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Factors Influencing the Behavioural Intention to Use AI-Generated Images in Business:

A UTAUT2 Perspective With Moderators

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ABSTRACT

Motivated by the need to better understand the ongoing role of artificial intelligence in businesses and to shift the focus from a purely technological and algorithmic perspective to one that encompasses human-computer interaction, this article aims to investigate people's intention to use AI for generating images in a business context. The present study employed structural equation modelling to analyse how factors from UTAUT2 such as perceived customer value, effort expectancy, social influence, and facilitating conditions affect behavioural intention. The research introduces new moderators (creativity and English language proficiency), in the context of generative AI. Language proficiency and gender impact AI usage, while the impact of effort expectancy is more pronounced in cases of low creativity.

KEYWORDS

AI-Generated Images, Behavioural Intention, Business, Creativity, Language Proficiency, UTAUT2

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INTRODUCTION

Artificial intelligence (AI) is a growing topic of discussion and research due to the multitude of applications developed with its help and its multiple implications on human activity. The spectacular results of AI range from practical speech recognition, autonomous vehicles, and household information of things (IoT) to other human-AI interactions like automated translation, chatbots, or systems capable of creating realistic and artistic images from a description made in natural language (for example, Dall-E, Stable Diffusion, Imagen, and Midjourney). The approach is still predominantly oriented toward technology and algorithmic development (technology-centred approach); however, specialists predict that the focus will increasingly shift to aspects related to human computer interaction (Xu et al., 2021).

This research aims to obtain pertinent answers to the question: Do people intend to use AI for generating images for business purposes? First, a review of the specialized literature was carried out using established models and the acceptance of new technology. It also considered factors that determine why a person may use a certain technology. This was followed by identifying the way in which AI is used in business, aiming to identify the factors that determine future specialists to use AI for generating artistic images for business purposes. Through complex research, the subjects were first asked to use AI technology to create business images on a given theme (sustainable use of energy). Then, they were interviewed about their intentions with regards to using AI technology based on factors like performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, customer value, and habit from the UTAUT2 model. Additionally, the study considered potential moderators like age, gender, English-language experience, and subjects' creativity.

The results of the analysis revealed a moderate to high value for the behavioural intention to use AI, showing that 69% of the variance can be attributed to determinant factors (e.g., perceived customer value, effort expectancy, facilitating conditions, habit, hedonic motivation, performance expectancy, social influence) and its moderators like creativity, knowledge of the English language, study domain, and gender. An interesting result regarding the way human-AI interaction is carried out is the ease of acceptance of this technology by those who are proficient in English given the fact that the software on which the image generation is based requires text in this language. Another result is related to the gender of the person interacting with AI. For instance, the effect of habit on behavioural intention is more pronounced for males in comparison with females. Finally, the most interesting result is related to creativity. In fact, the impact of effort expectancy over the behavioural intention is much stronger in cases of low creativity.

Starting from the mentioned premises, the article is structured in four parts. The first part is concerned with the analysis of the specialized literature regarding human-technology interaction and the role of AI in business. The second part investigates the research methodology. This is followed by a review of the results and discussions in the context of existing research. The final part includes conclusions, proposals, academic and practical implications, limitations, and future research directions.

LITERATURE REVIEW

UTAUT2 Model

The ever-higher level of sophistication of technologies and growing pace of their alteration and improvement bring permanent challenges to the human sphere. Adoption of innovative technologies like cloud computing, blockchain, robotics, the Internet of Things (IoT), Big Data, and AI is on the rise. Innovation behind technologies has changed the face of entire industries, leading (with astonishing speed) to the appearance of completely new fields like e-commerce, m-health, or fintech. People and organizations must, therefore, deal with these changes in technology and business models on an accelerated basis. Still, not all technologies and innovations on which they are based have the same success in society and economy. The key question is as follows: why do people adopt or reject certain innovative technologies?

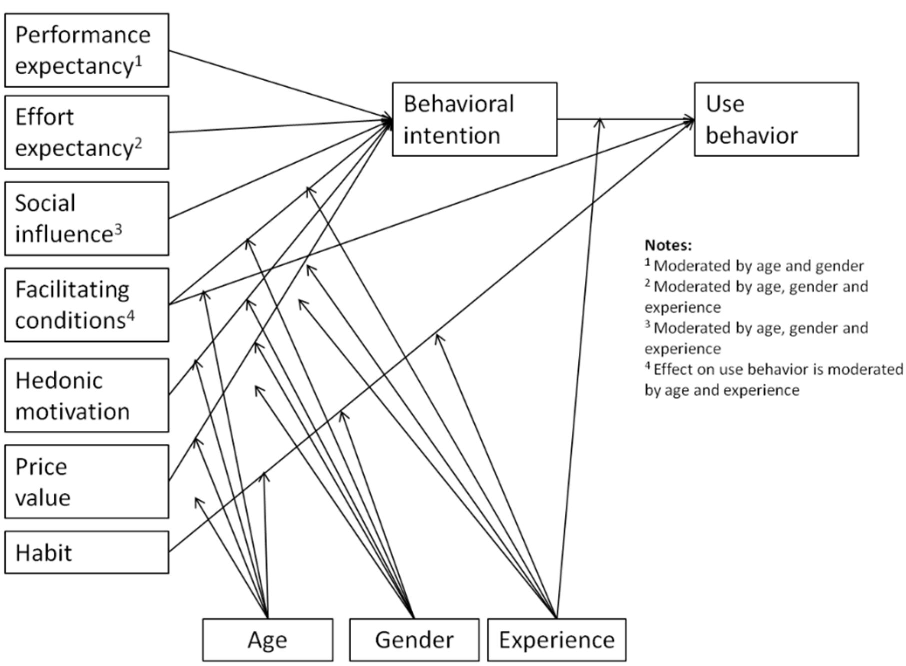
One of the most cited theories regarding the interaction between man and technology in terms on how a particular innovation is disseminated, known, used, and evaluated was developed by Rogers (1995). According to his research, people adopt an innovation based on its utility, characteristics, and their personal relative advantage. This, in turn, divides them into the following categories: (1) innovators; (2) early adopters; (3) early majority; (4) late majority; and (5) laggards. An increasingly important role is played by the mass media and (currently) the internet, which ensures the rapid spread of information about the existence and characteristics of an innovation or technology, respectively.

The Theory of Reasoned Action (TRA) and Theory of Planned Behaviour (TPB), developed by Fishbein (1979) and Ajzen (1991), brought clarifications regarding the way people think and act in various situations as influenced by their attitudes, subjective norms, and perceived behavioural control. People are more inclined to adopt a technology if they develop a positive attitude about it and if they see others using it. In addition, if people think a technology is useful and easy to use, they would be more inclined to adopt it than reject it according to the Technology Acceptance Model (TAM, Davis, 1985).

The Unified Theory of Acceptance and Use of Technology (UTAUT) emphasizes the following four factors in determining a person's intention to use a certain technology: (1) performance expectancy; (2) effort expectancy; (3) social influence; and (4) facilitating conditions. In more recent developments of this model (UTAUT2, see Figure 1), it is necessary to understand the adoption of technology by employees (as in the case of UTAUT) and consumers. Thus, use behaviour is the result of behavioural intention (mediated by age, gender, and experience) and determined by the factors from the UTAUT model (performance expectancy, effort expectancy, social influence, and facilitating condition) to which three factors were added: (1) hedonic motivation; (2) price value; and (3) habit (Venkatesh et al., 2003, 2012, 2016).

Figure 1. Original UTAUT2 model

Source: Venkatesh et al. (2012)



According to the authors of those theories, performance expectancy is defined as the belief that technology will help a person achieve their goals. On the other hand, effort expectancy refers to the perceived ease of use of technology. Both constructs are based on TAM. The social influence refers to the influence of other people on an individual's decision to use a technology. Facilitating conditions refers to the availability of organizational resources and support for using the technology. Hedonic motivation is the key to understanding why some technologies are considered fun and/or pleasant to interact with. The price value factor tells us how valuable a technology is in the eye of consumers (the lower the price of technology, the more intensive its use). Habit is defined as "the extent to which people tend to perform behaviours automatically" (Venkatesh et al., 2012, p. 161), which is in opposition with the reason-oriented framework (from TRA and TPB models).

