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Trust in AI-augmented design: Applying structural equation modeling to AI-augmented design acceptance

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ABSTRACT

With the emergence of Artificial Intelligence (AI) 2.0, computers are now equipped with new creative capabilities and are playing an increasingly significant role in design. The use of AI augmentation has the potential to enhance design performance, however, there is limited research on the acceptance of AI-augmented design. The research gap under consideration in this study is addressed by presenting an acceptance model designed for AI-augmented design. This model integrates a range of variables including perceived privacy risk, enjoyment, perceived value, perceived usefulness, perceived ease of use, perceived behavioral control, social influence, and behavioral intention. The proposed model was validated through a questionnaire survey of 249 designers in China.

The results reveal that enjoyment, perceived value, perceived ease of use, perceived behavioral control, and social influence have a significant positive impact on users' intention to use AI-augmented design, while perceived privacy risk has a significant negative impact. Perceived value was found to mediate the relationship between enjoyment and behavioral intention, while perceived behavioral control play a mediation role in the relationship between social influence and behavioral intention.

In conclusion, this study highlights the variables that influence the acceptance of AI-augmented design and provides valuable insights into the potential benefits and drawbacks of integrating AI technologies in design. The proposed acceptance model serves as a framework for future research in this area and can guide the development of more user-friendly and effective AI-augmented design tools and technologies.

1. Introduction

Innovation plays a critical role in shaping a nation's strategic advantage. Creativity research has the potential to enhance the inventive capacity of individuals, the technological advancement capabilities of enterprises, and the strategic technological and scientific power of the nation. Design intelligence, an essential field of artificial intelligence (AI), concentrates on integrating creativity, intelligent models, and algorithms into the design process. It has emerged as a major force propelling design research forward. Design intelligence can address challenges that arise throughout the design process and leverage AI techniques to generate innovative solutions [1].

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In accordance with the “three creative processes that can be modeled in AI” [2], namely exploratory, transformative, and combinatorial creativity, researchers have devised a range of design intelligence algorithms within the field of design research. These algorithms serve to aid designers in tasks such as user needs analysis [3–9] ideation support [10–14], intelligent content generation [15–19], and design evaluation [20,21,22]. The realm of AI-augmented design incorporates various key techniques, including machine learning, natural language processing, computer vision, and generative design.

The integration of artificial intelligence (AI) into design processes yields numerous advantages, including enhanced efficiency, accuracy, and creativity [23,24]. With AI augmented, designers can address knowledge limitations and generate a larger number of design options in a shorter time, while also being able to evaluate and optimize designs based on multiple criteria [25]. AI-based creative design systems have also proven to be useful in commercial applications [26], allowing for the production of large numbers of designs that can be quickly and easily selected by users. Moreover, artificial intelligence (AI) plays a pivotal role in augmenting the capabilities of enterprises [27–31], particularly in the realm of Business Intelligence. The deployment of Business Intelligence tools, such as data warehouses [27,28] and accounting information systems [29,30], aids business organizations in streamlining operations, monitoring performance, conducting competitive data analysis, scrutinizing consumer behavior, identifying challenges, and forecasting success.

Nonetheless, the degree of trust that designers place in AI-augmented design systems constitutes a pivotal factor capable of exerting a substantial influence on the ultimate application outcomes [32–34]. The lack of transparency and interpretability of AI algorithms can lead to mistrust and ethical concerns, thereby limiting the ability of AI to assist designers effectively. It is only when trust is established throughout the stages of development, deployment, and utilization that societies can achieve the full potential of AI [35,36]. To address this issue, we aim to conduct an in-depth study that examines the relationship between user trust and AI-augmented design, as well as the variables that influence the trust.

In this study, a systematic literature review was conducted to comprehensively delineate the factors influencing trust in AI-augmented design. Subsequently, a comprehensive structural equation model was formulated to assess the impact of each factor on behavioral intention. Empirical validation and discussion of this hypothesis were performed through empirical research. The subsequent sections of this paper are organized as follows: Section 2 offers an exhaustive review of pertinent theories in the domain of technology acceptance. Section 3 introduces a structural equation model tailored specifically to Trust in AI-augmented design and presents empirical findings. The conclusions and discussions stemming from the empirical research are presented in Sections 4 and 5 of this paper. Finally, in Section 6, concluding remarks are provided along with an exploration of potential avenues for future research.

The results of this study will provide valuable insights for design practice, software developers, and corporate investors on how to improve trust in AI- augmented design systems. Through our research, we aim to contribute to a better understanding of how trust can be established in AI-augmented design and to provide practical guidance on its implementation.

