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Behavioural Intention and Dependency on ChatGPT among College Students: Scale Development and Validation

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Abstract: ***The usage of ChatGPT has grown exponentially for various purposes. It's necessary to assess the motivation to use in academic context. This research aims to assess behavioural intention and dependency on ChatGPT among college students in India. The draft scale consisted of 21 items measuring eight different aspects such as performance anticipation, expected effort, enabling circumstances, educating value, hedonistic intent, habit, intentional behaviour and educatory use. The items were subjected to expert opinion for content validity and were modified accordingly. The study was carried out among college students (N=150) through an online survey. KMO sampling adequacy was found to be 0.919 and Bartlett's Test was significant (chi - square = 1536.374, df=45, p<0.001) and exploratory factor analysis was conducted to examine the construct validity of the scale. The results of the principal component analysis using varimax rotation indicated that two factors explained 77.71% of the total variance with factor loading values ranging between 0.652 and 0.906. Cronbach coefficient for the total of the 10 - item scale under two factors was calculated with Cronbach α as 0.886. It is found to reliable and valid to assess behavioural intention and dependency to use ChatGPT in Indian context.***

Keywords: ChatGPT, behavioural intention, dependency, performance anticipation

1. Introduction

ChatGPT has emerged as the most preferred tool recently across various fields. It helps users find information and ideas, translate texts, and provide alternative questions to deepen the understanding of the material (Firaina & Sulisworo, 2023); cultivating writing skills (Punar & Yangın, 2024); significantly increases both utilitarian value and satisfaction in workplace (Jo & Park, 2024). As adopting AI - powered tools like ChatGPT becomes increasingly prevalent, it is essential to understand the underlying factors influencing users' behavioral intentions and the potential development of dependency on such technologies, particularly among college students. This demographic segment represents a critical user base, about 33.1% of visitors (Similar Web, 2023), due to their tech - savvy nature, high digital literacy, and reliance on technology for academic, social, and personal purposes. Therefore, it is imperative to assess and understand the motive for ChatGPT usage for fine - tuning assignment design as well the customising ChatGPT.

2. Theoretical Framework

Behavioral intention is rooted in the Theory of Reasoned Action (TRA) and the Technology Acceptance Model (TAM). It provides a theoretical framework for examining individuals' predispositions to engage in specific behaviors. The theory of reasoned action and planned behavior concentrates on people's views on the likelihood that they will engage in a particular activity in the future (Fishbein & Azjen, 1975). Intention, a motivating construct seen as the most immediate driver of behavior, is the theory's primary concept. The degree to which a person is inclined to plan and put effort into engaging in a particular activity is reflected in their intention. As a result of two belief - based categories, attitudes and subjective norms, intention is viewed as a function. Subjective norms represent perceptions that significant others might want them to execute the conduct, whereas attitudes are favorable or unfavorable evaluations of executing the activity in the future.

One of the most popular models to describe user acceptance behavior is the Technology Acceptance Model (TAM). Davis (1986, 1989) proposed the constructs in the TAM Model as follows: attitude, perceived utility (PU), perceived ease of use (PEOU), and behavioral intention to use. PU and PEOU are two of the components that help forecast an end - attitude user toward a technology and, in turn, how likely they are to adopt it. TAM has garnered much attention and empirical support during the past ten years (e. g., Davis, 1989; Mathieson, 1991; Taylor & Todd, 1995a). Between 1989 and 2001, there were, in our estimation, around 100 investigations on TAM that were published in journals, conferences, or technical reports. This research involved comprehensive testing of TAM utilizing various representative samples and user groups inside or across enterprises, statistical tool analysis, and comparison with rival models (Gefen, 2000). It has been used with a variety of end - user technologies, including e - mail (Adams, Nelson & Todd, 1992; Davis, 1989), office software (Adams, Nelson & Todd, 1992; Davis, Bagozzi & Warshaw, 1989), groupware (Taylor & Todd, 1995b), spreadsheet applications (Agarwal, Sambamurthy & Stair, 2000; Mathieson, 1991), as well as the World Wide Web (Lederer, Maupin, Sena & Zhuang, 2000). Since TAM's conception, dozens of empirical researches have been undertaken on it. TAM is thought to be more economical, predictive, and resilient than its rival models (Venkatesh & Davis, 2000). As more and more individuals contributed to the pool of knowledge, other models, such as UTAUT and UTAUT 2,

emerged (Sharma & Yadav, 2022). The Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) is an expansion of the original UTAUT model, designed to better explain the elements that influence people's acceptance and adoption of technology in a variety of circumstances (Alalwan et al., 2020). Hence, the researchers have considered UTAUT2 and TRA as theory to understand the behavioural intention for ChatGPT usage.