Based on the UTAUT model, respectively the UTAUT2, other studies have been carried out (Kelly et al., 2023), the most recent of which seek to clarify the adoption of mobile banking services (Gharaibeh et al., 2018), conditionally automated cars (Nordhoff et al., 2020), mobile phones (Nikolopoulou et al., 2020), mobile health applications (Schomakers et al., 2022), AI-enabled tools (Jain et al., 2022), products that incorporate AI (Gansser & Reich, 2021), the use of mobile devices for learning (Lai, 2020), mobile 4.5G services (Daniali et al., 2022), or AI coach (Terblanche & Cilliers, 2020).

Other studies have emphasized the benefits and challenges in the adoption and use of new technologies. Among these technologies, and by far the most spectacular in evolution and which aroused public interest, are those related to the development of AI. A study by McKinsey (2020) revealed several organizational benefits, including revenue increases for inventory and parts optimization, pricing and promotion, customer-service analytics, and sales and demand forecasting, along with the optimization of talent management, call centre, and warehouse automation. Other studies have shown the benefits of using AI for the automation of processes at the municipal level (Schaefer et al., 2021) and, respectively, the development of the food supply chain (Dora et al., 2022).

The current research uses the UTAUT2 theory because it is a comprehensive model that is more adapted to the current context of technological expansion (Suo et al., 2021; Tamilmani et al., 2021). Compared with TAM, the UTAUT2 offers "a better explanation power" (Rondan-Cataluña et al., 2015), has a much higher predictive ability than other theories, and is considered useful and important for the business and academic environments (Tamilmani et al., 2021). Thus, in this study, the respondents (students) were targeted in a double role of future employees/entrepreneurs (who simulated the potential use of generative AI technology to create images for a promotional marketing campaign) and consumers (self-assessed by successively modifying the prompts before uploading their results online for the contest for the generated AI images).

The authors extended the UTAUT2 model by adding potential moderators like English language proficiency and subjects' creativity. Thus, the study attempts to close an existing gap in the literature.

Factors Influencing AI Use in Business

AI is considered one of four tools of new-age technologies (along with IoT, machine learning, and blockchain). These can be used for gaining a holistic understanding of consumer needs and behaviours (Kumar et al., 2021), personalizing their experience (Haleem et al., 2022), and having great potential for enabling marketing capabilities (Manis & Madhavaram, 2023).

AI has already boosted numerous famous businesses (Marr, 2019). In fact, it is on its way to changing entire economies and global societies (Ertel, 2019; Gupta et al., 2023; Manyika & Sneader, 2018; Pallathadka et al., 2023). For example, AI is used in retail and business-to-business (B2B) settings (e.g., JD, Alibaba, Amazon), luxury items, consumer goods, food and beverage (e.g., Burberry, Coca-Cola, McDonalds), media and social media (e.g., Netflix, TikTok, Facebook, Tencent), financial services (Mastercard, Salesforce), and the automotive industry (e.g., BMW, Tesla). Other small and large companies also try to include AI algorithms in their business to differentiate themselves from the competitors, be more efficient, and serve their customers in personalized ways (Pallathadka et al., 2023).

Studies have been developed that analyse the influencing factors of the use of technology. However, the current study looks at factors from another perspective. In the process of accepting AI generative technology in business, the individual attitude of people is not the only influencing factor. Indeed, specific factors like organizational culture (with emphasis on English proficiency in business), job roles, and job demands play a role on the acceptance of AI (IT skills and knowledge, creative skills; Imran et al., 2022).

The adoption and use of AI has profoundly transformed the relationships between companies and consumers (Haleem et al., 2022; Spada et al., 2022). It has also proven its impact on business success by significantly improving marketing practices (Sarath Kumar Boddu et al., 2022) and becoming a major survival requirement in an increasingly competitive global market (Fredström et al., 2022). Although it may seem paradoxical, some cases have shown that the technological discomfort felt by consumers has a positive influence on the adoption of AI (Flavián et al., 2022). For example, initial trust in chatbots (a newer AI technology) increases the intention to use them and encourages customer engagement (Mostafa & Kasamani, 2022).

Trust in technology (in general) is a key component of users' trust in AI applications and is the basis of their perceptions of AI (Yang & Wibowo, 2022). The novelty of this technology adds value both efficaciously and hedonistically (Jo, 2022). However, despite the already recognized potential of AI, there are problems related to the strategic use of this technology in creating business value (Borges et al., 2021; Stone et al., 2020).

Chatterjee et al. (2022) showed that the adoption of digital transformation at the enterprise level is significantly influenced by the skills and capabilities of the individuals. Huang and Rust (2021) and Peng et al. (2022) identified consumers' reluctance to accept AI (those who seem not yet ready), confirming the results of a 2019 study that revealed a reluctance and prejudice on the part of consumers toward chatbots. This occurs because potential consumers shorten their conversation and buy less product when it is known that that the interlocutor is not human (Luo et al., 2019). In addition, some consumers are concerned about the need for rules, education, and training regarding the use of AI (Kopalle et al., 2022; Vlačić et al., 2021).

Consumers believe that the use of AI in marketing communication is limited in terms of influencing product evaluation or shaping consumer behaviours (Chen et al., 2022). However, recent studies demonstrate that the use of AI positively influences consumer engagement in social media and optimizes the rate of conversion. Thus, marketers should design more interesting posts with images and videos to encourage consumers to share the content and, in turn, create new content via their social platforms (Nazir et al., 2023). Consequently, the generated content becomes an essential marketing tool with strong effects on "consumer loyalty, purchase intention and other consumer behaviors" (Ma & Gu, 2022, p. 1).

On the other hand, some studies raise questions about AI. Can we rely on AI to replace human activity and/or creativity? Can we trust that AI is doing a good job? Who will be the judge of the result (Anantrasirichai & Bull, 2022; Gobet & Sala, 2019; Griebel et al., 2020; Trajtenberg, 2019)?

Some researchers want to see more studies to gain a better understanding of human-AI interaction (Jermutus et al., 2022). AI and human intelligence must be viewed as a team in which human intelligence (marketers and consumers) uses increasingly developed AI. Thus, this collaborative intelligence can provide the highest-quality results (Huang & Rust, 2022).

For example, Bakpayev et al. (2022) showed that the use of AI is effective in the case of creating non-emotional (rational) content in advertising and for products of strict necessity. However, human intelligence is needed for the creation of emotional content. Also, Davenport et al. (2020) and Kelly et al. (2023) stated that the use of AI will be much more effective if it enhances (rather than replaces) the human factor. In fact, some cultures believe that the human presence cannot be replaced.

In the attempt to create AI-based software to be used in business, especially social media marketing, specialists have tried to identify and analyse the expectations of potential beneficiaries. They found that image analysis capabilities are considered the most important by the beneficiaries (Capatina et al., 2020). To study the effects of AI on creativity in marketing and to identify the customer journey points where AI can have the greatest impact, consideration must be given to the role and impact of different forms of AI, the national and cultural specificity, and a multi- and interdisciplinary approach (Ameen et al., 2022). Attention should also be given to socio-cultural backgrounds like age, gender, experience, fluency in expression, and creativity.

In this respect, some researchers have shown that a gender bias exists when adopting emerging technologies. This fact is due to the "lack of diversity in data and developers, the bias in society, and bias in data due to programmer conscious or unconscious bias" (Nadeem et al., 2020, p. 6).

The gender gap in digital skills has direct implications for the design and implementation of AI applications (Manasi et al., 2022). For instance, some studies based on touch gesture information in smartphone use show that smart systems can be personalized based on gender information to provide an improved user experience (Guarino et al., 2022). Likewise, it has been observed that the attitude and intention to use various applications (e.g., mobile wallets) is more pronounced in the case of men and young people (Chawla & Joshi, 2020). Gender and level of studies are also proven to be moderating factors in AI interaction in the medical field (Aboueid et al., 2019) or in differing attitudes toward the ethics of AI (Jang et al., 2022).

Also, language/English proficiency is an important factor in modelling the behavioural intention toward technology (De Jesus & Xiao, 2012; Xia et al., 2023), especially when language manipulation techniques are more used online (Fedushko & Davidekova, 2019). After age, education, and urbaneness, English proficiency is the next most important factor in the adoption and use of PIERCE technology (Pearce & Rice, 2014). Studies show that poor English skills can lead to online social exclusion, while online search results in English have a significantly higher quality than in other languages (Zoubi et al., 2022). In addition, because the AI models generating images in this study were based on the subset of English language LAION 5b, it is important to study this variable (foreign language) as a moderator in the developed model.

