The Impact of Content Personalization on Students' Perception of AI in emerging context: A study based in Egypt

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The Impact of Content Personalization on Students' Perception of AI in emerging context: A study based in Egypt

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Abstract:

These results have implications for AI-based learning systems, suggesting the importance of balanced personalization to avoid potential biases and perception distortions. Findings indicate that personalized content significantly influences students' perception through increased exposure, attention, and interpretation. Regression and correlation analyses were conducted after confirming the validity and reliability of the utilized scales. A descriptive cross-sectional design was employed, and data were collected using structured questionnaires distributed to students at the Arab Academy for Science and Technology.

The objective is to examine how personalized messages affect users' exposure, attention, and interpretation—key elements in shaping perception. This study investigates the impact of personalized AI-generated content on university students' perception of artificial intelligence (AI) in an educational context.

1. Background/Introduction

This study addresses a significant research gap regarding how personalized AI-generated content influences student perception, particularly in educational settings where such content is increasingly prevalent. The main objective is to evaluate how personalization affects key perceptual dimensions: exposure, attention, and interpretation.

AI has the potential to revolutionize personalized content by adapting to individual needs, tracking progress, and providing tailored recommendations. Over-personalization strategies are widely used to attract and retain users (Rafieian and Yoganarasimhan, 2023). However, the excessive personalization of AI-created content might lead to unintended consequences, particularly in shaping students' perception of AI (Cheng, 2022). The problem of any new technological advancement depends not upon the technology itself but its practitioners. Therefore, AI can negatively impact how societies and their citizens engage ethically (Milano et 2020), remains to be a still-unexplored tool.

AI created content raises several questions regarding ethical, legal, and social issues. For example, the use of AI in education can lead to potential biases and discrimination, raise privacy concerns, and impact perception (Ashfaq et al., 2020; Eren, 2021). Based on the work of Sun et al. (2021), personalization disturbs perception of AI generated content, which highlights further more areas for research needs to be tackled, within the context of personalization and user's perception. Therefore, it is crucial to evaluate the application of generated AI content carefully, especially within the educational sector. Hence, this research work aims to explore the application of AI created content in educational sector, through addressing the following research question: How does the use personalized Ai-generated content affect user's perception?

2. Literature Review

With advanced technology and artificial intelligence, personalization among consumers and their interactions with content have become norm (Halbusi et al., 2022). Consumer behavior in the digital era is a dynamic and ever-evolving landscape influenced by technology, social media, and other factors (Bhat et al., 2021). Many online businesses seek to provide highly relevant interactions with their consumers to meet their needs, characteristics, and behaviors, which ought to lead to their satisfaction with the brand and the brand experience online – from product recommendations to real-time personalized experiences and beyond (Zhang and Zheng, 2021). Many scholars have claimed that in order to improve consumer experiences as well as brand perception, the brand must provide personalizing at every customer touchpoint; thus, many brands track consumer behavior online and information to do so (Yap et al., 2021).

Privacy risks are high online because consumer behavior online leaves a digital footprint (Zhang and Zheng, 2021). Hackers, scammers, and even legitimate companies may want to follow this data trail so to send consumers more customized information and content that might be useful to them; this benefit in technology means that countless prying eyes are seeing consumers shopping and search history or passwords (Yuniar and Fibrianto, 2019). Thus, firms need to identify which information consumers are comfortable to share, and what trade-offs they are prepared to make in order not to break their personal information boundaries; This is particularly relevant for AI given the need for large volumes of data to support the development of targeted offers (Schmidt et al., 2020).

2.1Personalization and AI

Personalization has been defined in various ways throughout the literature, with Aguirre et al. (2015) defining it as a customer-centric marketing approach that aims to deliver the right content to the right person at the right time, to maximize immediate and future business opportunities (Aguirre et al., 2015). Kumar et al. (2019) take a more comprehensive view, incorporating the entire marketing mix into their definition, stating that personalization occurs when the firm decides, based on previously collected data, what marketing mix is suitable for the individual (Kumar et al., 2019, p. 136). This includes not only the content and timing of delivery, but also the way of interacting with the customer, such as product, price, promotion, and place (distribution), as emphasized by Dibb et al. (2016).