3. Review of Literature

This section provides an overview of the existing tools measuring technological acceptance and usage. The following table 1 lists the important psychological tools developed in assessing user acceptability of technology.

Table 1: Measures of Technological Acceptance and Usage

Name of the Measure	Author (Year)	Measurement	Scaling
The Media and Technology Usage and Attitudes Scale	Rosen, Whaling, Carrier, Cheever & Rokkum (2013)	66 items concerning technology and media usage, along with 18 additional items assessing attitudes toward technology. Consists of 11subscales representing smartphone usage, general social media usage, Internet searching, e - mailing, media sharing, text messaging, video gaming, online friendships, Facebook friendships, phone calls, and watching television in addition to four attitude - based subscales: positive attitudes, negative attitudes, technological anxiety/dependence, and attitudes toward task - switching	5 - point scale ranging from 1 to 5 reflecting the intensity of their attitudes or behaviors.
TAM	Silva (2015)	Perceived Usefulness (PU) and Perceived Ease of Use (PEOU)	Likert scale represent the extent to which participants perceive the technology as useful, easy to use, or favorable.
TAM 2	Wu, Chou, Weng & Huang (2011)	It extends the original Technology Acceptance Model (TAM) and incorporates additional factors such as subjective norms, system characteristics, and external variables. TAM2 helps assess users' beliefs, attitudes, and intentions towards adopting new technology, providing insights into factors that influence technology acceptance and usage.	TAM2 typically uses a Likert scale to measure users' beliefs, attitudes, and intentions towards adopting new technology. This scale typically ranges from strongly agree to strongly disagree or from very positive to very negative, allowing users to indicate their level of agreement or disagreement with specific statements or items. The Likert scale provides a standardized way to quantify users' perceptions and attitudes towards technology acceptance.
Unified Theory of Acceptance and Use of Technology	Ahmad (2014)	The model is based on four key constructs: Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions. It has been validated and replicated in several studies, demonstrating its applicability in different cultures and contexts.	Likert scale used in UTAUT2 usually ranges from 1 to 7, with 1 representing "strongly disagree" and 7 representing "strongly agree".
Unified Theory of Acceptance and Use of Technology 2	Ain, Kaur & Waheed (2015)	Usefulness, ease of use, social influence, facilitating conditions, enjoyment, price worthiness, habit, and behavioural intention.	Likert scale used in UTAUT2 usually ranges from 1 to 7, with 1 representing "strongly disagree" and 7 representing "strongly agree".

Need of the Study

The widespread interest and use of ChatGPT has sparked many questions and concerns over ethics and fair use (Zhou, 2023), especially in academia. The structure of intellect model (Guildford, 1961) posits that intelligence is the systematic abilities of combining content, operate and product. So, when students use it to generate ideas for writing assignments (Varghe, 2023), the cognitive processes and divergent thinking is executed by the AI which inhibits the critical thinking and comprehensive ability of students. Hence, it is essential to assess the underlying motive of ChatGPT usage among students in Indian context to promote responsible integration of AI technologies in higher education settings.

4. Method

Item generation

Review of literature was carried out on the behavioural intention to use technology. Items were extracted from UTAUT - 2 model (Ain, Kaur, & Waheed, 2016) and extended it to the usage of ChatGPT in academic context. A total of 28 items were generated and subjected to expert opinion.

Content validity

The items were circulated to five experts in psychology and education technology for their opinion. Based on their feedback, certain items were rephrased and kept simple for better understanding. The draft scale consisted of 21 items grouped under 8 themes.