MATERIALS AND METHODS

Objectives and Hypothesis

Starting from the first research question (Do people intend to use AI for generating images for business purposes?), the authors provided potential business users with text-to-image AI models to unveil outcomes that define AI usage for marketing purposes. With this aim, two objectives (together with the associated hypotheses) were formulated:

O1: To validate the UTAUT2 usage for business by using text-to-image diffusion models. For this purpose, the following hypothesis was formulated:

H.1. The UTAUT2 related to text-to-image diffusion AI technology for business is valid.

O2: To identify user behaviour moderators when using text-to-image diffusion models.

Based on this objective, four hypotheses were formulated:

H2.1. Gender moderates the UTUAT2 components in the relationship with behavioural intention.
H2.2. Creativity moderates the UTUAT2 components in the relationship with behavioural intention.
H2.3. English language proficiency moderates the UTUAT2 components in relation to behavioural intention.
H2.4. Study domain affects behavioural intention.

The research method on which the study was based is mixed. It includes the direct involvement of the participants in the process of content generation (see Figure 2). The current study used the non-probability sampling method, applying a complex questionnaire that consisted of 29 questions. It was organized into several dimensions in a correlational survey suitable for the UTAUT2 analysis.

First, the recruitment and instruction of participants took place. The university where the questionnaire was applied is comprehensive, with a focus on entrepreneurship and innovation. It has nine faculties with a technical profile and nine with a socio-humanistic profile. Male students are almost on par with female students (51% males). The population is made up of 20,500 students who represent potential interview subjects. The researchers used the university's platform to invite and instruct the students as participants in a contest and survey, respectively. Data has been collected between November 2022 and January 2023. The study followed the principles of the Declaration of Helsinki. It was approved by the council of the Faculty of Economic Sciences and Business Administration after checking ethical standards for human research studies.

In the recruitment stage, the researchers sent invitations to all students. They also sent several reminders. Students received an e-mail invitation to a contest on sustainability and the use of green energy. They were asked the following question: Have you thought that you can use AI applications to generate images very easily? Before entering the contest for developing an advertisement using text-to-images diffusion models, the participants were asked to experiment with free and open-source image generative AI.

Therefore, participants played the role of test-takers. The subjects were asked to use generative AI technologies to create images for a promotional marketing campaign related to sustainability and green energy. The role of empirical tests in technology acceptance is recognized as a research method in the specialized literature (Chau, 1996; Rahman, 2016) because the obtained results can represent a starting point in the development, evaluation, validation, or rejection of certain hypotheses. These also serve for the presentation of certain limits (Bakhtiary et al., 2020; Choma et al., 2019; Nanthaamornphong & Bressan, 2019).

Afterwards, the collected data was sent to researchers. The method of collecting the content generated by the participants was based on a survey. At the end, the respondents had to upload their generated images along with the prompts used to create the images. The final sample included 403

Figure 2. Activity flow

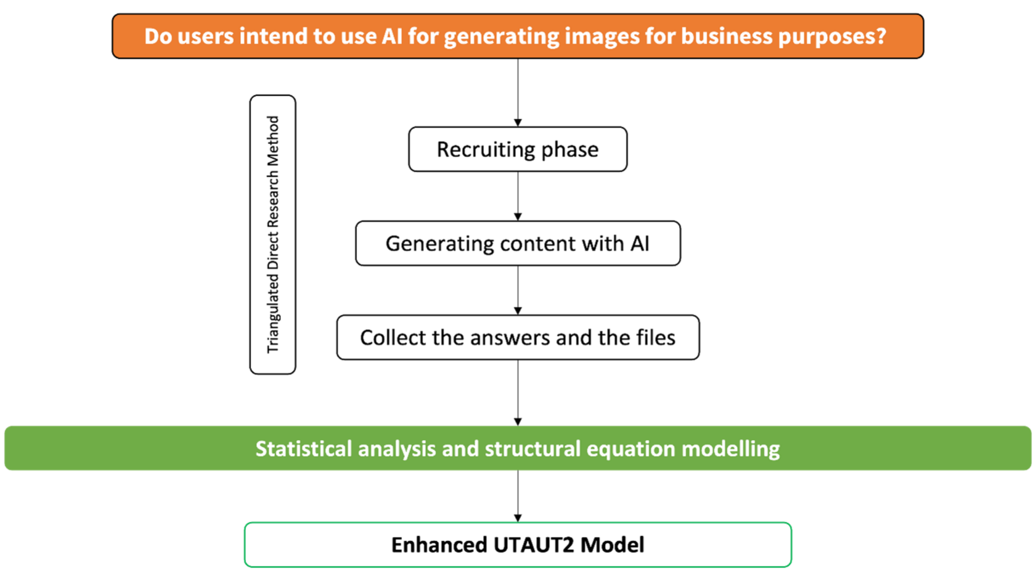


Table 1. Sample structure

Arts and Humanities (Literature, Music)	4.71%
Engineering	34.49%
Natural and Applied sciences (Chemistry, Informatics, Mathematics, Material Science)	24.07%
Social Sciences (Economics, Sociology, Psychology)	36.72%

participants (see Table 1), who filled out the survey and uploaded the generated files at the end of the survey.

Instruments

Technology Acceptance

Technology acceptance was measured using a 29-item questionnaire for the UTAUT2 (Venkatesh et al., 2012). The questionnaire included four items related to performance expectancy (the benefits consumers believe they will gain from using a specific technology to perform certain activities), four items related to effort expectancy (measuring the ease associated with technology use), four items for social influence (measuring the importance users place on the opinion of others about their use of certain technologies), four items related to facilitating conditions (consumers' perceptions of the resources and support available to them to perform online activities), three items related to hedonic motivation (fun or pleasure derived from using technology), three items related to perceived customer value (the trade-off between the perceived benefits of the applications and the cost of using them), four items related to habit (prior behaviour or the extent to which individuals believe their behaviour to be automatic), and three items related to behavioural intention (intention to use technologies in the future). The questionnaire was adapted to fit the AI art generation for advertising. It was evaluated using a five-point Likert scale. (See Appendix 1.)

Creativity

Creativity was measured using the divergent association task (Olson et al., 2021), a prompt assessment tool used to measure verbal creativity and divergent thinking. This denotes the capacity to generate diverse and distinct solutions to open-ended issues. The task involves thinking (and writing) 10 words that are as different from each other as possible. Individuals who demonstrate higher levels of creativity generally produce words with greater semantic distances. The measurement of semantic distances is inferred by examining the co-occurrence of words in similar contexts.

English Language

The English-language self-assessment was based on the Common European Framework of Reference for Languages (CEFR), which measures listening, reading, spoken interaction, spoken production, and writing (Council of Europe, 2023). It categorizes language proficiency into six levels, ranging from A1 to C2. These can be classified into three overarching levels: (1) basic user; (2) independent user; and (3) proficient user. The levels are established through descriptors of one's abilities and competencies, indicating what an individual can do with the language ("can-do" statements). The assessment was accomplished using a six-point Likert scale. (See Appendix 2.)

Socio-Demographic Data Questionnaire

This questionnaire requests the specification of the fundamental field in which the student learns (biological and biomedical sciences, engineering sciences, mathematics and natural sciences, social sciences, sports and physical education science, humanities and arts) and gender.

RESULTS: MEASUREMENT MODEL

The present study employed structural equation modelling (SEM) and the partial least squares method (PLS) to analyse data via SmartPLS (Ringle et al., 2015). Hypotheses were tested with bootstrapping of 10,000 resamples. To analyse the mediation effects, the study used a recommendation by Preacher and Hayes (2004). The results interpretation was guided by Chin (2010). The analysis of variance inflation factors (VIF) values for the assessment of multicollinearity showed VIF values lower than 1.990. This suggests that collinearity is not an issue.

Testing for bias was accomplished by using common method variance. The study first tested the model using Harman's single factor test (Chin et al., 2012), obtaining 32.89% of the total variance (lower than the 50% suggested threshold). The second test was accomplished by using VIF (Kock, 2015). All the VIF values were lower than the 3.3 suggested threshold. Based on the data from both tests, this model can be considered free of common method bias.