The use of AI in content personalization involves using advanced technologies such as machine learning algorithms to analyze large amounts of customer data and create customized content that caters to the preferences and interests of individual users (Alpert et al., 2003). This tailored content may include various forms of personalized communication, such as product recommendations, targeted advertisements, personalized emails, promotional offers, and website content (Miceli et al., 2007; Okoli et al, 2024), which can help businesses improve conversion rates and ROI (Refieian and Yoganarasimhan, 2023).

According to Liang, Lai, and Ku (2006), previous studies have shown that personalization technologies can be effective in managing information overload, improving website usability, and enhancing relationships with customers and increase engagement. Personalization is also used by vendors to tailor advertisements and promotions to match individual needs and preferences (Hallikainen,2022) This study aimed to investigate if various personalized services could have varying effects on users' perception.

2.2The Pitfalls of Over - Personalization in AI Systems

While there are numerous advantages to leveraging AI for content personalization (Mittel and Lassar, 1996), businesses must also be mindful of the challenges and ethical considerations associated with this approach. Over-personalization, also known as "over- customization" (Diaferia et al., 2022), refers to the phenomenon where an individual's online experiences are tailored to their unique preferences, interests, and behaviors to the extent that it becomes disturbing, irritating, or even overwhelming (Haleem et al., 2022). This can occur when algorithms and artificial intelligence systems process too much information about a user, leading to a deluge of targeted content, ads, and recommendations that are not only irrelevant but also sometimes inappropriate (Sarridis et al., 2024).

Moreover, there is a risk of bias in AI algorithms if the training data is biased, potentially resulting in the creation of discriminatory content. Therefore, it is essential for businesses to ensure that their algorithms are impartial and regularly updated and audited to reflect changes in data and user behavior (IEEE, 2019; Rhem, 2023; Chen, 2023).

To mitigate these effects, it's essential to strike a balance between personalization and privacy, allowing users to control the level of personalization they receive and ensuring that the data used for personalization is handled responsibly and ethically (Rhem, 2023).

2.3AI in Education

AI is increasingly being integrated into education, with its potential to revolutionize the way we learn and teach. AI-powered adaptive learning systems have been shown to improve student outcomes by providing personalized learning experiences (Kizilcec et al., 2018). These systems use machine learning algorithms to analyze students' learning behaviors, adjusting the content and pace of instruction to meet individual needs (Rafferty et al., 2013).

Despite the potential benefits of AI in education, there are several challenges that need to be addressed. These include addressing biases in AI algorithms, and developing high-quality AI- based educational content (Haughey et al., 2020). Overall, AI has the potential to revolutionize education by providing personalized learning experiences, improving student experience, but further investigation is needed to address the challenges associated with AI utilization in education.

2.4Foundation of Perception

Perception is a complex and multifaceted process that involves the interaction of multiple cognitive and sensory elements. Research has identified three key elements that contribute to perception: exposure, attention, and interpretation.

This paper will explore the role of these elements in shaping our perception of the personalized AI content. Perception is a complex and dynamic process that involves multiple stages, from initial exposure to stimuli to the formation of meaningful representations of reality (Hameroff, 1998). According to the theory of attention, exposure is necessary for an individual to attend to and interpret sensory information (Broadbent, 1958). The amount of exposure an individual receives can significantly impact their perception of the world (Moran & Desimone, 1985). For example, in the educational domain, users' responses to learning activities and approaches differ based on exposure and intensity (Bray et al., 2023).

