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Chatbot Adoption Model in Determining Student Career Path Development: Pilot Study

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Abstract*—A career decision is incredibly essential in one's life. It shapes one's future role in society, influences professional development, and can lead to success and fulfillment. Making a sound and consistent career decision based on skills and interests is critical for personal and professional development. Since generative AI is an emerging and revolutionizing technology industry in the market, which is very good in generating contents, providing consultancies and answering questions in humanly fashion, integrating AI chatbots into the career planning process can help students to get more accurate and personalized advice for their future career. This pilot study emphasized the student's adoption of chatbot technology for career selecting processes utilizing the extended Unified Theory of Acceptance and Use of Technology (UTAUT2) model with four additional constructs which influence the student's career selection, namely: Perceived Student's External Factors (PEF), Perceived Student's Interest (PSN), Perceived Career Opportunities (PCO) and Perceived Self-Efficacy (PSF). An online survey was conducted, and 37 responses were received and analyzed. The measurement model produced a promising result, and the discriminant validity, construct reliability and validity of the model were confirmed with a Cronbach's alpha (α) above 0.70 threshold and AVE over 0.5 cut-off for most of the constructs including the four above mentioned latent variables. However, the Price Value (PPV) and Facilitating Conditions (PFC) UTAUT2 constructs produced alpha (□) of 0.680 and 0.611 respectively which is still adequate since their AVE is above the 0.5 threshold. Consequently, their interpretation and conclusions should be approached with caution.

***Keywords*— ChatGPT, Chatbots, Determinants, Large Language Models, Structural Equation Modeling (SEM).**

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I. Introduction

The transformation of career development is not only the evolving landscape [1], [2], [3], but the teenagers' lives, ages and interests have changing effects on their career selection as well [2], [4]. Besides that, the students' decisions on their career choice usually have a lasting effect on their future life. Therefore, choosing the right option determines their personality, income level, social status, utilization of their potential and predicts the nature of their future jobs. On the other hand, career misalignment can lead to lack of efficiency, inability to achieve their goals, less productivity and problems due to the expectations of parental and cultural contexts and poor academic performances [5], [6], [7], [8].

Nevertheless, career counseling puts all aspects of career development into practice. Traditionally it has depended on assessments and standardized tests, career fairs and resume reviews, personal and mock interviews, on campus recruiting and internship programs and subjective insights of parents, teachers, peers and counselors. However, these methods have proven inadequate and often fall short in addressing the entire career development theory [9].

Artificial Intelligence (AI) technologies are increasingly advancing and affecting most of human life activities nowadays. AI is now being widely used in almost every sector of business such as transportation, health care, banking, education, research, entertainment, retail and e-commerce. One of the hottest AI applications is chatbot which is a Natural Language Processing (NLP) based computer program that simulates human conversations by generating human mimicked responses. Intelligent chatbots can analyze, comprehend, manipulate or interpret human languages and can provide an automated (24hour/7days) service, support and consultancy to customers, students etc.

Since Artificial Intelligence (AI) touches almost every aspect of the human life, incorporation of generative AI technologies such as chatbots into the educational environment increased not only the chances of maximizing teaching and learning strategies but also revolutionized the generation of personalized humanly responses that can assist the guidance of students towards their future career [10], [11], [12].

The challenges of determining the best student career routes have traditionally been provided by school/faculty councilors, which was useful for a while but frequently lacks the ability to deliver fully personalized advice due to its reliance on generalized approaches. Meanwhile, machine learning algorithms provided more specialized recommendations, but they could be inaccessible and difficult for average users. Students can benefit from more personalized and accessible tools for making informed career selections by implementing generative AI tools such as chatbots, which combine the strengths of both approaches - human insight from traditional advice and precision from machine learning.

Professional counsel needs to become more accurate, dynamic, and individualized as the job market gets more complicated. Generative AI technology provides a creative answer because of its capacity to analyze large volumes of data and identify text patterns [13]. This article's goals are to investigate how chatbots can help students make informed career decisions, address the present shortcomings of traditional counseling techniques, and make sure that integrating generative AI is done in an ethical and efficient manner that will benefit both students and teachers.