The study evaluated the measurement model prior to evaluating the research model. The model specified in this study has eight constructs with reflective measurements. As part of the measurement model evaluation, some items were deleted for insufficient loadings or multicollinearity: one item from social influence; one item from facilitating conditions; and one item from habit.

To test the reliability of the constructs, this study used Cronbach's alpha (CA) and composite reliability (CR). All CRs for reflective constructs were higher than the recommended value of 0.700. The CA for each reflective construct exceeded the 0.700 threshold. Average variance extracted (AVE) was also acceptable. Factor loadings for the reflective constructs are presented in Table 2.

Discriminant validity was assessed by HeteroTrait-MonoTrait (HTMT) ratio of correlations (Henseler et al., 2015), with values below the threshold of 0.90. Hence, discriminant validity is established.

Goodness of Fit

To assess the goodness of fit, the coefficient of determination (R^2), the effect size (f^2), and the predictive relevance (Q^2) were determined in the present study. The results of the analysis reveal a moderate to high R^2 value of .690 for behavioural intention, showing that 69% of the variance can be attributed to perceived customer value, effort expectancy, facilitating conditions, habit, hedonic motivation, performance expectancy, and social influence. It can also be attributed to its moderators: creativity; knowledge of the English language; study domain; and gender.

The influence of the predictor variables on behavioural intention are assessed through the *t* test (Hair et al., 2013). The results are presented in Table 3, partially confirming H1: the UTAUT2 as a valid model for text-to-image diffusion technology adoption in business.

Effect size for predictive relevance (Q^2) of behavioural intention was negative in the full moderated model, showing no predictive relevance. This happens due to the mediators. A model without them shows a Q^2 value of .601, meaning medium-to-high predictive relevance. The impact of the predictor is high at the structural level if f^2 is at least 0.35. It is medium if f^2 is 0.15 and small if f^2 is 0.02 (Cohen, 1988). The f^2 effect size for a model shows how much latent variable contributes to an endogenous latent variable R^2 value. In other words, it shows the magnitude or strength of relationship between the latent variables. The results show that f^2 effect size is negligible (see Table 4).

Apart from the mentioned statistics, standardised root mean square residual (SRMR) can be used as a measure of fit. In the present study, SRMR = 0.07, which is lower than the 0.08 (or 0.10) threshold.

Moderation Analysis and Hypothesis Testing

To test the hypothesis (H2.1 – H2.4), the study runs several mediation analyses using perceived customer value, effort expectancy, facilitating conditions, hedonic motivation, habit, performance expectancy, social influence as antecedents, and behavioural intention as effect. This also includes several moderators (see Figure 3).

Table 2. Loadings, reliability, validity

	Coef.	CA	CR	AVE
Behavioural Intention (BI)		.835	.840	.752
BI1	.873			
BI2	.864			
BI3	.853			
Perceived Customer Value (PCV)		.838	.885	.750
PCV1	.808			
PCV2	.894			
PCV3	.877			
Effort Expectancy (EE)		.766	.771	.586
EE1	.788			
EE2	.748			
EE3	.764			
EE4	.727			
Facilitating Conditions (FC)		.717	.730	.639
FC2	.708			
FC3	.836			
FC4	.825			
Habit (H)		.701	.739	.618
H1	.773			
H2	.713			
H3	.835			
Hedonic Motivation (HM)		.720	.737	.641
HM1	.744			
HM2	.865			
HM3	.767			
Performance Expectancy (PE)		.812	.814	.640
PE1	.774			
PE2	.763			
PE3	.837			
PE4	.802			
Social Influence (SI)		.717	.764	.635
SI1	.823			
SI2	.863			
SI3	.662			

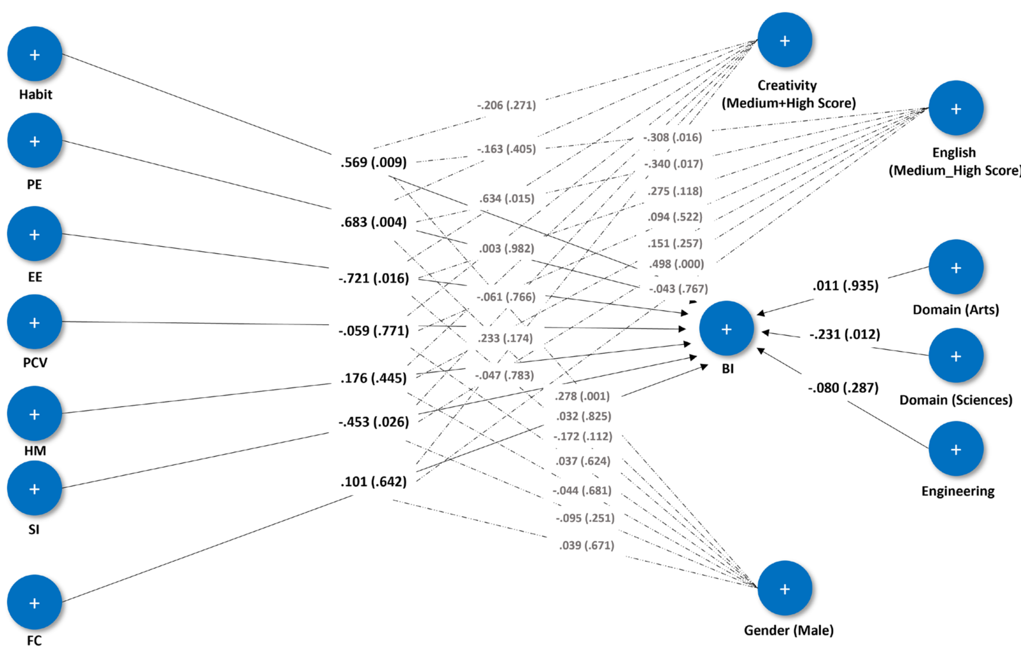
Table 3. Direct effect size

Path	Coef.	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
PCV → BI	-.045	.200	.227	.821
EE → BI	-.748	.297	2.521	.012
FC → BI	.095	.214	.442	.659
HM → BI	.175	.229	.765	.444
Habit → BI	.572	.216	2.656	.008
PE → BI	.689	.233	2.964	.003
SI → BI	-.454	.203	2.237	.025

Table 4. Explanatory power for two models: without and with moderating effects

	No Moderators				Moderators			
Path	Beta	P values	f^2	R^2	Beta	P values	f^2	R^2
PCV	.093	.012	.017	0.611	-.045	.821	.000	0.69
EE	-.030	.490	.001		-.748	.012	.032	
FC	.080	.055	.012		.095	.659	.001	
HM	.157	.002	.029		.175	.444	.002	
Habit	.328	.000	.153		.572	.008	.025	
PE	.301	.000	.108		.689	.003	.037	
SI	.094	.029	.013		-.454	.025	.023	

Figure 3. Final tested model



H2.1: Gender as a Moderator

The study assessed the moderating role of gender on the relationships between perceived customer value (PCV), effort expectancy (EE), facilitating conditions (FC), hedonic motivation (HM), habit (H), performance expectancy (PE), social influence (SI) and behavioural intention (BI). With the inclusion of just this interaction term, the R^2 was .636, showing an increase of 4.09% in the variance explained in the dependent variable (BI) over the base model. The significance of the moderating effects was also analysed. The results reveal significant interactions (see Table 5). The effect of (H) on (BI) is more pronounced for males in comparison with females (the relationship between (H) and (BI) is positively strengthened in the case of males). Other interactions could be observed in the slope analysis, showing that the negative relationship between (EE) and (BI) is stronger in the case of males. The effect size is small in one case and almost zero in the other case; thus, the study can conclude that gender plays a small but statistically significant role in the intention to use generative AI for images. H2.1 hypothesis is, therefore, partially confirmed.

H2.2: Creativity as a Moderator

The study also assessed the moderating role of creativity on the relationships between perceived customer value (PCV), effort expectancy (EE), facilitating conditions (FC), hedonic motivation (HM), habit (H), performance expectancy (PE), social influence (SI) and behavioural intention (BI) In this study, creativity is measured with the help of words. More creative people tend to think of words with greater “distance” between them. The creativity score could be classified in three categories: (1) under 50 is poor; (2) the average is between 75 and 80; and (3) 95 is a very high score (Olson et al., 2021). To identify the category each participant falls into, the study used K-means clustering with three clusters for low, medium, and high creativity. The final clusters are presented in Table 6.

