBC has the opposite effect. Results are intended to provide valuable insight into the main factors that influence type 1 diabetic patients to adopt IoT-CGM in Saudi Arabia.

The study was conducted on Saudi Arabian citizens with type 1 diabetes, and the findings revealed new avenues for future research. The study recommends that future research should focus on specific areas, such as software development models and process structure models, to better understand the factors that contribute to acceptance and the hurdles that must be overcome. This research emphasizes the importance of addressing adoption challenges to improve healthcare delivery.

The future work will involve testing the IAI-CGM framework using qualitative approach based on 15 semi-structured interviews. The study will be conducted on T1DM patients admitted in diabetes primary care stage. The patients will be recruited from King Khalid Hospital, located in Najran, Saudi Arabia. Based on the qualitative results, the model will have the potential to be further improved. Qualitative results will help to identify other critical factors for adoption intention (AI) for IAI-CGM framework.

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