The aim of this study is to investigate the influences of the student's acceptance and use of AI chatbots from the perspective of the student's career determinations. The study adopts the extended version of Unified Theory of Acceptance and Use of Technology (UTAUT2) with four additional constructs which are more related to the student's career selection, namely: Perceived Student's External Factors (PEF), Perceived Student's Interest (PSN), Perceived Career Opportunities (PCO) and Perceived Self-Efficacy (PSF).

A. Career Development

A career is essentially a series of paid or unpaid roles in work that an individual performs throughout their life [14]. Additionally, [15] concluded that all individuals who work have a career and defined career theory as "all generalizable bodies which try to explain the phenomenon of career." Alternatively, [16] and [14] defined career development as any specific lifetime task that each person endeavors to manage, such as work, study, and other developments to increase the efficiency of the work and improve interaction with society.

Because career choice uncertainty has a significant impact on high school students, as stated in [7], [8], [18], selections made based on immaturity and a lack of knowledge of the field may result in an increase in dropout rates and program switching in the future, resulting in time and financial waste. To avoid such occurrences, adequate guidance and counselling are required. According to [19], incorporating machine learning technologies within the framework of career counselling services can improve career assistance. However, machine learning techniques lacked the real time interaction and human mimicking capabilities and based their counseling on only data from secondary sources like student records while traditional counselling has human inconsistent quality like fatigue, bias and time and location barriers. Therefore, chatbot counselling can combine the advantages of both techniques to leverage AI capabilities and instant interaction and real-time conversations of traditional counselling.

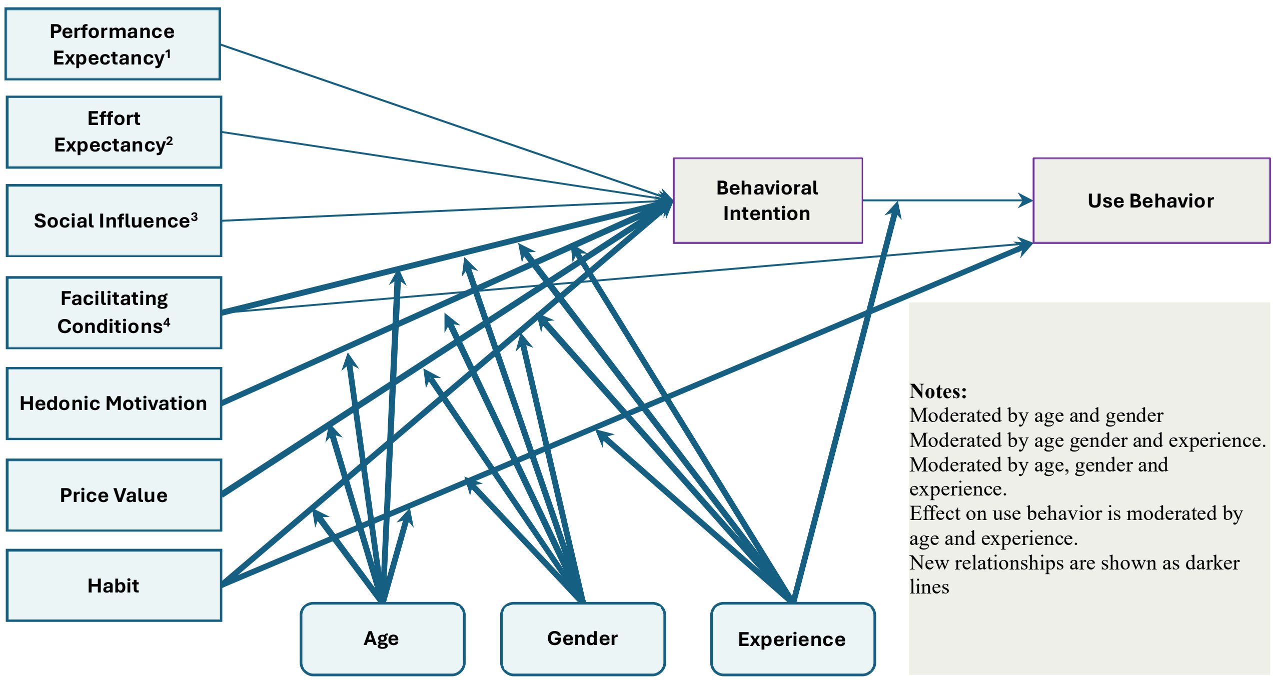

Fig. 1 UTAUT2 Model [17]