With the inclusion of creativity as the unique interaction term, the R^2 was .640. This shows an increase of 4.74% in the variance explained in the dependent variable (BI) over the base model. Significance of the moderating effects was also analysed. The results reveal significant interactions. Creativity reduces the negative relationship between (EE) and (BI), making (EE) more significant

Table 5. Gender moderating effects

	Beta	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values	f^2 Effect Size
Male → BI	-.085	.067	1.261	.207	.005
Male x Habit → BI	.285	.085	3.339	.001	.026
Male x EE → BI	-.173	.108	1.606	.108	.009
Male x FC → BI	.036	.092	.397	.691	.001
Male x SI → BI	-.088	.081	1.078	.281	.003
Male x PE → BI	.036	.143	.249	.803	.000
Male x PCV → BI	.028	.076	.374	.708	.000
Male x HM → BI	-.051	.106	.480	.631	.001

Table 6. Creativity: Final cluster centers

	Cluster		
	Medium Creativity	Low Creativity	High Creativity
Creativity Score	68.30	49.81	77.79

(see Table 7). In other words, the impact of (EE) over (BI) is much stronger in case of low creativity (you must work harder for the same result). Considering only the slope analysis between the terms, other interactions occur between (PE), (H), and (SI). Creativity reduces the positive relationship between (PE) and (BI). The impact of (PE) over (BI) is stronger in the case of low creativity. Also, creativity reduces the positive relationship between (H) and (BI) (or the impact of (H) over (BI) is stronger in the case of low creativity). Finally, creativity reduces the negative relationship between (SI) and (BI). The effect size of f^2 is small in one case and almost zero in the other case; thus, the study can conclude that creativity plays a small but statistically significant role in the intention to use generative AI for images, H2.2 being partially confirmed.

H2.3: English Proficiency as Moderator

The study also assessed the moderating role of English language knowledge on the relationships between perceived customer value (PCV), effort expectancy (EE), facilitating conditions (FC), hedonic motivation (HM), habit (H), performance expectancy (PE), social influence (SI) and behavioural intention (BI). With the inclusion of this interaction term alone, the R^2 was .654. Thus, it shows an increase of 7.03% in the variance explained in the dependent variable (BI) over the base model. The significance of the moderating effects was also analysed. The results reveal significant interactions (see Table 8). The biggest effect size was observed for (SI). Medium and advanced knowledge of English language strengthens the positive relationship between (SI) and (BI). This shows that the impact of (SI) on (BI) is stronger for the participants with medium/high knowledge of English compared to the ones with lower language skills.

Table 7. Creativity moderating effects

	Beta	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values	f^2 Effect Size
Creativity → BI	.073	.140	.522	.602	.001
Creativity x PCV → BI	-.000	.147	.000	1.000	.000
Creativity x HM → BI	-.066	.205	.325	.745	.000
Creativity x EE → BI	.644	.258	2.499	.012	.033
Creativity x PE → BI	-.166	.192	.863	.388	.003
Creativity x SI → BI	.236	.170	1.386	.166	.009
Creativity x FC → BI	-.046	.167	.274	.784	.000
Creativity x Habit → BI	-.206	.186	1.106	.269	.004

Table 8. English language proficiency: Moderating effects

	Beta	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values	f^2 Effect Size
English_Intermediate_Advanced → BI	-.058	.098	.595	.552	.001
English_ Intermediate_Advanced x EE → BI	.289	.172	1.681	.093	.013
English_ Intermediate_Advanced x HM → BI	.158	.133	1.189	.235	.004
English_ Intermediate_Advanced x FC → BI	-.033	.141	.232	.817	.000
English_ Intermediate_Advanced x SI → BI	.492	.133	3.686	.000	.057
English_ Intermediate_Advanced x Habit → BI	-.316	.126	2.500	.012	.024
English_ Intermediate_Advanced x PCV → BI	.088	.147	.601	.548	.001
English_ Intermediate_Advanced x PE -→ BI	-.342	.142	2.415	.016	.025

Another weak effect (significant in one-tail analysis) was observed on the interaction on (EE) and English language strengthening the positive relationship between (EE) and (BI). This shows that the impact of (EE) on (BI) is stronger in the case of medium/high knowledge of English language. Regarding the interaction between English and (H) or (PE), both have weak but statistically significant effects on (BI). Thus, English knowledge reduces the positive relationship between (H) (or PE) and (BI). The impact of (H) (or PE) on (BI) is stronger in the case of low English knowledge. In other words, if you work harder, you will become habituated. Thus, for the future use of AI technology, English knowledge will count less. This is the same for performance expectancy. The effect size is small in one case and almost zero in the other case. Therefore, the study can conclude that knowledge of the English language plays a small but significant role in the intention to use generative AI for images. H2.3 is partially confirmed.

H2.4: Study Domain Affects Behavioural Intention

Controlling for study domain (as a proxy for experience) resulted in significant differences for the sciences domain (mathematics, informatics, chemistry, and material sciences in our university) compared to the reference domain (social sciences in our model). These students show a lower behavioural intention in comparison with the reference domain. Further, this shows that the study domain partially affects behavioural intention.

DISCUSSION

The need for a thorough understanding of the drivers behind the acceptance of image diffusion AI models in business (O1) and the moderators of user behaviour toward technology (O2) stems from the multitude of implications for the development and progress of a range of business domains. Moreover, the outcomes of the research unveiled several unexpected results that place the study as an important contribution to the theoretical lens indicating interesting aspects of AI usage in business.

According to the technology acceptance literature, behavioural intention (BI), which determines the acceptance of image diffusion AI in business, can be attributed to perceived customer value (PCV), effort expectancy (EE), facilitating conditions (FC), habit (H), hedonic motivation (HM), performance expectancy (PE) and social influence (SI). The results obtained from the research show that, in the analysed context, the statistically relevant factors are (EE) and (SI), as confirmed by other studies (Daniali et al., 2022; Lai, 2020; K. Sharma & Madan, 2022; Terblanche & Cilliers, 2020) and PE as in research conducted by Daniali et al. (2022), Gansser and Reich (2021), Lai (2020), K. Sharma and Madan (2022), and Terblanche and Cilliers (2020).

Perceived customer value was not among the statistically relevant factors. This may occur because the participants in this research have not yet identified ways in which they could use image-based AI in business. In addition, they have not identified the benefits that the use of this technology could provide in business. Hedonic motivation was not shown to be statistically significant. In the view of the current research participants, image creation is associated with art. Thus, users are not yet ready to associate art with AI although demonstrations have shown that AI can be used successfully in areas like art, including fashion or beauty (Harreis et al., 2023). Facilitating conditions were also not found to be a significant variable. It is possible that users were not properly informed that they could have access to such technologies, did not consider themselves to have the necessary knowledge to use this technology, or applications like Stable Difussion were considered difficult to use (S. Sharma et al., 2022).

At the same time, the present research studied several moderating factors related to behavioural intention to accept AI image diffusion in business. This includes gender, English language proficiency, creativity, and experience (using the year of study and specialization as a proxy).

Several studies have looked at the way in which gender affects behavioural intention related to technology and AI. Some confirm the role of this demographic variable as a moderator. A study examining the use of mobile computing devices for learning among older adults based on the relationships between performance expectancy, effort expectancy, social influence, facilitating conditions, behavioural intention, use behaviour, and the moderating effect of gender (Lai, 2020) concluded that the demographic variable of gender has a significant moderating effect between effort expectancy and the participants' behavioural intention. Another study demonstrates the moderating role of gender in the relationship between antecedents like ease of use, usefulness, trust, security, facilitating conditions, and lifestyle compatibility. One study found that the attitude and behavioural intention of mobile wallet is stronger for men (Chawla & Joshi, 2020). An analysis conducted to investigate the moderating effect of gender in relation to performance expectancy, cost, effort expectancy, and social influence showed that gender is not a moderator for students' intentions to use 4.5G mobile phones (Daniali et al., 2022). Our study's results indicate that gender plays a significant moderating role between effort expectancy, habit, and behavioural intention. The relationship between habit and behavioural intention is positively strengthened for males. This is also a stronger negative relationship between effort expectancy and behavioural intention for males.