2. Literature review

Technology Acceptance Model (TAM) [37], Value-based Adoption Model (VAM) [38], Theory of Planned Behavior (TPB) [39], and Unified Theory of Acceptance and Use of Technology (UTAUT) [40] are the four most widely used models in the field of consumer acceptance and trust of new technologies. Among them, TAM is the most influential [41] and robust model [42,43], has been widely used to explain user behavior intentions in areas such as automated vehicles [44], intelligent medical systems [45,46], Web 3.0-based intelligent learning environments [47], intelligent advertising systems [48], intelligent robots [49], smart wearable devices [50–52], business intelligence systems [53], smart health monitoring systems [54], smart home services [55], smart phone credit cards [56], accounting information systems [29,30], and other areas of user behavior intentions. The VAM model has been used to explain the user behavior intention of IPTV adoption [57], mobile payment acceptance [58], smart home services acceptance [55], and so on. TPB is used to describe the use of wearable devices [59,60], smart home services [61], mobile data services [62], health cloud systems [46], smart gaming services [63], intelligent transportation systems [64,65], and automated vehicles [44]. User acceptance of smart medical systems [66–68], wearable devices [69,70], smart recommendation systems [71,72], and virtual reality education systems [73] are explained using UTAUT.

It should be noted that there are similar variables in these theoretical models (e.g., Perceived usefulness in TAM is similar to performance expectancy in UTAUT and usefulness in VAM; Perception ease of use in TAM is similar to effort expectancy in UTAUT, etc.). To address this issue, we aim to incorporate the factors from previous models and investigate designers’ trust in the context of AI-augmented design.

TAM derives from the Theory of Reasoned Action (TRA) [37,74]. According to the TAM hypothesis, Perceived usefulness (PU) and perceived ease of use (PEoU) are major determinants of behavioral intention (BI), with PEoU having a greater influence on BI than PU. Furthermore, scholars across diverse academic domains have developed various extended TAM models. Within these extended models, researchers have introduced novel technological constructs tailored to the unique characteristics of their respective research domains. These include constructs such as perceived privacy risk [41], compatibility [51,75], self-efficacy [75], visual attractiveness [51], health concern [60], and others.

The VAM model is an evolution of the TAM-based model that retains the VAM effects while adding enjoyment (Enj) and perceived fee (PF) [38] to describe the effect of information and communication technologies on user acceptance from a cost-benefit perspective. According to the VAM model, perceived value (PV) mediates individual decision making and influences people’s assessment of their willingness to adopt new technologies. However, due to the diversity of software and platforms, it is challenging for customers to have a consistent perception of technology and cost in AI-augmented design research.

Similarly, TPB is an extended model based on TRA that introduces the constructs of perceived behavioral control (PBC), attitude

(A), and subjective norms (SN) to explain behavioral intention [39]. All three of these factors have a significant influence on behavioral intention. Although similar to PU in TAM, PBC is more concerned with ease of use and access to the system itself [76]. TPB has been used to examine the impact of external factors, such as social factors, on the acceptance of innovative products.

UTAUT is a more integrated definition of technology acceptance theory based on theories such as TRA, TAM, and TPB [40]. It considers the impact of individual perspectives on technology, as well as social and environmental factors. Performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitation conditions (FC) are the variables included in UTAUT.

While there are similarities among the variables in these theoretical models, specialized research models should be selected or established based on the topic under investigation [77,78].

3. Materials and methods

3.1. Model hypothesis

In order to obtain a comprehensive understanding of the important influencing variables mentioned above, this study conducted an in-depth analysis of all measurement items through literature review, pre-experiment, and expert focus group discussions. Finally, seven important independent variables were selected to investigate their relationship with behavioral intention, as shown in Table 1. (1) In accordance with the TAM model, this study adopted the two influencing criteria of perceived usefulness (PU) and perceived ease of use (PEoU) as important variables. (2) The designer's assessment of the basic circumstances of AI, such as knowledge, competence, and technology, were considered important factors, and as such, perceived behavioral control (PBC) from the TPB model was used to define this independent variable. (3) Privacy is one of the essential elements influencing users' behavioral intentions in the digital era, especially in the context of intelligence [79,80], and thus, perceived privacy risk (PPR) was included as one of the independent variables in this study. (4) Enjoyment (Enj), as one of the main variables of the VAM model, was included in this study as it focuses on the value and enjoyment provided to users when adopting new technologies. (5) As an emerging technology, external factors have a greater impact on its acceptance, and thus, social influence (SI) must also be considered. (6) Perceived value (PV) is the overall evaluation of product utility formed by consumers based on their perceptions of benefits and payoffs [81–84], and usually value perception changes consumers' behavioral intentions. Therefore, PV can be used as a mediating variable to moderate the relationship between Enj and BI.

Based on the identified variables and the four models mentioned above, this experiment presents the following experimental hypotheses (Fig. 1).

According to the TAM model, PU and PEoU are significant predictors of BI, with PU mediating the influence of PEoU on BI, although the mediation is insufficient. Therefore, we hypothesize that.