TABLE I
ADDITIONAL DETERMINANTS AND THEIR DEFINITIONS

Determinants	Definitions
Perceived self-efficacy	The degree to which a person believes he or she can achieve a given task and feel more confident in overcoming barriers or accomplishing challenges [21][22], [23].
Perceived career opportunity	The students' perceptions refer to the numerous paths within and beyond the organization that drive them towards their career goals, allowing them to seek gratifying work and fulfil their professional aspirations [23], [24], [25], [26], [27].
Perceived external factors (influencers)	External factors are influencers that affect a student's career decisions which include parents, family members, teachers, peers, and other career advisers [23], [28], [29], [30], [31].
Perceived student interest	A psychological state characterized by focused attention and emotion towards a certain item or subject [23], [32].

B. Theoretical Background

Theoretical frameworks underpinning career selection often incorporate elements of technology acceptance to understand how individuals adopt and integrate technological tools in their decision-making processes. Drawing from models like the Technology Acceptance Model (TAM) or the Unified Theory of Acceptance and Use of Technology (UTAUT), researchers explore the interplay between technology, individual attitudes, and career decision-making [20].

These frameworks suggest that factors such as perceived usefulness, ease of use, and social influence significantly impact individuals' willingness to incorporate technological solutions into their career selection processes. By examining how individuals perceive and interact with career-related technologies, researchers gain insights into the drivers and barriers influencing technology adoption in the context of career decision-making. This understanding is crucial for designing effective career guidance systems and interventions that leverage technology to support individuals in making informed and fulfilling career choices [33].

With in this regard, [34] developed Unified Theory of Acceptance and Use of Technology (UTAUT) which stems from several other theories and models such as Theory of Reasoned Action (TRA) [35], [36] [37], Theory of Planned Behavior (TPB) [38], [39], [40], Social Cognitive Theory (SCT) [41], [42][43] and Technology Acceptance Theory (TAM)[44], [45] and its variation TAM2 [46]. UTAUT comes up with four constructs namely, performance expectancy, effort expectancy, facilitating conditions and social influences which predict the user's behavioral intention to technology. Researchers applied these theories over the years until [21] inspired TAM3. Additionally, [17] developed extended UTAUT2, an offspring of UTAUT theory with additional 3 more constructs which are price value, hedonic motivation and habit to improve its functionality.

The study will implement UTAUT2 and most of its constructs and moderators. In addition to that, there will be other four constructs dealing with the career determination from the student's perspective, namely, student self-efficacy which refers to the student's confidence to himself/herself, career opportunity which refers to opportunities that take the students closer to their career, student's interest which relates to student's positive inclination to particular task or course and students' external factors which influences their career selections such as their families, peers and school members. These constructs were adopted by [23] in their model who applied the Vroom's Expectancy Theory of Motivation (ETM) [47] and their definitions were shown in table 1.

II. Materials and Method

This section delves into the methodical strategy utilized to examine the integration of chatbot AI technology in shaping professional career decisions. This part outlines the study model design, data collection procedures, and analytical strategies used to comprehend how chatbot AI tools affect and direct student's career decisions. The study aims to provide a thorough analysis of chatbot AI's role in career counseling, emphasizing quantitative approach. It also highlights the validity and reliability of the instruments used, and describes the steps taken to ensure ethical considerations and accurate representation of findings.

In this study, a quantitative method was employed to conduct a survey approach. A primary data collection was undertaken by an online survey method using a questionnaire instrument. Closed end questions were employed in the questionnaire in the form of five-point Linkert scale to measure the survey participants' opinion and perception towards adopting technology in determining career choice. The scale is organized with the values of 1-5, starting (1) for strongly disagreeing to (5) for strongly agreeing. Participants shall answer all questions, there is no optional question.

Cleaning, processing and data analyzing was carried out descriptively applying Structural Equation Modelling (SEM) using Smart-PLS version 4.1. The SEM analysis was used to investigate the relationship between the variables (constructs) under study. SEM is a multivariate statistical analysis tool that may test complex research models simultaneously while also analyzing factors that cannot be directly quantified.

Since the design of the questionnaire usually concerns deciding the questions that are most relevant to the topic of research [48]. This study emphasizes testing the factors that support the student's intention towards use of AI chatbots. To validate the interaction between the constructs of the model in Fig. 2, a descriptive online survey was conducted. The targeted audiences of the questionnaire were both the perspective and current students in several universities in Mogadishu, Somalia. These students were in the range of 18-38 years of age.