The fact that there is a relationship between the gender of the technology user, effort expectancy, and behavioural intention has implications for the future of education and assigning tasks to workplaces. Girls are less inclined to apply for academic training in the science, technology, engineering, and mathematics (STEM) field (Chan, 2022; Vooren et al., 2022), which in the future may lead to talent shortage and/or a strong masculinization of the field of digital technologies.

Furthermore, this study shows that technologies like the one analysed assume that the user has information technology knowledge and a relatively high level of creativity. This is an aspect that syncs with current trends regarding the most requested skills, namely analytical and creative thinking (World Economic Forum, 2023b).

In this study, important results were obtained regarding users' creativity in relation with the UTAUT2 and generative AI for images. First, creativity affects performance expectancy. Low creativity moderates the impact of performance expectancy over behavioural intention. In fact, it strengthens it. The study demonstrated that creativity distorts individuals' perceptions about current performance. Thus, the case of lack of creativity generates a negative self-perception regarding the competence of solving tasks that require this type of technology, leading to the intention of not adopting it. Another finding is the identification of the impact of habit on behavioural intention. This is stronger in the case of low creativity, showing that habit plays a significant role over behavioural intention to use AI in business. Finally, the findings of the study bring fresh perspectives, stating that creativity reduces the negative relationship between social influence and behavioural intention.

An additional finding related to creativity is that it moderates effort expectancy (by decreasing it). The results generated by interpreting the relationship between effort expectancy and behavioural intention highlights that an individual with low creativity performances must compensate more in terms of the use of technology based on AI. Creativity also has a positive impact on perceived customer value, which means that the potential of AI is perceived more easily by creative human beings.

Therefore, creativity plays a small but statistically significant role in the intention to use AI technology for image generation with business purposes. This makes sense in the context of professionals who work in marketing departments and are responsible for creative components. Their skills and orientation to be open-minded determine a constant behaviour of seeking and adopting new tools (generative AI for images in this case) necessary for their creative work.

Regarding the relationship between language proficiency and acceptance of image diffusion AI in business, there is very little research to date. However, studies have found a positive relationship between effort expectancy and the intention to use technology (Moya et al., 2018). This research complements these findings, noting that the impact of effort expectancy on behavioural intention is stronger in the case of medium/high knowledge of the English language.

While other research confirms the positive relationship between habit (for internet/online use) and behavioural intention, the results obtained in the present study demonstrate that English knowledge reduces the positive relationship between (H) and (BI). The impact of habit on behavioural intention is stronger in the case of low English knowledge. The same is valid in the case of performance expectancy. The most significant result obtained is related to the positive relationship between social influence and behavioural intention, showing that the impact of social influence on behavioural intention is stronger for participants with medium/high English proficiency compared to those with lower English proficiency.

The fact that technology acceptance is related to English/language proficiency is also explained by the fact that people make decisions (sometimes "unconsciously") regarding their courses of action. What they are going to do is influenced by how much effort they think they must put in, conditioned by how fluent they think their course of action will be (Johnson, 2021).

The fact that the emerging digital technologies support the English language is an aspect that resonates with the need for the social and economic transformation toward digitalization to be sustainable and inclusive. In this sense, we are witnessing the emergence of new applications that make it possible to easily use any language for AI image generation apps in business. These are the so-called Large Language Models (LLMs), which allow the automatic generation of text needed for image generation applications. One such combination is between ChatGPT and Stable Diffusion (Jin & Song, 2023).

Regarding student specialization, students from the science domains show a lower behavioural intention to use AI image generation applications in business. This may be because the students have not found relevant application domains in business as compared with social sciences students. On the other hand, students in the engineering and arts domains could more quickly identify practical applications of image diffusion AI technology to replace or augment human actions or expertise.

This study presents new information to a dynamic and innovative field, addressing reasons to accept AI image diffusion technology in business.

CONCLUSION

This article aims to contribute to the field by examining the factors that drive the acceptance of image diffusion AI models in business. It also investigates the moderators that influence user behaviour toward this technology. It specifically focuses on understanding the reasons behind the acceptance and intention to use AI-generated images, emphasising factors like perceived customer value, ease of use, resource availability, habit, and social influence. Finally, the study explores how moderators like gender, English language proficiency, creativity, and experience impact users' intentions to use these systems. By analysing these factors and moderators, the article provides novel insight into the acceptance and usage of AI-generated images, particularly in a business context.

Moreover, the study has several valuable scientific and practical implications. From a scientific point of view, the study facilitates a better understanding of the factors that contribute to the adoption of an emerging technology, adding new moderators to the UTAUT2 model. First, the novelty of the research enriches the literature by contributing real insight into the use of AI for business purposes from a practical point of view, emphasising the moderator role of creativity and English language fluency. Second, the results help the academic environment better understand curricular aspects that need attention to enhance the professions of the future. It also helps managers outline business models and strategies in an increasingly digitized world.

Implications for the Academic Environment

Factors like perceived customer value, facilitating conditions, and hedonic motivation can influence the intention to adopt and use AI technology for generating images. There are significant benefits of using AI from the academic point of view. First, there can be improved learning outcomes. For instance, by generating information in a visual format, students will gain a deeper understanding of various theoretical concepts. A second benefit is increased clarity and communication. Academics can identify patterns, trends, and insights within data. It can also communicate research findings more clearly and effectively by presenting complex data in an easy-to-understand visual format. Consequently, AI diffusion images can enhance communication and facilitate knowledge transfer. However, special attention should be paid to intellectual property rights. A third benefit is the saving of time. By automating tasks like chart visualization, students and professors will save time that can be allocated to other academic activities. Finally, students can gain a significant competitive advantage by learning how to use AI diffusion technology in an effective manner. Students can apply for better job opportunities because jobs in the AI context require more creative skills and critical thinking capabilities (World Economic Forum, 2023).

To increase the behavioural intentions for using AI diffusion image technology by looking at facilitating conditions, universities should provide adequate resources and equitable access to the necessary hardware equipment, software licences, and other resources needed to use AI diffusion image technology effectively. Likewise, universities should offer technical support (a helpdesk or other support system) to academics who are using AI diffusion image technology. Also, universities should offer training (workshops and online courses) to ensure academics have the skills and knowledge to use AI diffusion image technology effectively. Equally important, universities should create a supportive environment, offering incentives to encourage the use of AI diffusion image technology. Finally, in this context, it is crucial for universities to pay attention to legal stipulations in the domain of intellectual property rights protection concerning the image generating process for educational purposes (European Parliament, 2023; Księżak & Wojtczak, 2023).

In the end, universities that provide easy-to-use open-source tools and reliable technical supports will facilitate future specialists with emerging technologies. Thus, the perceived value of AI diffusion technology can be increased, leading to greater adoption and use among students.

Of course, there is another critical issue that must be addressed, namely the collaboration between universities and the business environment. To remain relevant and increase perceived customer value for future specialists, universities should consider the development of technologies and future professions required by the labour market. Thus, universities should adapt the development of curriculum (Shewakena Tessema, 2017) to include elements related to the economic utility of AI software-generating images in various disciplines. In this way, future specialists will have a better perception of the valuable knowledge and use of the technology.

In addition, hedonic motivation may play a role in the adoption and use of AI diffusion technology. For instance, some students may find technology enjoyable or entertaining to use. For that, the universities should design course content in a way that is visually appealing, interactive, and enjoyable to use. This can include incorporating engaging features like animation, interactive elements, contests, and gamification. Additionally, providing opportunities for students to experiment and play with the technology can foster a sense of curiosity and exploration. This will, in turn, increase hedonic motivation and lead to greater adoption or use.

Interaction with AI image diffusion technology requires proficiency in the English language and a highly creative personality. Thus, interested students and professors should be offering courses in creative writing in English (as an organizational incentive) for a better adaptation to the future labour market requests. Manyika et al. (2017) illustrated that “automation and AI will lift productivity and economic growth, but millions of people worldwide may need to switch occupations or upgrade skills” (p. X). Therefore, creative people (e.g., artists, designers, entertainers, and media workers) need to invest in lifelong learning programs to stay relevant within the labour market. For example, healthcare specialists will be able to work with AI-generated images if they receive proper training. Plus, future engineers can analyse and better understand how complex systems like a car or aircraft perform under tremendous stress.