H1. *PU has a significant positive effect on BI.*

H2a. *PEoU has a significant positive effect on BI.*

H2b. *PU as a mediating variable moderates the effect of PEoU on BI.*

In addition, PPR is a significant predictor of BI in the extended TAM. Therefore, we hypothesize that

H3. *PPR has a significant negative impact on BI.*

According to the TPB model, PBC and subjective norms (SN) are significant predictors of BI, with social influence (SI) from UTAUT being related to SN. Hence, we declare that

H4. *PBC has a significant positive effect on BI.*

H5a. *SI has a significant positive effect on BI.*

H5b. *PBC as a mediating variable moderates the effect of SI on BI.*

According to the VAM model, Enj is a significant predictor of PV, and PV mediates the effects of Enj on BI. Therefore, we consider that

Table 1
Variables and their literature sources.

No.	Variables		Model	Literature sources
1	PU	perceived usefulness	TAM	Davis, 1989 [37]
2	PEoU	perceived ease of use	TAM	Davis, 1989 [37]
3	PBC	perceived behavioral control	TPB	Ajzen, 1991 [39]
4	PPR	perceived privacy risk	Extended TAM	Kalantari&Rauschnabel, 2018 [41]
5	Enj	enjoyment	VAM	Yang et al., 2016 [51]
6	SI	social influence	UTAUT	Venkatesh et al.c, 2003 [40]
7	PV	perceived value	VAM	Kim et al., 2007 [38]
8	BI	behavioral intention	TAM,PBC,UTAUT	Davis, 1989 [37], Ajzen, 1991 [39], Venkatesh et al., 2003 [40]

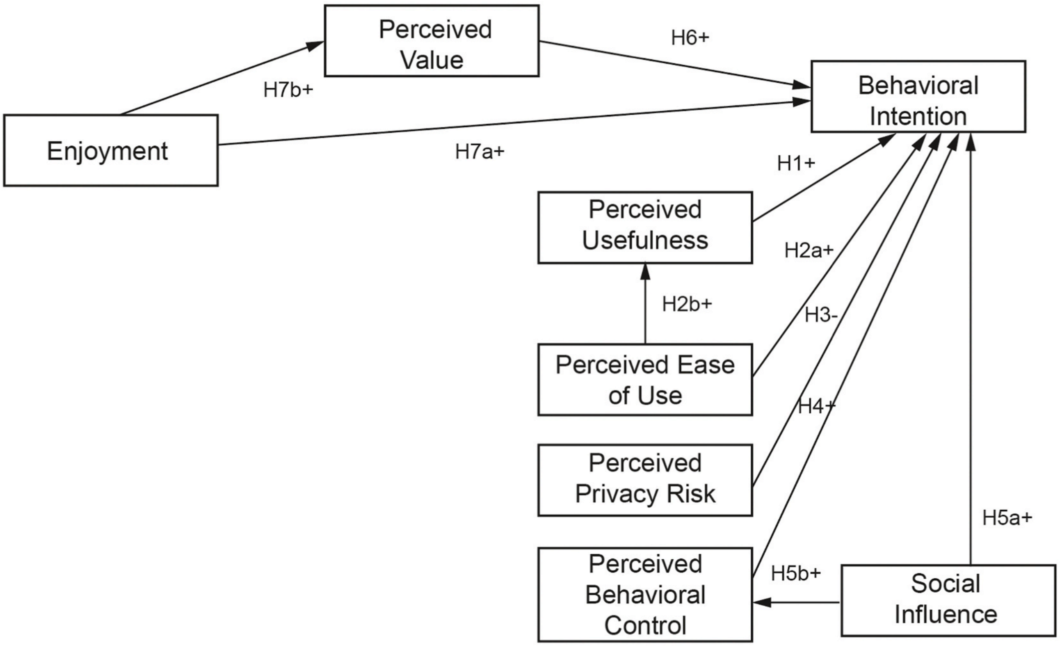

Fig. 1. Experimental hypotheses.

H6. *PV has a significant positive effect on BI.*

H7a. *Enj has a significant positive effect on BI.*

H7b. *PV as a mediating variable moderates the effect of Enj on BI.*

3.2. Questionnaire design

In order to ensure the quality and effectiveness of the questionnaire, a thorough review and revision process was conducted by experts in artificial intelligence and technology acceptance theory. After this process, the final 8 variables were divided into 27 questions, as presented in Table 2. The experts affirmed that the structure and quality of the questionnaire were of high standard. To cater for the participants, the questionnaire was created in a bilingual format, both in English and Chinese. All participants provided informed consent to participate in the study.

Table 2
Measurement items and their sources.