Rating scale format

Each item was rated on a 5 - point Likert - type scale ranging from “Strongly Disagree”, “Disagree”, “Neutral”, “Agree” and “Strongly Agree”. The positive items were scored from 1 to 5 starting with “Strongly Disagree”; and the negative statements were scored from 5 to 1 starting with “Strongly

Disagree". The lowest positive score is 21 and the highest is 105. The higher score indicates that an individual had higher intention to use ChatGPT.

Data Collection and Sample

The questionnaire was designed in Google Form and circulated to university students studying UG. Out of 165 participants, 129 females, 33 males and 3 non binaries aged between 17 - 22years old.73.9% of the participants were from Social Sciences, 13.9% were from Business Studies, 6.7% from Computer Science and the remaining from Medical Science background. Students were informed about the purpose of the study and the participation was voluntary; anonymity of the participation was assured.

Statistical Analysis

The data was analyzed using SPSS software to establish construct validity through factor analysis and Cronbach's Alpha was calculated as co - efficient of reliability. Kaiser - Mayer - Olkin and Bartlett's test were used to determine the sample adequacy and suitability of the data for factor analysis.

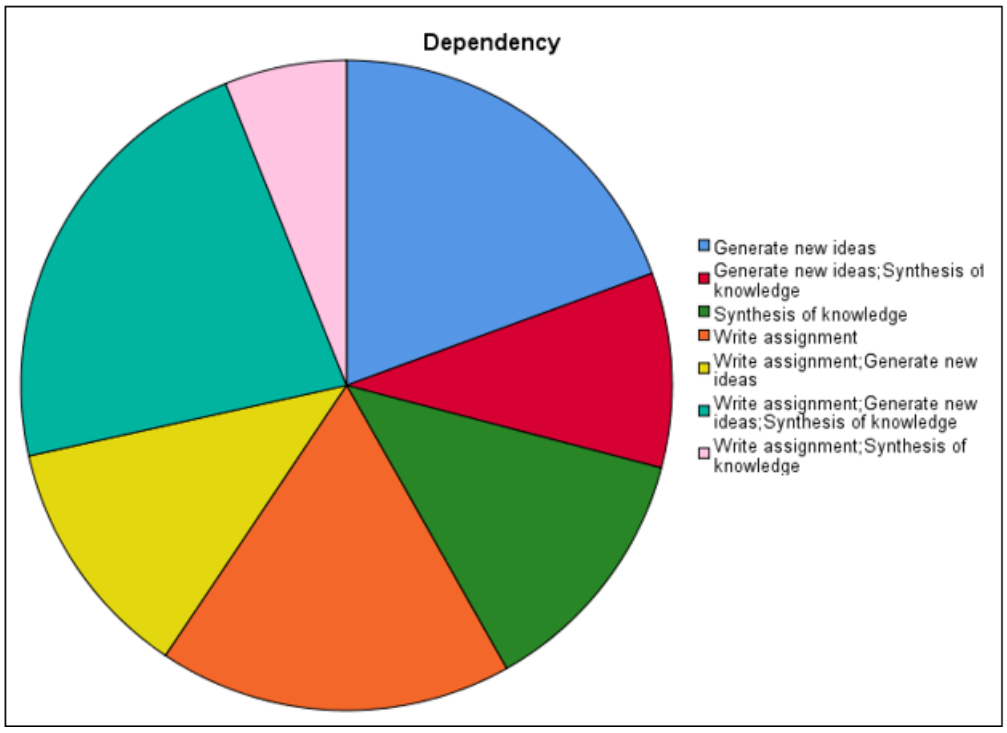
5. Results and Discussion

Dependency on ChatGPT

The "Dependency on ChatGPT" dataset provides a detailed analysis, broken down by frequency and percentage distributions, of the reasons users interact with the ChatGPT language model. These objectives are divided into many categories by the dataset, which includes tasks like coming up with original ideas, combining information, and writing assignments. The statistics indicates that coming up with new ideas is the most often identified goal (19.4% of all occurrences), closely followed by writing assignments (17.6% of all occurrences). Additionally, the data shows examples of how users mix goals, including combining assignment writing and knowledge synthesis with idea generating. These results highlight ChatGPT's adaptable and comprehensive usefulness in supporting users with a variety of tasks. With 165 cases total, the dataset offers a thorough picture of the various ways users utilise ChatGPT to assist and enhance their cognitive activities.