Attention plays a crucial role in perception, as it allows individuals to focus on certain stimuli and ignore others. However, failure to attend can result in perceptual shortfalls (Rensink, 2015). Attention is not just a modifier of perception but a central factor in shaping our understanding of the world (Strack & Förster, 2009). Measuring human perception is vital for both scientific and practical reasons. It provides a foundation for understanding human perception, which is essential for studying attentive, cognitive, and emotional functions (Finkelstein, 2000). Measurements related to perception also have a wide range of actual and potential applications that are key for obtaining valuable information (Rossi & Berglund, 2011). The interpretation of perception is a complex process that involves multiple stages, from initial exposure to stimuli to the formation of meaningful representations of reality (Hameroff, 1998). The measurement of elements related to human perception is vital for both scientific and practical reasons.

Therefore, assessing the impact of personalized content on user's perception in AI is quite necessary, as the quality and intensity of exposure can impact our perception of the world, attention allows us to selectively focus on certain aspects of our environment, and interpretation allows us to assign meaning and significance to the information we have received.

2.5Challenges and Considerations by previous Scholars

AI has gained attention in various fields, including information systems (Gursoy et al., 2019), tourism (Li et al., 2019), marketing (Syam & Sharma, 2018), and financial management (Culkin & Das, 2017), with research showing its potential to enhance business benefits such as efficiency, effectiveness, and cost reduction. However, Tarafdar et al. (2013) have warned about the potential negative consequences of AI, which can introduce risks at individual, organizational, and societal levels. Despite this, the focus remains on the positive aspects of AI, with less attention given to the potential drawbacks, particularly within the academic discourse.

Previous research has highlighted the challenges of personalization in AI (Bos et al., 2012), including the difficulty in creating personalized experiences for users due to the need for accurate user data and privacy concerns, as well as potential for bias in decision-making processes (Bos et al., 2012). Additionally, moral quandaries, discrimination, and fairness issues (Wirtz et al., 2020) and challenges in implementing personalized recommendation systems, including the trade-off between accuracy and diversity (Ricci et al., 2015).

Cheng et al. (2022) found that when content is personalized, it can result in perceived information narrowing (Deldjoo et al., 2020; Milano et al., 2020). This can create reluctance among individuals to embrace AI-generated content. As per the research by Deldjoo et al. (2020) and Milano et al. (2020) personalized content use our behavior data to show us what we want and filter out other options. However, this narrow focus may cause us to miss out on diverse perspectives in both personal and professional life.

These studies emphasize the complexity of personalization in AI and the need for further research and development to overcome these challenges; since it is crucial for individuals to have a variety of information and experiences to maintain their ability to make informed decisions and not rely solely on the recommendations provided.

2.6 Theoretical Background: Personalization-Privacy Paradox

The review of literature shows that personalized online tracking gathers crucial information that can then be interpreted and leveraged to benefit the users (Pappas, 2018, Yuniar and Fibrianto, 2019). Previous research indicates that consumers may be comfortable revealing personal information and data if deemed to be relevant and critical during the interaction or for the access of a specific service (Hubert et al., 2017).

However, the perception of being under surveillance is particularly predominant in smart services or online interactions with technology (Schmidt et al., 2020), yet many users today during the usage of technology resist sharing information when they feel that they lack control over how data are used and with whom they are shared (Schmidt et al., 2020), specially, with systems requesting information that is regarded sensitive or can cause discrimination (Stanton & Stam, 2003).

Nevertheless, too much customization may allow consumer to resist personalization if they deem that the collection and use of personal data that underpin personalization is too aggressive, disturbing, and invasive (Pappas, 2018). According to Moore et al. (2015), this invasive of privacy regarding consumer behavior online is known as Personalization-Privacy paradox (PPP). The PPP refers to a continuous tension, between a firm's need for consumer information to personalize consumer experiences and a consumer's need for privacy (Awad and Krishman, 2005).