Construct	No.	Measurement items	Reference
Perceived Ease of Use	PEoU1	Learning to use AI-augmented to design would be easy.	Venkatesh & Davis, 2000 [85]
	PEoU2	Interaction with the AI-augmented to design would be clear and understandable.	
	PEoU3	I would find the AI-augmented design difficult to use.	
Perceived Usefulness	PU1	Using the AI-augmented would improve my design performance.	Venkatesh & Davis, 2000 [85]
	PU2	Using the AI-augmented would be helpful in my work.	Venkatesh et al., 2003 [40]
	PU3	Using the AI-augmented would enhance the effectiveness of my work.	
	PU4	I would find the AI-augmented useful in my design work.	
Perceived Behavioral Control	PBC1	Using AI-augmented in design is entirely within my control.	Taylor & Todd, 1995 [78], Rahman et al., 2017 [86]
	PBC2	I have enough ability to use AI-augmented in design.	
	PBC3	I have the ability to use the AI-augmented in design.	
	PBC4	I have the resources necessary to use the AI-augmented in design.	
	PBC5	I have the knowledge necessary to use the AI-augmented in design.	
Perceived Privacy Risk	PPR1	I am concerned that use AI-augmented to design will collect too much personal information from me.	Kalantari & Rauschnabel，2018 [41]
	PPR2	I am concerned that AI-augmented will use my personal information for other purposes without my authorization.	
	PPR3	I am concerned that AI-augmented will share my personal information with other entities without my authorization.	

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Table 2 (*continued*)

Construct	No.	Measurement items	Reference
Enjoyment	Enj1	Using the AI-augmented would provide me with a lot of enjoyment.	Yang et al., , 2016 [51]
	Enj2	I would have fun interacting with the AI.	
	Enj3	I would enjoy using the AI-augmented.	
Social Influence	SI1	People who influence my behavior would think that I should use the AI-augmented in design.	Yang & Jolly , 2009 [62]; Venkatesh et al., 2003 [40] Mandigan et al., 2017 [87]
	SI2	People who are important to me would think that I should use AI-augmented in design.	
	SI3	I think I am more likely to use AI-augmented in design if my friends or classmates used it.	
Perceived Value	PV1	Compared to the fee I would need to pay, the AI-augmented offers value for money.	Kim et al., 2007 [55]; Sirdeshmukh al., 2002 [88]
	PV2	Compared to the effort I would need to put in, the AI- augmented is beneficial to me.	
	PV3	Compared to the time I would need to spend, the AI- augmented is worthwhile to me.	
Behavioral Intention	BI1	I intend to use the AI-augmented in the future.	Rahman al., 2017 [86]
	BI2	I intend to use the AI-augmented t in design frequently.	
	BI3	I intend to recommend that other people use the AI- augmented.	

3.3. Research procedures and data collection

To ensure the reliability and validity of the study, a 7-point Likert scale was used to score the questionnaire, with 1 indicating "strongly disagree" and 7 indicating "strongly agree". The questionnaire was distributed through a targeted web-based survey, with all participants required to have taken courses or possessed knowledge of AI-augmented design, as well as designers who had experience using AI-augmented systems or software. After removing incomplete or inaccurate responses, a total of 249 valid questionnaires were collected for analysis. Detailed information about the respondents is presented in Table 3.

Table 3
Descriptive characteristics of respondents.

Characteristics		Number	Proportion
Gender	Male	118	47.4 %
	Female	131	52.6 %
Design learning years	2–4 years	165	66.3 %
	≥5 years	84	33.7 %
Education	Undergraduate students	165	66.3 %
	Designers with a master's degree or above	84	33.7 %

Table 4
Factor analysis for model validation.

Path Relationships			Standardized factor loadings	AVE	CR	Cronbach coefficient
PU	→	PU1	0.715	0.536	0.822	0.815
	→	PU2	0.798			
	→	PU3	0.677			
	→	PU4	0.734			
PEoU	→	PEoU1	0.662	0.514	0.76	0.752
	→	PEoU2	0.765			
	→	PEoU3	0.721			
PBC	→	PBC1	0.705	0.608	0.885	0.884
	→	PBC2	0.816			
	→	PBC3	0.75			
	→	PBC4	0.775			
	→	PBC5	0.845			
PPR	→	PPR1	0.881	0.810	0.928	0.920
	→	PPR2	0.937			
	→	PPR3	0.881			
Enj	→	Enj1	0.745	0.612	0.824	
	→	Enj2	0.685			0.824
	→	Enj3	0.901			
	→	SI1	0.78	0.501	0.747	0.733

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Table 4 (*continued*)

Path Relationships			Standardized factor loadings	AVE	CR	Cronbach coefficient
SI	→	SI2	0.752			
	→	SI3	0.572			
PV	→	PV1	0.686	0.637	0.839	0.816
	→	PV2	0.815			
	→	PV3	0.881			
BI	→	BI1	0.801	0.643	0.843	0.841
	→	BI2	0.752			
	→	BI3	0.849			

Note: Kronbach Coefficient ranges from 0 to 1. Higher Kronbach Coefficient values are more reliable.

3.4. *Questionnaire reliability analysis*

In this study, the reliability of the data was examined using SPSS 24 to calculate the Cronbach's alpha coefficient, which is a measure of the internal consistency of each dimension. The results showed that the reliability coefficients of each secondary dimension ranged from 0.7 to 1, indicating that the scales used in this study were internally consistent and reliable (see Table 4).