Table 2: Showing the dependency on ChatGPT

Purpose	Frequency	Percentage
Generate new ideas	32	19.4
Generate new ideas; Synthesis of knowledge	16	9.7
Synthesis of knowledge	21	12.7
Write assignment	29	17.6
Write assignment; Generate new ideas	20	12.1
Write assignment; Generate new ideas; Synthesis of knowledge	37	22.4
Write assignment; Synthesis of knowledge	10	6.1
Total	165	100.0



Construct Validity

Factor analysis was carried out to establish the construct validity of the tool. Kaiser - Mayer - Olkin measure of sampling adequacy showed 0.919, indicating goodness of fit of the dataset. Bartlett's test of sphericity (chi - square 1536.374, df=45, $p<0.001$) indicated that the dataset was suitable for factor analysis.

Exploratory factor analysis with varimax rotation was carried out to establish construct validity of the tool. Absolute values less than 0.4 were suppressed. After removing cross loadings, two factors emerged explaining 77.71% of variance. The findings are tabulated in table 3 and table 4. Items related to expected effect, enabling circumstances are loaded on Factor - II, labelled as User Attitude and items related educating value, habit and intentional behaviour are loaded on Factor – I, labelled as Intentional Behaviour.

Table 3: Showing results of factor analysis before and after the rotation

Factor	Initial Eigen value			Loadings after Rotation		
	Total	Percentage of variance	Cumulative Percentage of variance	Total	Percentage of variance	Cumulative Percentage of variance
1	6.298	62.981	62.981	5.360	53.595	53.595
2	1.47	14.737	77.718	2.412	24.123	77.718

Table 4: Showing results of factor loading for each construct

Items	Dimensions	
	Intentional Behaviour	User Attitude
Expected Effect 3		.772
Enabling Circumstances 1		.848
Enabling Circumstances 2		.853
Educating Value 1	.652	
Habit 2	.886	
Habit 3	.886	
Intentional Behaviour 1	.898	
Intentional Behaviour 2	.899	
Intentional Behaviour 3	.906	
Intentional Behaviour 4	.885	
Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.		
a. Rotation converged in 3 iterations.		

Reliability

Cronbach's Alpha coefficients were calculated for each factor and the overall scale to establish the internal consistency of the tool. The cronbach's alpha coefficient was 0.930 for the overall scale. If the alpha value is greater than 0.80, it is considered as highly reliable, shown in table 5. Hence, it is concluded that all items care suitable for this scale and can be included in the scale. And this tool is considered to be reliable to measure the behavioural intention to use ChatGPT in Indian academic context.

Table 5: Showing the internal consistency of the Scale

	User Attitude	Intentional Behaviour	Total
Item Number	3	7	10
Cronbach's Alpha	0.798	0.901	0.886

Table 6: Showing the item - total correlation

Item	Overall Total
Expected Effort 3	0.572**
Enabling Circumstance 1	0.486**
Enabling Circumstance 2	0.533**
Habit 2	0.786**
Habit 3	0.767**
Intentional Behaviour 1	0.806**
Intentional Behaviour 2	0.813**
Intentional Behaviour 3	0.834**
Intentional Behaviour 4	0.768**

From table 6, it can be observed that item - total correlation value ranged between r=0.4867 to r=0.834 significant at p<0.001. It can be inferred that each item measures the same characteristics measured by the overall scale. Hence, it is concluded that all items care suitable for this scale and can be included in the scale.

6. Conclusion

The purpose of this study was to develop a scale to measure behavioural intentional and dependency on ChatGPT among Indian students. Based on the review of literature and expert opinion 21 items were framed on a 5 - point Likert type format. Exploratory factor analysis was to establish construct validity.10 items under two dimensions viz user attitude and intentional behaviour had high factor loading. Cronbach Alpha coefficient value (α=0.886) indicated that the scale was highly reliable. Hence it is concluded that this tool is reliable and valid measure to assess the behavioural intention and dependency on ChatGPT.

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