Sustainable human activity is an important long-term goal across the globe. Future environmental specialists could use AI-generated images to better understand trends and potential threats caused by certain phenomena. They can also detect threats that are considered “critical for ensuring the security of users and preventing suspicious activities" (Fkih & Al-Turaif, 2023, p.39). Lastly, legal specialists can use AI-generated images to understand criminal patterns and crime scenes. In turn, they can contribute to public safety improvements.

Universities must consider both ethical and legal aspects related to the use of AI. Teachers need to understand and convey clear information about how AI works and influences decision-making processes. Students must be taught to use this technology responsibly, treating it as an advantageous tool with limitations. AI needs to be presented to students as a resource to help in making decisions without replacing human judgment.

Implications for Businesses

Generative AI images refer to the use of AI-powered visual representations (e.g., charts, graphs, and dashboards) to analyse and communicate complex data in a concise manner. These images can be used by managers in their organizations in a variety of ways to improve decision-making processes, increase efficiency, and enhance overall performance.

Managers can make more informed decisions by using AI-generated images to analyse large amounts of data quickly and easily. Charts and graphs can be used to identify trends, patterns, and outliers that may be hard to identify. Managers can track and monitor key performance metrics (e.g., sales, revenue, profit, cash-flow, and customer satisfaction) by using AI-generated dashboards to view real-time data and identify areas for improvement in more creative ways. They can also use visual representations to analyse data and identify patterns that may indicate potential risks for their organizations. At the same time, they can forecast future trends by analysing patterns. Equally important, they can use visual representations to present data in a way that is easy to understand for all stakeholders.

Text-to-image AI technology has the power to modify traditional business models in various ways because "Stable Diffusion technology will enable billions of individuals to produce beautiful works of art in a few seconds" (Syed sha et al., 2023, p.1). Businesses like those in the tourism and advertising sectors can rely on this powerful tool for presenting a more appealing product. Likewise, companies in various domains can involve customers in the co-creation of their product or service through AI-generated images (Sjödin et al., 2021). Furthermore, a company manager can improve customer experience by providing personalized and relevant content based on visual searches. This may, in fact, lead to a cost reduction due to the possibility of automating image-related tasks that would require human intervention.

Some companies will take the opportunity to monetize the result of AI by including AI-generated images in books, albums, or personalized advertising materials. The fashion industry will be one of the early beneficiaries of this new technology, enriching the creation process with the help of AI agents. Human fashion creators will obtain a boost in content development, styling recommendations, and the customer's ability to try on clothing online (Harreis et al., 2023).

There are many possible economic applications of AI-generated images with respect to improving our way of living and learning. Basarir-Ozel et al. (2022) stated that a key driver of smart home technology adoption is image, which is linked to prestige and social recognition. With the help of AI technology, for example, it is possible to generate a revolutionary and unique design for home appliances that will create a desired image for the customer.

Museums and anthropologists could also benefit from the development of AI image technology in generating images based on text description and images from historical documents to make their activity more attractive and understandable for the public (Taormina & Baraldi, 2022). Educational companies have already taken advantage of AI diffusion technology by using online applications to help people learn words in a new language via AI-generated images. Other companies are developing AI design software platforms for video game images or providing support that will enhance mental health via AI-generated images (Lian et al., 2023).

However, not only small and innovative companies are benefiting from the adoption of this technology. Google announced that it would use diffusion technology for boosting its business (Elias, 2023). Other uses could be related to graphic design (e.g., Adobe Firefly) or the generation of videos based on prompts (e.g., Meta and other newcomers).

Managers have a lot of opportunities to develop businesses or boost traditional businesses. Still, with great opportunity comes great risk, including the use of emerging technology. For instance, jobs will be lost, and people will be deceived through fake news in mass media. There are concerns about privacy, bias, and discrimination based on using AI-generated images. Therefore, companies should develop adequate, ethical strategies to deal with such issues.

Overall, the use of AI image diffusion in business and academia requires cautious and careful assessment of potential risks. It must also consider the benefits and limitations of the technology. It is important, therefore, to approach the use of AI-powered images in a responsible, legal, and ethical manner. Both for business and academia, it is important to develop qualitative research to navigate the motivation for use and source of barriers in case of rejection of AI use.

Limits and Future Research Directions

Regarding limitations, the current study's sampling method is non-probabilistic. Thus, bias or issues related to sampling may exist. Despite the limits, the method in the study presents advantages in obtaining the results necessary to explain behaviours related to technology (e.g., low cost of applying, efficient feedback). Sampling methods represent research methods for relevant studies in the field, especially in the case of observational analysis (Altmann, 1974; Damilola Akinyemi & Williams Onifade, 2023).

Another limit is represented by the relatively small sample (considering the size of the population to be researched and length of the data collection period). Regarding the use of the UTAUT2 model, there is a risk of speculation about the predictive power of each theory. This is due to a lack of testing and comparison of empirically dominant models of technology acceptance.

Although probabilistic sampling is not used, the study used a volume of the sample relevant for the generation of research directions in the future. Also, the study performed a sample validation with t-Student test. This is similar to the structure of the university.

The researchers acknowledge the potential for bias due to relying on self-reported data. Therefore, they consider the importance of incorporating alternative data collection methods to enhance the validity of the findings. Recommended approaches include user engagement metrics and business impact indicators. By including objective measures of user engagement (e.g., click-through rates, dwell time, or interaction patterns with AI-generated images, measured using A/B testing perhaps, or social sharing), the study can obtain quantitative insights into how users perceive and engage with the content. These metrics provide valuable data that is less susceptible to response bias and subjective interpretations. Additionally, incorporating business impact indicators like conversion rates, sales revenue, customer satisfaction scores, or market performance metrics (e.g., for Web pages that incorporate AI-generated images) allows for an objective assessment of the tangible effects of AI-generated images on business outcomes. By integrating these objective measures along self-reported data, research can provide a more comprehensive and reliable analysis regarding the adoption of AI for image generation in business contexts. It will also minimize potential biases associated with self-reporting alone.

Future research could broaden the scope of the current study within the business domain by examining factors that drive the application of AI among employees across various fields. It could also investigate specific business sectors that adopt AI-generated images. Another opportunity could focus on the ethical, legal, and social implications associated with the acceptance and use of AI-generated images in business settings. Areas of interest may include managerial accountability, data privacy, bias mitigation, and decisional transparency.

Considering existing concerns regarding human-AI interaction, a research direction worth exploring would involve studying how individuals interact with this emerging technology in terms of trust, collaboration, and communication. In addition, it would be valuable to investigate the ways in which the decision-making process can be enhanced to uncover new business opportunities while accounting for variables like cultural background.

Creativity is the most human characteristic. Therefore, future research could explore the potential of AI-generated images when investigating the recognition of emotions and its use in domains like psychology, psychiatry, marketing, and entertainment.

Finally, a future research direction could investigate how algorithmic creativity can allow us to push the boundaries of classic artistic practices. We need to put more effort into adapting to a market in which businesses align with the characteristics of Industry 5.0 (Akundi et al., 2022; Rožanec et al., 2022). This need, in turn, complies with the current research results. People with high creativity performance will interact seamlessly with AI technologies in business processes as compared to those with low levels of creativity.

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APPENDIX 1

Answer the following questions about how you have used and currently use artificial intelligence (AI) applications for generating images for advertisements (AI_Art).
1 = strongly disagree, 2 = disagree 3 = neither disagree nor agree, 4 = agree, 5 = strongly agree

Performance Expectancy

PE1. I find AI_Art for advertising useful in my daily life.
PE2. Using AI_Art for advertising increases my chances of achieving things that are important to me.
PE3. Using AI_Art for advertising helps me accomplish my goals more quickly.
PE4. Using AI_Art for advertising increases my productivity.

Effort Expectancy

EE1. It is easy for me to learn how to use AI_Art for advertising.
EE2. I clearly understand how to use AI_Art for advertising.
EE3. Using AI_Art for advertising is simple for me.
EE4. I can easily develop my skills in AI_Art for advertising.

Social Influence

SI2. People who are important to me think I should use AI_Art for advertising.
SI1. People who influence my behaviour think I should use AI_Art for advertising.
SI3. My colleagues help me in using AI_Art for advertising.
SI4. In general, the university uses research and resources to support the use of AI_Art for creating advertisements.