4. Results

4.1. *Measurement model reliability*

To perform the fit test of the AI-augmented design confidence scale validated factor analysis (CFA) model, we used Amos 24 in this study. The results of the model fitness test in Table 5 revealed that the CMIN/DF = 1.834 and RMSEA = 0.058. Furthermore, the IFI, TLI, and CFI all reached the level of 0.9 or higher, indicating that the CFA model of the AI-augmented design confidence scale has good fitness.

AVE = $(\sum\lambda 2)/N$ (λ: Standardized factor loadings，N: The number of measurement indicators for this factor)

CR = $(\sum\lambda)2/(\sum\lambda)2+\sum\delta$ (δ：Residuals)

The validity test results in Table 4 indicated that each dimension had strong convergent validity and combined reliability, as the AVE values for each dimension were above 0.5 and the CR values were above 0.7. Furthermore, the standardized correlation coefficients between the two variables were lower than the square root of the AVE values corresponding to the variables， indicating that the dimensions had strong discriminant validity (Table 6).

Table 5
Validated factor analysis model fit test.

Indicators	Reference Standards	CFA Model	SEM Model
CMIN/DF	1-3 is excellent, 3–5 is good	1.694	2.375
RMSEA	<0.05 is excellent, <0.08 is good	0.053	0.074
IFI	>0.9 is excellent, >0.8 is good	0.943	0.879
TLI	>0.9 is excellent, >0.8 is good	0.933	0.863
CFI	>0.9 is excellent, >0.8 is good	0.942	0.877

Under the premise that the CFA model of the questionnaire has good fit, we further examined the AVE and CR of each dimension of the scale.

Table 6
Model differential validity tests for each dimension.

Dimension		1	2	3	4	5	6	7	8
1	PU	0.536							
2	PV	0.566	0.637						
3	PPR	0.027	−0.088	0.81					
4	Enj	0.45	0.583	0.012	0.612				
5	SI	0.677	0.561	0.075	0.466	0.501			
6	PEoU	0.681	0.436	0.124	0.516	0.594	0.514		
7	PBC	0.331	0.378	0.107	0.4	0.416	0.485	0.608	
8	BI	0.499	0.751	−0.106	0.701	0.565	0.549	0.468	0.643
Square root of AVE value		**0.732**	**0.798**	**0.900**	**0.782**	**0.708**	**0.717**	**0.780**	**0.802**

4.2. Structural model assessment

After conducting explicit statistical analysis of the questionnaire data, the mean values of all variables as observed, fell between 4 and 6. Additionally, the absolute values of the skewness and kurtosis coefficients for each item were within the typical range [89] (Table 7). Therefore, in conclusion, the data for each measurement item conform to an approximate normal distribution and are acceptable for statistical analysis. Table 8 below presents the correlation analysis between the variables.

Amos 24 was used for data analysis and structural equation model (SEM) of the AI-augmented design trust scale. The pre-hypothesis model was used to design the structural equation model, and the final results are shown in Table 9. The CMIN/DF of the SEM model (Fig. 2) is 2.375, the RMSEA is 0.74, and the other tests of IFI, TLI, and CFI are all above 0.8, indicating an overall good model fit (Table 5).

In terms of the hypotheses tested, the results indicate that PU did not have a significant effect on BI, which suggests that the usefulness of AI-augmented design tools may not be the most important factor in determining users' behavioral intentions. This finding is in contrast to some previous studies that suggest that perceived usefulness is a significant determinant of trust in technology [56,90, 91], but is consistent with Kwonsang Sohn et al.'s [92] findings on the trustworthiness of smart products. On the other hand, the results provide support for H3, which posits that PPR has a significant negative effect on BI ($\beta = -0.130$, $p < 0.05$). This finding highlights the importance of addressing privacy concerns in the development and implementation of AI-augmented design tools to promote user trust and adoption. Additionally, the results provide support for H4, which suggests that PBC has a significant positive effect on BI ($\beta = 0.14$, $p < 0.05$), indicating that users' confidence in their ability to use AI-augmented design tools effectively and efficiently is an important

Table 7
Descriptive statistics for each dimension and normal distribution of measurement questions.