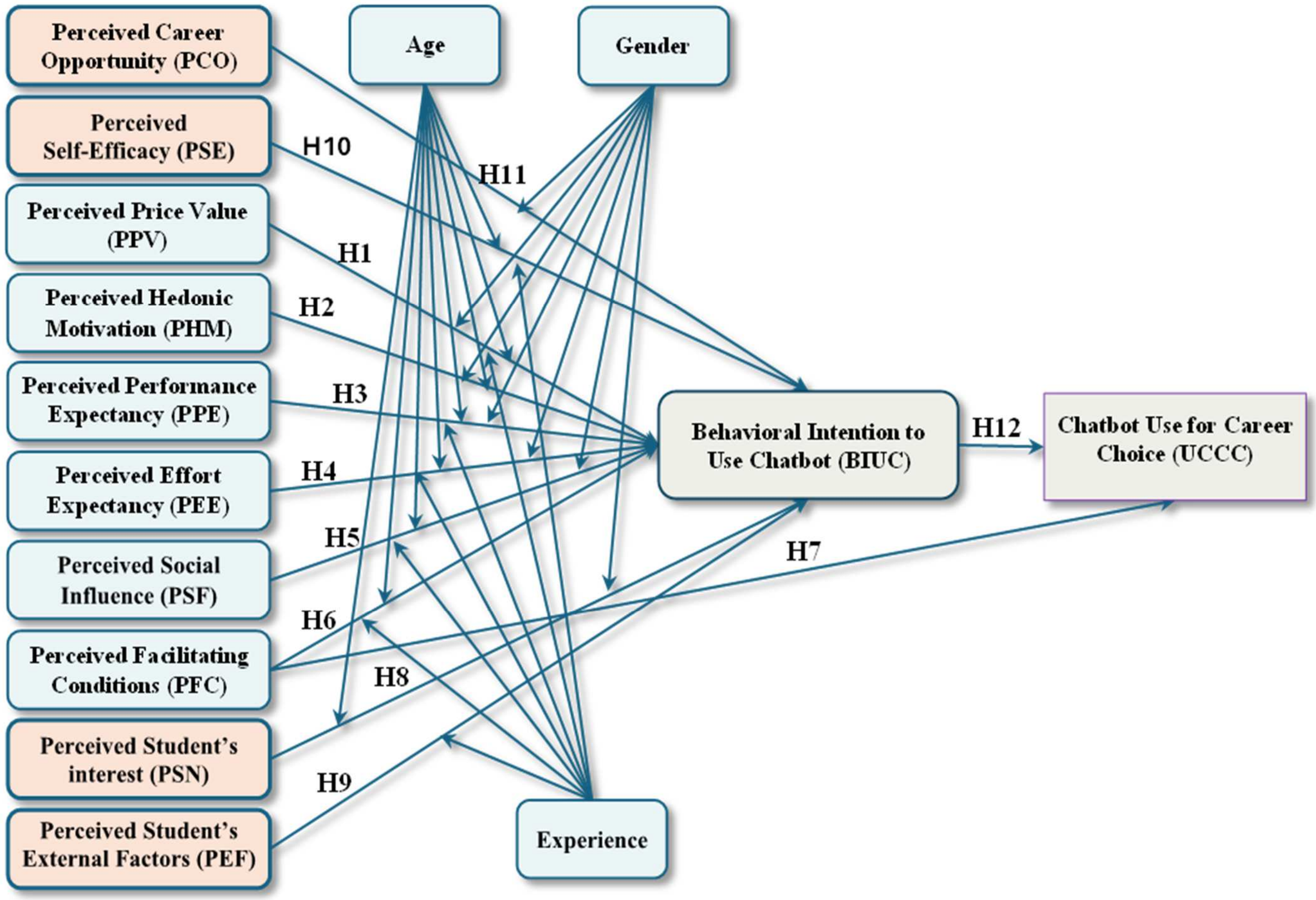

Fig. 2 Research Module

Since the main aim of this pilot study is not hypothesis testing, there is no need to calculate sample size but as a rule of thumb 30 samples are enough to test measurement model [49], [50], [51], hence, 37 questionnaire responses which is slightly above 10% of the actual sample size were received [50]. Seven students of the respondents (18.9%) were female while the remaining 30 respondents (81.1%) were male. Besides that, 15 respondents (40.5%) were bachelor students, while 20 respondents (54.1%) were master students and the rest of the 2 respondents (5.4%) were PhD students as shown in Table 2.