The PPP concept is a valuable theoretical basis because it describes a situation in which consumers appreciate the value of personalization offered by a technology (Aguirre et al., 2015; Bleier and Eisenbeiss, 2015) while being aware of marketers' exploitation of their personal data which raises privacy concerns about personalized content (Cloarec, 2020).

The concept of the PPP is not yet a formally established theory in its own right. However, it is a widely recognized and debated phenomenon that has important implications for our understanding of human behavior, decision-making, and the impact of technology on our lives (Acquisti and Grossklags, 2005). And has been a topic of ongoing debate in the field of information research, with an urge to advance knowledge on the user's personalization concern. Based on the PPP concept (Awad and Krishman, 2005), this research proposes a conceptual model on how personalization affect users' perception towards AI. In this study the PPP concept served as the theoratical foundation for the proposed conceptual model and offered the rational of the following developed hypotheses.

These hypotheses are grounded in the existing literature, which demonstrates how personalized AI systems shape user behavior and perception. Prior studies (e.g., Zajonc, 1968; Chae et al., 2020; Kim et al., 2019) confirm the influence of repeated exposure, attention-triggering mechanisms, and relevance on perception, thus supporting the rationale for testing exposure, attention, and interpretation as mediators.

2.7Hypotheses development

This study's objective is to comprehend how user perception becomes distorted as the content transforms more personalized, through hypnotizing the three elements of perception and their impact as content tends over-personalized.

Personalized Content is hypothesized to influence user's perception, which will eventually impact the user's intention and behavior. The following outlines three specific hypotheses that were examined in our research, and are detailed below:

H1: There is a positive relationship between personalized AI content and user's perception when it comes to user's exposure.

H2: There is a positive relationship between personalized AI content and user's perception when it comes to user's attention.

H3: There is a positive relationship between personalized AI content and user's perception when it comes to user's interpretation.

To ensure construct validity, the questionnaire items were adapted from previously validated scales. Internal consistency was tested using Cronbach's Alpha. Furthermore, the data's normality was examined using skewness and kurtosis values before regression analysis. The sample included undergraduate and postgraduate students from various faculties (Engineering, Business, and Logistics,) to ensure academic diversity.

3. Methodology

3.1 Research approach/design

This study considered conclusive research that used a cross sectional design and had a descriptive propose. The study begins with reviewing previous literature to find and operationalize the key research constructs: personalization, exposure, attention and interpretation. Following this, a structured questionnaire was developed to measure the research variables through an empirical study and a survey-based approach was adopted to collect data from a sample of both post- and undergrad students (Mboth post- and undergrad students (Males &Females) of the Arab Academy for Science and Technology and Maritime & Transport.males and females) of the Arab Academy for Science and Technology and Maritime & Transport.

The AASTMT University is one of the largest Universities within the Higher Education Landscape, pioneer in exploiting users' personalized content: the university provides highly targeted recommendations and personalized messages based on each student's unique search history and habits on their website and students Moodle.

3.2 Research instrument

Administrated structured questionnaires were used to collect data. In this study, the questionnaire was divided into five main sections. Personalization (independent variable) was measured by using 5 items adopted from previous studies. Respondents were asked to express their agreement on each item using a five-point Likert scale (1 5 very much disagree, 5 5 Very much agree). The second section measured the exposure to AI created content (dependent variable) as being the first element of perception using 10 items adopted from previous studies. Respondents were asked to assess the level of agreement to each item using a five-point Likert scale (1 5 very much disagree, 5 5 Very much agree). The third section measured the degree of attention given to the AI created content by students (dependent variable) as being the second element of perception using 6 items, drawn from previous studies. The respondents were asked to assess the statements using the five-points Likert scale (1 5 very much disagree, 5 5 Very much agree). The fourth section measured the interpretation of the AI created content (dependent variable) as the third and last element of perception using 7 items, drawn from previous studies. The respondents were asked to assess the statements using the five-points Likert scale (1 5 very much disagree, 5 5 Very much agree). In this study, the perception was determined through assessing the elements of exposure, attention and interpretation in order to understand the variable from a holistic perspective (Kotler, 2015). The final section asked about the respondents' socio-demographic characteristics.