Dimension	Items	M	SD	Skewness	Krutosis	Overall M	Overall SD
PEou	PEoU1	5.3855	1.30907	−0.656	−0.050	5.4113	0.96601
	PEoU2	5.4378	1.17309	−0.484	−0.289		
	PEoU3	5.4096	1.04769	−0.161	−0.692		
PU	PU1	5.6988	1.0821	−0.7050	0.2774	5.7952	0.7781
	PU2	5.9036	0.9107	−0.6151	−0.0312		
	PU3	5.8193	0.9814	−0.5075	−0.3889		
	PU4	5.7590	0.8970	−0.2493	−0.5546		
PBC	PBC1	3.8353	1.51903	0.379	−0.351	4.3146	1.11396
	PBC2	4.2129	1.45319	−0.042	−0.425		
	PBC3	4.6024	1.31007	−0.263	−0.205		
	PBC4	4.3253	1.40370	−0.004	−0.405		
	PBC5	4.3173	1.47279	−0.202	−0.408		
	PBC6	4.5944	1.42279	−0.197	−0.381		
PPR	PPR1	4.6627	1.62845	−0.375	−0.713	4.8648	1.49162
	PPR2	4.8956	1.63046	−0.556	−0.442		
	PPR3	5.0361	1.56148	−0.765	0.154		
Enj	Enj1	5.0361	1.2126	−0.2338	−0.2531	5.2021	1.06202
	Enj2	5.1888	1.1573	−0.2170	−0.3368		
	Enj3	5.7510	1.0824	−0.7023	0.0412		
SI	SI1	4.8594	1.42286	−0.283	−0.559	5.3253	0.9303
	SI2	4.5020	1.40024	−0.182	−0.461		
	SI3	4.6707	1.46050	−0.282	−0.589		
PV	PV1	4.8474	1.16085	−0.057	0.302	5.0549	0.94192
	PV2	5.1486	1.07295	0.036	−0.360		
	PV3	5.1687	1.06808	0.079	−0.378		
BI	BI1	5.2972	1.21484	−0.641	0.514	4.8785	1.06897
	BI2	4.7631	1.32443	−0.260	−0.098		
	BI3	4.9880	1.30286	−0.397	0.029		

Table 8
Pearson correlation analysis results for each dimension.

Dimension	1	2	3	4	5	6	7	8
1.PEou	1							
2.PU	.538**	1						
3.SI	.453**	.563**	1					
4.PBC	.428**	.292**	.345**	1				
5.PPR	0.082	0.011	0.072	0.096	1			
6.Enj	.367**	.357**	.351**	.333**	0.026	1		
7.PV	.336**	.470**	.456**	.322**	−0.072	.473**	1	
8.BI	.424**	.416**	.445**	.419**	−0.105	.568**	.607**	1

Note : **. At the 0.01 level (two-tailed), the correlation is significant. *. At the 0.05 level (two-tailed), the correlation is significant.

Table 9
Structural equation model path coefficients and hypothesis testing results.

Hypothesis	Path relationship	Total effect	Direct effect	Indirect effect	Supported
H1	PU→BI	−0.064			No
H2a	PEoU→BI	0.2*			Yes
H2b	PEou→PU→BI	0.152*	−0.041	0.193	No
H3	PPR→BI	−0.13*			Yes
H4	PBC→BI	0.14*			Yes
H5a	SI→BI	0.15*			Yes
H5b	SI→PBC→BI	0.331*	0.092*	0.239	Full mediation
H6	PV→BI	0.458***			Yes
H7a	Enj→BI	0.586***			Yes
H7b	Enj→PV→BI	0.702**	0.3***	0.402**	Partial mediation

Note : ***P < 0.001,**0.001 ≤ P < 0.01,*0.01 ≤ P < 0.05.

factor in promoting adoption. Finally, the results support H6 ($\beta = 0.468$, $p < 0.001$), which posits that PV has a significant positive effect on BI, suggesting that users' perception of the value of AI-augmented design tools may be an important factor in determining adoption.

This study utilized the Bootstrap (MEDIATION) method to investigate the mediating effects of PU, PBC, and PV in the hypothesized model, namely experimental hypotheses H2, H5, and H7. To begin with, the original data ($N = 249$) was employed as the sampling population, and generated 2000 Bootstrap samples using the put-back random sampling method. The parameter estimation method was subsequently employed to estimate the hypothesized model through the maximum likelihood approach. The results of our analysis revealed that hypothesis H2a, which postulated that PEoU had a significant positive effect on behavioral intention, was supported ($\beta = 0.2$, $p < 0.05$). However, H2b, which proposed that PU acted as a mediating variable to mediate the effect of PEoU on behavioral intention, was not supported. Furthermore, H6a, which posited that Enj had a significant positive effect on BI, was supported ($\beta = 0.359$, $p < 0.001$), and that PV plays a mediation role between Enj and BI, with a confidence interval of [0.52–0.934] for the total effect, thus supporting hypothesis H6b. In conclusion, the analysis conducted in this study unveiled that hypothesis H7a received empirical support, signifying a noteworthy positive impact of SI on BI ($\beta = 0.15$, $p < 0.05$). Furthermore, the findings also elucidated the moderating influence of PBC in attenuating the SI-to-BI effect, substantiated by a total effect confidence interval spanning [0.063–0.727]. Consequently, it is judicious to affirm the validation of hypothesis H7b, as documented in Table 9.

5. Discussion

5.1. Theoretical implications

This study employed structural equation modeling to investigate the various that influence trust in AI-augmented design in accordance with the research hypotheses. The results indicate that trust in AI- augmented design is strongly affected by PV, Enj, PPR, PEou, PBC, and SI.