TABLE II
STUDIES DEMOGRAPHIC SUMMARY

Demographics	Frequency	Percentage
Respondent Gender		
Female	7	19%
Male	30	81%
Total	**37**	**100%**
Age categories		
18-24	18	49%
25-31	13	35%
32-38	6	16%
>=39	0	0%
Total	**37**	**100%**
Level of education		
Bachelor students	15	41%
Master students	20	54%
Doctoral (phd) students	2	5%
Total	**37**	**100%**

III. Result and Discussion

A. Measurement Model

This pilot study focuses on only the measurement model evaluation or the outer model evaluation which is one of the two main evaluation models of SEM analysis in the partial least square approach. The measurement model defines the latent variables and their indicators. The parameters of the measurement model (Cronbach's alpha, composite validity, convergent validity and discriminant validity) are obtained through the outer model's iterative algorithm for solving the blocks of the measurement model and estimating the path coefficients later in the structural model [31], [52], [53]

We assessed the psychometric features of each assessment scale using indicator reliability, construct reliability, and validity. [32] evaluated specific statistical tests. We first evaluated the indicator's dependability using the outside loadings of each indication. With the exception of PCO1, PCO2, PFC1, PFC3, PFC4, PPE1 and PPV2, all other 33 indicators outer loading values exceeded the 0.708 criterion as shown in both fig. 3 and table 3. Five of these seven items were not excluded from the analysis due to content validity issues and their closeness to the threshold. However, PCO2 and PFC4 were removed from the loading which in turn improved the AVE value to reach the 0.5 criterion.