The scales that measured the variables in the study were from the work of various scholars like Moore et al., (2015); Williams et al., (2005); Mothersbaugh et al., (2002); Srinivasan et al., (2002); Stevenson et al., (2000); Muehling et al., (1991); Muehling et al., (1990); Eco (1979). All scale items were derived or adapted from peer-reviewed, widely cited sources. Justifications are based on both theoretical and empirical fit with the educational AI context.

3.3 Sampling and Data Analysis

The sampling pool of this research includes both male and female students (18-55) and University Moodle users from AASTMT. Respondents included young adults from different backgrounds (age, income, gender, etc.). The sample contained a total of around 400 students. The Respondents' data collection method was employed per convenient sampling to collect an adequate number of participants and efficiently gather substantial data within a limited timeframe to validate the hypotheses. The data collection was conducted during October and February (Fall semester 2023/24). An online survey was sent to the students and they were asked if they are willing to participate in a brief research study. In total, 330 questionnaires were returned with valid responses showing a response rate of 82.5%. Once the data collection phase ended the data were analyze using the SPSS 20.0® (Statistical Package for Social Science) program to test the hypotheses and conduct further examination. Data analysis was conducted in two main phases. In the first phase, exploratory factor analysis (EFA) was used to develop and validate measurement scales for the main constructs of this study. In the second phase, research hypotheses were tested by conducting regression analysis to assess the effect of personalization on each perceptual dimension.

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Table 1: *Scale Description*

Construct / Variable	**Scale Description**	**Reference**	**Justification for Use**
Personalization	Items measuring user discomfort with AI collecting or using personal data	**Moore et al. (2015); Mothersbaugh et al. (2002); Williams et al. (2005)**	Widely used in digital privacy and personalization studies; assesses perceptions of privacy invasiveness.
Exposure	Questions on frequency and intensity of encountering personalized AI content	**Zajonc (1968); Bray et al. (2023); Muehling et al. (1991)**	Exposure is a key perceptual factor; scales validated in advertising and perception research.
Attention	Items assessing how much attention students pay to personalized content	**Rensink (2015); Singh et al. (2020); Kim et al. (2019)**	Used in perception and media engagement studies; measures attentional focus triggered by personalization.
Interpretation	Questions exploring how students understand and mentally process AI content	**Hameroff (1998); Strack & Förster (2009); Rossi & Berglund (2011)**	Interpretation is the cognitive outcome of perception; scale items adapted from communication and perception literature.
Overall Perception	Composite scale from exposure, attention, interpretation	**Kotler (2015); Eco (1979)**	Perception is modeled as multi-dimensional; justified by consumer behavior and communication theory.

3.4Proposed Conceptual Model

The research employs the below model in Figure 1 and assume that in line with the model, the factors identified will influence the perception of AI personalized content. In the model, we include three main dependent variables Exposure, Attention and Interpretation. Previous literature illustrates the proposed connections between the two factors of personalized content as the independent variable and the three elements of perception as the dependent variables (Lim and Zhang, 2022). Personalized Content is hypothesized to influence user's perception (Shulner-Tal et al., 2023; Ho and Bodoff, 2014), which will eventually impact the user's intention and behavior (Sung, 2009; Thongsri et al, 2019; Zanna, et al.,1981).