The analysis reveals that (1) PV and Enj can have a positive influence on BI, which is consistent with the VAM model [38,51]. As AI-augmented design tools are transitioning from the innovation phase to the early adoption phase, users tend to be curious about new technologies. Moreover, learning about new technologies is often perceived as enjoyable [93]. Therefore, users' curiosity about new experiences and technology may positively affect their behavioral intentions in terms of enjoyment and value judgments. (2) PPR may negatively impact behavioral intention, which aligns with the findings of the previous TAM extension model [41]. Users are increasingly aware of privacy risks and the importance of safeguarding their intellectual property rights. Additionally, people are concerned about privacy risks due to the lack of transparent system settings. (3) In line with UTAUT [40], SI can influence potential users' BI and can be effectively leveraged in promoting new AI-augmented design tools or platforms. (4) PEoU can significantly influence users' BI, which is consistent with the VAM [37] model that emphasizes ease of use and system accessibility as key factors that affect users' trust. (5) Additionally, PBC is one of the independent variables that significantly influences users' BI; users' evaluation of whether they possess the requisite knowledge, skills, and technology to use AI-augmented design affects their BI, which aligns with the TPB model [39].

The study findings suggest that the influence of PU on trust in AI-augmented design is not significant, which may be attributable to various factors. Firstly, users may resist innovation due to negative emotions such as fear, uncertainty, and doubt, as posited by the innovation resistance model [94]. Secondly, AI-augmented design is still in its nascent stages, and there is a considerable gap between the assistance it provides for design needs and the core innovation points that designers have yet to propose. Nevertheless, design education could play a crucial role in bridging this gap. As more research is conducted on AI-augmented design tools, users' sense of usefulness is likely to improve, leading to a change in their confidence in AI-augmented design.

5.2. Practical implications

The present study posits a trustworthiness model tailored to the assessment of AI-augmented design acceptance, thereby illuminating this pivotal phenomenon. The practical implications of our findings are significant for the design industry. First and foremost,

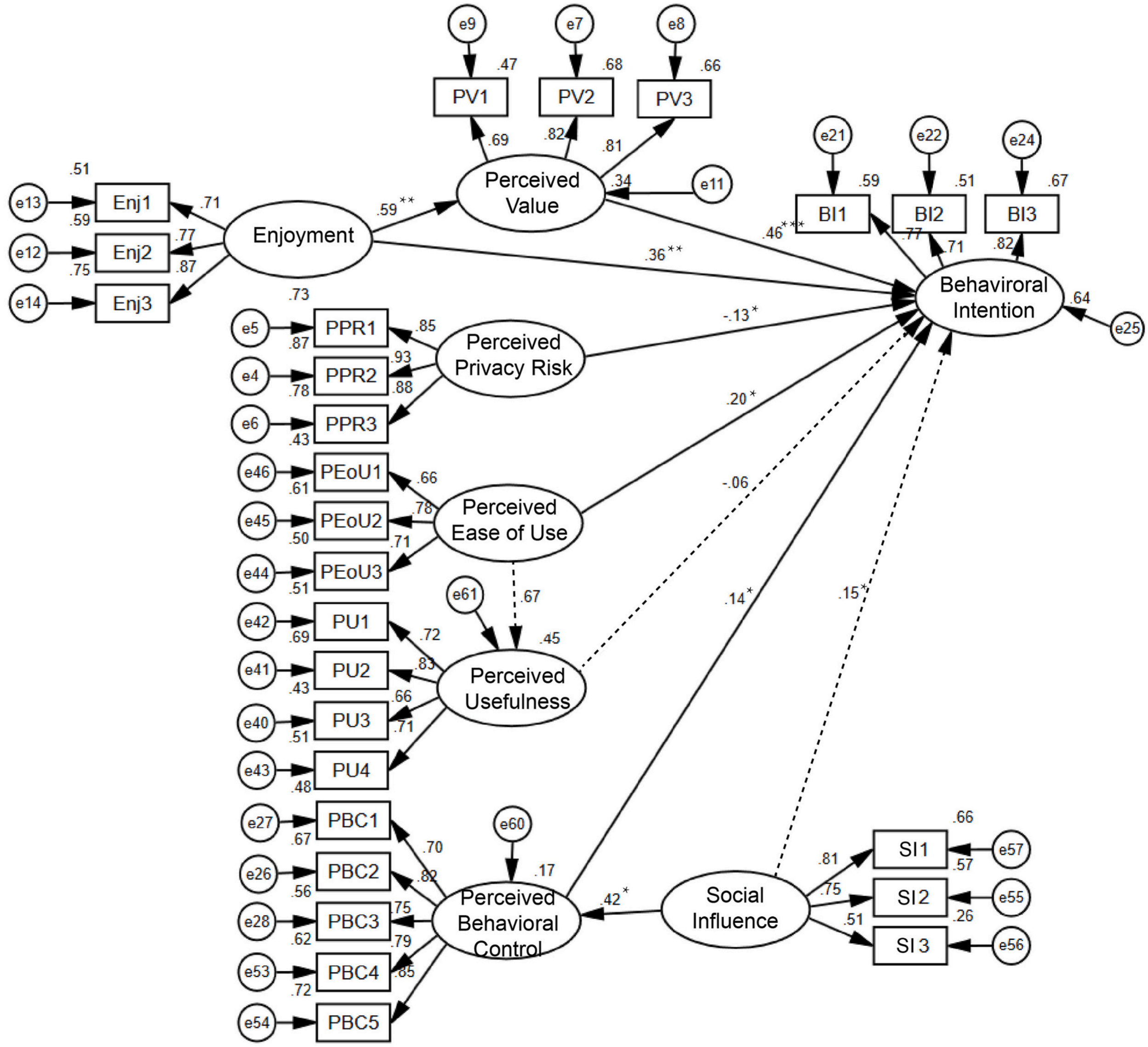

Fig. 2. SEM model.