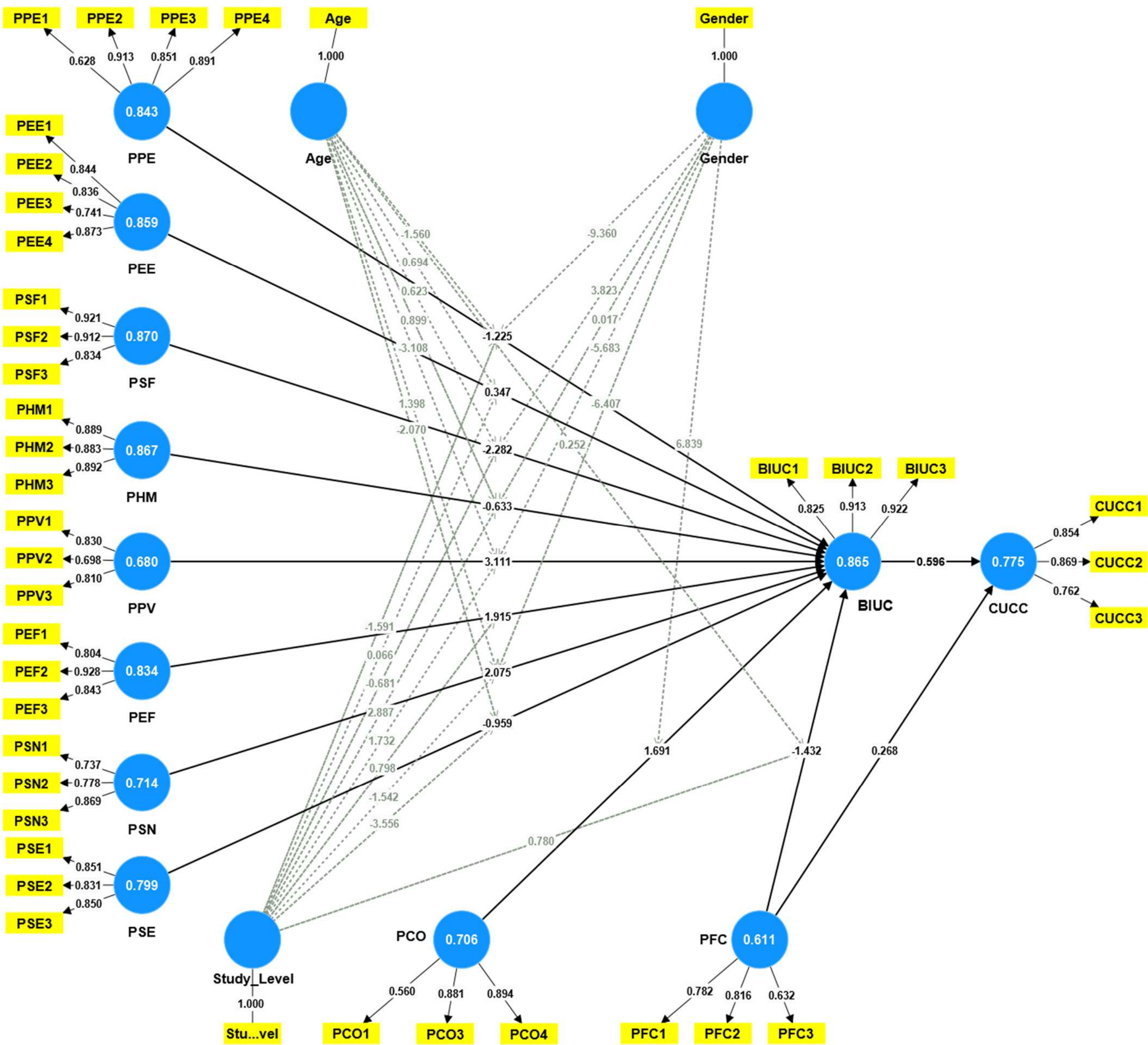

Fig. 3 Measurement model

On the other hand, it is important to assess discriminant validity of variables to investigate the existence of high inter-correlation between the constructs [55]. [56] clarified that discriminant validity refers to the extent to which the constructs differ from each other empirically. It also assesses the degree to which the overlapping constructs differ [57], [58]. The discriminant validity can be assessed using the Fornell and Larcker criterion, indicator cross-loading, the heterotrait-monotrait (HTMT) correlation ratio and full collinearity for reflective and formative constructs [59]. The Fornell-Larcker criterion states that your diagonal value should be greater than any other value in the same row or column. Thus, according to Table 3, the CR for all constructs is greater than 0.70, and the AVE values are between 0.559 and 0.792, and in Table 4, the [60] were employed to assess discriminant validity through the comparison of the correlation coefficients (off-diagonal) to the square root of each AVE on the diagonal for each construct in the corresponding rows and columns. Generally, the below result in Table 4 confirms the support of the discriminant validity for the constructs of this measurement model, since all their diagonal values proved to be greater than any value in their respective rows or column.

TABLE III
CONSTRUCT COLLINEARITY, RELIABILITY AND VALIDITY WITH OUTER-LOADINGS

Construct	Indicators	Outer loadings	Cronbach's alpha	Composite Reliability	Average Variance (AVE)	VIF
Behavioral Intention to Use Chatbot	BIUC1	0.825	0.865	0.918	0.788	1.760
	BIUC2	0.913				2.897
	BIUC3	0.922				3.072
Use Chatbot for Career Choice	CUCC1	0.854	0.775	0.869	0.688	1.649
	CUCC2	0.869				2.045
	CUCC3	0.762				1.494
Perceived Career Opportunity	PCO1	0.560	0.706	0.831	0.630	1.166
	PCO3	0.881				1.782
	PCO4	0.894				1.762
Perceived Effort Expectancy	PEE1	0.844	0.859	0.895	0.681	2.683
	PEE2	0.836				2.405
	PEE3	0.741				1.994
	PEE4	0.873				1.590
Perceived Student's External Factors	PEF1	0.804	0.834	0.894	0.739	1.961
	PEF2	0.928				2.086
	PEF3	0.843				1.803
Perceived Facilitating Conditions	PFC1	0.782	0.611	0.790	0.559	1.229
	PFC2	0.816				1.267
	PFC3	0.632				1.170
Perceived Hedonic Motivation	PHM1	0.889	0.867	0.918	0.789	2.575
	PHM2	0.883				1.943
	PHM3	0.892				2.552
Perceived Performance Expectancy	PPE1	0.628	0.843	0.896	0.686	1.384
	PPE2	0.913				3.174
	PPE3	0.851				2.144
	PPE4	0.891				2.821
Perceived Price Value	PPV1	0.830	0.680	0.824	0.611	1.529
	PPV2	0.698				1.232
	PPV3	0.810				1.381
Perceived Self-Efficacy	PSE1	0.851	0.799	0.882	0.713	1.918
	PSE2	0.831				1.640
	PSE3	0.850				1.670
Perceived Social Influence	PSF1	0.921	0.870	0.919	0.792	2.643
	PSF2	0.912				2.531
	PSF3	0.834				1.987
Perceived Student's interest	PSN1	0.737	0.714	0.838	0.635	1.413
	PSN2	0.778				1.323
	PSN3	0.869				1.601