Facilitating Conditions

FC1. I was told where I can find the resources needed to use AI_Art in making advertisements.
FC2. I have the knowledge I need for using AI_Art for advertising.
FC3. AI_Art for advertising is compatible with other technologies/applications that I use.
FC4. I can get help from others when I have difficulties using AI_Art for advertising.

Hedonic Motivation

HM1. It is easy to use AI_Art to make advertisements.
HM2. It is nice to use AI_Art for making advertisements.
HM3. It is fun to use AI_Art to make advertisements.

Perceived Customer Value

PCV1. I think I understand the advantages of my advertising team's use of AI_Art for making advertisements.

PCV2. My colleagues and I would benefit from using AI_Art for making advertisements.
PCV3. My colleagues and I can use AI_Art to make advertisements on various devices.

Habit

H1. Using AI_Art to make ads has become a habit for me.
H2. I feel addicted to using AI_Art for making advertisements.
H3. I feel like I need to use AI_Art for making advertisements.
H3. I use AI_Art for making advertisements without problems.

Behavioural Intention

BI1. I plan to continue using AI_Art for making advertisements.
BI2. I will try to use AI_Art regularly for making advertisements.
BI3. I intend to continue to use AI_Art frequently for advertising.

APPENDIX 2

Indicate the level at which you think you are currently for each of the following five language skills for English.

Listening (Levels)

- (A1) I can recognise familiar words and very basic phrases concerning myself, my family and immediate concrete surroundings when people speak slowly and clearly.
- (A2) I can understand phrases and the highest frequency vocabulary related to areas of most immediate personal relevance (e.g., very basic personal and family information, shopping, local area, employment). I can catch the main point in short, clear, simple messages and announcements.
- (B1) I can understand the main points of clear standard speech on familiar matters regularly encountered in work, school, leisure, etc. I can understand the main point of many radio or TV programmes on current affairs or topics of personal or professional interest when the delivery is relatively slow and clear.
- (B2) I can understand extended speech and lectures and follow even complex lines of argument provided the topic is reasonably familiar. I can understand most TV news and current affairs programmes. I can understand the majority of films in standard dialect.
- (C1) I can understand extended speech even when it is not clearly structured and when relationships are only implied and not signalled explicitly. I can understand television programmes and films without too much effort.
- (C2) I have no difficulty in understanding any kind of spoken language, whether live or broadcast, even when delivered at fast native speed, provided I have some time to get familiar with the accent.

Reading

- (A1) I can understand familiar names, words and very simple sentences, for example on notices and posters or in catalogues.

- (A2) I can read very short, simple texts. I can find specific, predictable information in simple everyday material such as advertisements, prospectuses, menus and timetables and I can understand short simple personal letters.
- (B1) I can understand texts that consist mainly of high frequency every day or job-related language. I can understand the description of events, feelings and wishes in personal letters.
- (B2) I can read articles and reports concerned with contemporary problems in which the writers adopt particular attitudes or viewpoints. I can understand contemporary literary prose.
- (C1) I can understand long and complex factual and literary texts, appreciating distinctions of style. I can understand specialised articles and longer technical instructions, even when they do not relate to my field.
- (C2) I can read with ease virtually all forms of the written language, including abstract, structurally or linguistically complex texts such as manuals, specialised articles and literary works.

Spoken Interaction

- (A1) I can interact in a simple way provided the other person is prepared to repeat or rephrase things at a slower rate of speech and help me formulate what I'm trying to say. I can ask and answer simple questions in areas of immediate need or on very familiar topics.
- (A2) I can communicate in simple and routine tasks requiring a simple and direct exchange of information on familiar topics and activities. I can handle very short social exchanges, even though I can't usually understand enough to keep the conversation going myself.
- (B1) I can deal with most situations likely to arise whilst travelling in an area where the language is spoken. I can enter unprepared into conversation on topics that are familiar, of personal interest or pertinent to everyday life (e.g., family, hobbies, work, travel and current events).
- (B2) I can interact with a degree of fluency and spontaneity that makes regular interaction with native speakers quite possible. I can take an active part in discussion in familiar contexts, accounting for and sustaining my views.
- (C1) I can express myself fluently and spontaneously without much obvious searching for expressions. I can use language flexibly and effectively for social and professional purposes. I can formulate ideas and opinions with precision and relate my contribution skilfully to those of other speakers.
- (C2) I can take part effortlessly in any conversation or discussion and have a good familiarity with idiomatic expressions and colloquialisms. I can express myself fluently and convey finer shades of meaning precisely. If I do have a problem I can backtrack and restructure around the difficulty so smoothly that other people are hardly aware of it.

Spoken Production

- (A1) I can use simple phrases and sentences to describe where I live and people I know.
- (A2) I can use a series of phrases and sentences to describe in simple terms my family and other people, living conditions, my educational background and my present or most recent job.
- (B1) I can connect phrases in a simple way in order to describe experiences and events, my dreams, hopes and ambitions. I can briefly give reasons and explanations for opinions and plans. I can narrate a story or relate the plot of a book or film and describe my reactions.
- (B2) I can present clear, detailed descriptions on a wide range of subjects related to my field of interest. I can explain a viewpoint on a topical issue giving the advantages and disadvantages of various options.

- (C1) I can present clear, detailed descriptions of complex subjects integrating sub-themes, developing particular points and rounding off with an appropriate conclusion.
- (C2) I can present a clear, smoothly flowing description or argument in a style appropriate to the context and with an effective logical structure which helps the recipient to notice and remember significant points.

Writing

- (A1) I can write a short, simple postcard, for example sending holiday greetings. I can fill in forms with personal details, for example entering my name, nationality and address on a hotel registration form.
- (A2) I can write short, simple notes and messages relating to matters in areas of immediate needs. I can write a very simple personal letter, for example thanking someone for something.
- (B1) I can write simple connected text on topics which are familiar or of personal interest. I can write personal letters describing experiences and impressions.
- (B2) I can write clear, detailed text on a wide range of subjects related to my interests. I can write an essay or report, passing on information or giving reasons in support of or against a particular point of view. I can write letters highlighting the personal significance of events and experiences.
- (C1) can express myself in clear, well- structured text, expressing points of view at some length. I can write about complex subjects in a letter, an essay or a report, underlining what I consider to be the salient issues. I can select style appropriate to the reader in mind.
- (C2) I can write clear, smoothly flowing text in an appropriate style. I can write complex letters, reports or articles which present a case with an effective logical structure which helps the recipient to notice and remember significant points. I can write summaries and reviews of professional or literary works.

Source: https://rm.coe.int/CoERMPublicCommonSearchServices/DisplayDCTMContent?documentId=090000168045bb52

Accordingly, for the five self-evaluation questions, the maximum points were 30, approximatively the same as C2. Users who self-evaluated with a score lower or equal than 12 were classified as “Low proficiency”, while users with a score higher than 13 as “medium and high proficiency” in English.

Mapping between the CEFR English levels and scores was accomplished using the following table

CEFR	EF (Points) (https://www.efset.org/english-score/)
A1 Beginner	11 - 30
A2 Elementary	31 - 40
B1 Intermediate	41 - 50
B2 Upper Intermediate	51 - 60
C1 Advanced	61 - 70
C2 Proficient	71 - 100

Catalin Ioan Maican has teaching and research interests in business information systems and computer programming. He is a passionate user and supporter of open source software. He owns Interactivia.ro, an interactive application for teaching and enhancing general culture.

Silvia Sumedrea is a management professor with research interest in the organizational development in the 4.0 Industry era.

Alina Tecau is a university professor, qualified in the field of marketing studies and has experience in marketing research. Her research interests include sustainability and she is particularly focused on sustainability in education, work and tourism. She published several articles and papers on these topics in reputed academic journals.

Eliza Nichifor is Exploring Academic World to inhale scientific knowledge and exhale opportunities for enterprises' growth strategy. Believing in shifting from the mind-blowing outputs of research to the best solutions for businesses. Demonstrating high interest in online communication through artificial intelligence, customer journey and touchpoints, customer experience, mobile page speed and connected customer behaviour in the digital age. This concern led her to teach students Cybermarketing, Information Technology, and Marketing at Transilvania University of Brasov Faculty of Economic Sciences and Business Administration. She is the project manager of a research project financed by the University and author and co-author of several scientific articles related to digital marketing, technology, and consumer behaviour.

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