developers should concentrate on the development of AI-augmented design tools characterized by enhanced explainability [95], user-friendliness, and accessibility. Achieving this entails the design of user-friendly interfaces and the provision of explicit instructions and robust support mechanisms for users [96]. Second, developers should pay more attention to privacy protection and intellectual property rights when developing AI-augmented design tools. This can help to increase users' trust and reduce their concerns about privacy risks. Third, developers should consider the role of enjoyment and perceived value in promoting the adoption of AI-augmented design tools. By emphasizing the benefits of using AI-augmented design tools, developers can increase users' curiosity and interest in these tools. Fourth, developers should provide adequate training and support to users to improve their knowledge, skills, and technology related to using AI-augmented design tools. This can help to increase users' confidence in using these tools and improve their behavioral intention to adopt them.

5.3. Limitations and future work

There are several limitations to this study that should be considered. First, the sample size is relatively small, which may limit the generalizability of the findings. Future research should consider using a larger sample size to improve the reliability and validity of the results. Second, this study only focused on the influence of specific variables on trust in AI-augmented design. Future research should consider other variables that may influence users' trust in AI-augmented design, such as demographic factors. Third, this study only examined the relationship between trust and behavioral intention. To provide a more comprehensive understanding of the adoption of

AI-augmented design tools, future research endeavors should contemplate delving into users' actual usage behavior, as well as the unique user interface and usability of AI-augmented design tools. This expanded scope of investigation can yield more holistic insights. Such endeavors may involve assessing dimensions like information and system quality [97] to gain a more in-depth understanding of the dynamics of adoption. Fourth, this study only examined the mediating effects of PU, PBC, and PV. There is a call for further research and comprehensive discussion on the interconnections among these factors and how they mutually influence BI. A deeper exploration of the relationships between these parameters should help elucidate certain outcomes, such as the non-significance of PU in the study's findings. Subsequent research efforts should consider examining the mediating effects of additional variables, including but not limited to cognitive load and perceived control. Finally, this study only examined the influence of AI-augmented design on trust from the user's perspective. Future research should also consider the influence of AI-augmented design on trust from the developer's perspective.

6. Conclusion

In conclusion, this study has illuminated the factors influencing trust in AI-augmented design. The findings indicate that users' perceptions of value (PV), enjoyment (Enj), privacy risk (PPR), ease of use, perceived behavioral control (PBC), and social influence (SI) all play significant roles in shaping their trust in AI-augmented design. Specifically, PV and Enj exhibit a positive influence on behavioral intention (BI), while PPR may negatively impact it. Additionally, PV acts as a mediator between Enj and BI. The study further elucidated the moderating influence of PBC in attenuating the SI-to-BI effect. However, the influence of perceived usefulness (PU) on trust in AI-augmented design is not significant, possibly attributable to the innovation resistance model and current limitations in the capabilities of AI-augmented design itself.

Despite limitations, such as a relatively small sample size, this study provides novel insights into AI-augmented design. Product developers are encouraged to prioritize these identified factors to enhance overall product satisfaction. This involves mitigating privacy risks, improving ease of use and interaction, and meeting user needs. Additionally, efforts to enhance AI-related design education can play a crucial role in advancing the field of AI-augmented design. Moving forward, emphasis on practicality and social influence should be paramount to facilitate the widespread adoption of AI-augmented design products.

Future research should consider exploring other variables that may influence users' trust in AI-augmented design, including demographic factors. It is recommended that future studies examine the mediating effects of various variables, such as cognitive load and perceived control. Subsequent research endeavors should delve into users' actual usage behavior, taking into account the unique user interface and usability of AI-augmented design tools. Furthermore, future research should investigate the influence of AI-augmented design on trust from the developer's perspective.

In summary, this study provides valuable insights for both researchers and practitioners on effectively developing and promoting AI-augmented design products that instill trust in consumers.

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Data availability statement

Data included in article.

Additional information

No additional information is available for this paper.

CRediT authorship contribution statement

Chuyi Zhou: Writing - review & editing, Writing - original draft, Project administration, Data curation, Conceptualization. **Xuanhui Liu:** Data curation, Conceptualization. **Chunyang Yu:** Conceptualization. **Ye Tao:** Conceptualization. **Yanqi Shao:** Investigation, Data curation.

Declaration of competing interest

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