TABLE IV
DISCRIMINANT VALIDITY FORNELL–LARKER CRITERION

	BIUC	**CUCC**	**PCO**	**PEE**	**PEF**	**PFC**	**PHM**	**PPE**	**PPV**	**PSE**	**PSF**	**PSN**
BIUC1	**0.825**	0.494	0.668	0.179	0.363	0.372	0.623	0.514	0.600	0.686	0.604	0.608
BIUC2	**0.913**	0.671	0.480	0.525	0.294	0.483	0.446	0.475	0.537	0.579	0.462	0.581
BIUC3	**0.922**	0.741	0.488	0.425	0.206	0.394	0.396	0.454	0.531	0.435	0.524	0.508
CUCC1	0.691	**0.854**	0.305	0.393	0.234	0.569	0.385	0.225	0.390	0.278	0.363	0.555
CUCC2	0.550	**0.869**	0.562	0.277	0.439	0.371	0.234	0.346	0.426	0.272	0.480	0.510
CUCC3	0.530	**0.762**	0.509	0.300	0.481	0.391	0.396	0.581	0.588	0.457	0.607	0.588
PCO1	0.252	0.483	**0.560**	0.175	0.331	0.357	0.351	0.196	0.187	0.321	0.401	0.557
PCO3	0.530	0.374	**0.881**	0.287	0.334	0.242	0.313	0.335	0.407	0.576	0.608	0.496
PCO4	0.582	0.485	**0.894**	0.155	0.496	0.171	0.333	0.327	0.475	0.698	0.616	0.561
PEE1	0.253	0.325	0.066	**0.844**	-0.074	0.547	0.413	0.399	0.002	0.145	0.013	0.273
PEE2	0.283	0.176	0.025	**0.836**	-0.004	0.507	0.309	0.384	-0.128	0.149	-0.003	0.152
PEE3	0.182	0.212	0.048	**0.741**	-0.102	0.525	0.320	0.349	-0.097	0.113	0.006	0.146
PEE4	0.526	0.464	0.442	**0.873**	0.239	0.595	0.478	0.591	0.157	0.484	0.320	0.494
PEF1	0.145	0.352	0.476	0.201	**0.804**	0.324	0.240	0.156	0.182	0.362	0.504	0.498
PEF2	0.359	0.429	0.472	0.090	**0.928**	0.196	0.261	0.244	0.289	0.425	0.600	0.371
PEF3	0.240	0.352	0.327	-0.030	**0.843**	0.021	0.206	0.246	0.291	0.395	0.584	0.351
PFC1	0.444	0.386	0.226	0.567	0.086	**0.782**	0.418	0.448	0.399	0.307	0.143	0.399
PFC2	0.409	0.469	0.302	0.526	0.197	**0.816**	0.437	0.279	0.266	0.349	0.265	0.603
PFC3	0.140	0.378	0.051	0.364	0.140	**0.632**	0.206	0.259	-0.080	-0.092	0.043	0.189
PHM1	0.428	0.375	0.239	0.448	0.137	0.541	**0.889**	0.321	0.377	0.512	0.188	0.468

	BIUC	CUCC	PCO	PEE	PEF	PFC	PHM	PPE	PPV	PSE	PSF	PSN
PHM2	0.542	0.412	0.469	0.465	0.385	0.450	**0.883**	0.535	0.383	0.660	0.538	0.609
PHM3	0.455	0.301	0.320	0.360	0.172	0.327	**0.892**	0.324	0.234	0.470	0.361	0.493
PPE1	0.287	0.554	0.250	0.330	0.316	0.319	0.430	**0.628**	0.179	0.033	0.365	0.242
PPE2	0.506	0.320	0.307	0.506	0.231	0.418	0.435	**0.913**	0.303	0.355	0.329	0.220
PPE3	0.501	0.311	0.428	0.328	0.296	0.211	0.216	**0.851**	0.312	0.362	0.577	0.264
PPE4	0.449	0.384	0.224	0.681	0.057	0.538	0.480	**0.891**	0.219	0.313	0.247	0.251
PPV1	0.482	0.391	0.311	-0.097	0.063	0.222	0.271	0.240	**0.830**	0.442	0.410	0.407
PPV2	0.425	0.379	0.221	-0.027	0.260	0.335	0.272	0.229	**0.698**	0.446	0.349	0.351
PPV3	0.542	0.515	0.550	0.166	0.382	0.181	0.332	0.261	**0.810**	0.648	0.473	0.577
PSE1	0.464	0.231	0.621	0.181	0.322	0.127	0.447	0.141	0.610	**0.851**	0.430	0.544
PSE2	0.537	0.442	0.626	0.326	0.495	0.393	0.533	0.313	0.544	**0.831**	0.536	0.598
PSE3	0.580	0.318	0.539	0.333	0.342	0.226	0.587	0.398	0.535	**0.850**	0.475	0.491
PSF1	0.584	0.530	0.570	0.181	0.552	0.282	0.373	0.487	0.484	0.447	**0.921**	0.587
PSF2	0.566	0.582	0.607	0.155	0.630	0.194	0.433	0.436	0.516	0.529	**0.912**	0.570
PSF3	0.398	0.366	0.712	0.087	0.585	0.075	0.312	0.256	0.401	0.582	**0.834**	0.510
PSN1	0.387	0.507	0.552	0.004	0.345	0.293	0.429	0.151	0.444	0.438	0.566	**0.737**
PSN2	0.507	0.499	0.431	0.592	0.370	0.620	0.622	0.379	0.474	0.637	0.407	**0.778**
PSN3	0.589	0.579	0.575	0.260	0.353	0.417	0.390	0.161	0.472	0.465	0.546	**0.869**

TABLE V
DISCRIMINANT VALIDITY – CROSS LOADING

	BIUC	CUCC	PCO	PEE	PEF	PFC	PHM	PPE	PPV	PSE	PSI	PSIN
BIUC	**0.888**											
CUCC	0.722	**0.830**										
PCO	0.605	0.534	**0.794**									
PEE	0.435	0.397	0.254	**0.825**								
PEF	0.318	0.444	0.486	0.083	**0.860**							
PFC	0.471	0.549	0.282	0.661	0.188	**0.748**						
PHM	0.541	0.412	0.397	0.480	0.273	0.494	**0.888**					
PPE	0.538	0.442	0.369	0.559	0.260	0.443	0.454	**0.829**				
PPV	0.622	0.554	0.478	0.028	0.306	0.306	0.376	0.312	**0.781**			
PSE	0.629	0.397	0.702	0.339	0.460	0.300	0.625	0.348	0.664	**0.844**		
PSI	0.591	0.567	0.693	0.165	0.658	0.220	0.424	0.457	0.530	0.571	**0.890**	
PSIN	0.633	0.663	0.646	0.381	0.444	0.565	0.597	0.290	0.580	0.643	0.627	**0.797**

Alternatively, discriminant validity can be evaluated using indicator cross-loading method. Cross loadings predict that a specific indicator should have higher loadings on its own parent construct than on any other constructs in the context of the study. If an item loads well in another construct compared to its own parent variable, discriminant validity concerns arise [61], [62]. Table 5 presents that each indicator has its best loadings with its own construct and hence, discriminant validation is confirmed as well.

IV. CONCLUSION

In conclusion, the instrument used in this survey showed good result from the perspective of discriminant validity, construct reliability and validity and collinearity statistics (VIF) although there was a small setback in two constructs namely, Facilitating Condition (FC) and Price Value (PV) with Cronbach's alpha (α) value of 0.680 and 0.611 respectively which is slightly below the 0.70 cut off. This implies that the internal consistency and the reliability of these two constructs are lower than the rest of the latent variable, hence their conclusions and interpretations should be treated with caution. However, as this is a pilot study and the data sample employed is minimal, its result cannot be generalized, and a thorough investigation is required to get the full focus of the research.

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