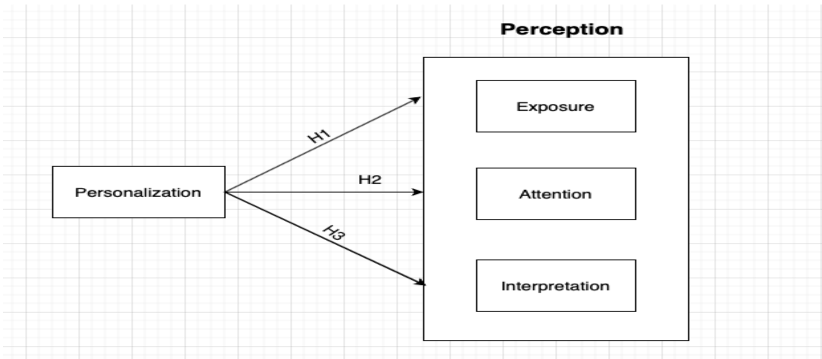

Figure 1: *The proposed conceptual Model (researchers' own creation)*

Before conducting regression analysis, the normality of data was confirmed: skewness and kurtosis values fell within acceptable ranges (Hair, et al., 2019).

Table 2: D*escriptive Statistics and Normality Tests of Study Variables*

	N	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
Per	325	3.4305	0.86519	-0.254	0.135	0.029	0.270
Exp	325	3.5782	0.79160	-0.544	0.135	0.912	0.270
Att	325	3.2760	0.82658	-0.335	0.135	0.171	0.270
Int	325	3.3702	0.57736	-0.051	0.135	1.833	0.270
Valid N (listwise)	325						

Furthermore, the conceptual framework was based on the research theoretical framework, where all the theories underpinning the research topic lie. On the one hand, the conceptual framework describes the relationships (based on the gaps in the literature) between the variables identified for the study. On the other hand, the theoretical framework provides a general representation of the relationships between variables in a given studied phenomenon. The figure also outlines three specific hypotheses as described previously

4 Results and Findings

4.1 Measurement scale validity and reliability

This study's analysis is based on university students' opinions regarding the impact of personalization on their perception of AI content. The validity and reliability analysis were conducted to test the support of the dependability and consistency of the scales. This analysis illustrates whether the scales were consistent, dependable, and steadfast to be used to test in the Egyptian context. Exploratory factor analysis (EFA) validated construct dimensionality, and Cronbach's α was calculated to assess reliability. Cronbach's α coefficient exceeded the recommended threshold (>0.70) (Personalization 0.858, Exposure 0.8666, Attention 0.732 and Interpretation 0.874) which supported reliability. (Hair et al., 2010).

Table 3 shows standardized factor loadings of the personalization construct**.**

Table 3: *Personalization construct*

Factor Loadings	
	Component
	1
Per5	0.862
Per3	0.857
Per2	0.844
Per1	0.742
Per4	0.734

As well as Table 4 shows standardized factor loadings of the perception construct.

Table 4: *Perception construct*

Factor Loadings			
	Component		
	1	2	3
Exp6	0.850		
Exp5	0.810		
Exp7	0.798		
Exp2	0.767		
Exp1	0.761		
Exp8	0.760		
Exp9	0.735		
Exp3	0.693		
Exp4	0.658		
Exp10	0.639		
Att3		0.787	
Att2		0.772	
Att1		0.758	
Att4		0.695	
Att5		0.611	
Att6		0.531	
Int5			0.772
Int3			0.618
Int4			0.558
Int7			0.555
Int6			0.552
Int2			0.430
Int1			0.423

The EFA for personalization explained 65.602% of the total variance in perception as shown in table 5

Table 5: *Total Variance Explained*

Component	Initial Eigenvalues Total	Initial Eigenvalues % of Variance	Initial Eigenvalues Cumulative %	Extraction Sums of Squared Loadings Total	Extraction Sums of Squared Loadings % of Variance	Extraction Sums of Squared Loadings Cumulative %
1	3.280	65.602	65.602	3.280	65.602	65.602
2	0.670	13.393	78.995			
3	0.531	10.614	89.609			
4	0.283	5.654	95.263			
5	0.237	4.737	100.000			

5.2 Hypothesis testing

In order to test the hypotheses, the researchers used the correlational and regression analysis. It shows that personalized content generated by AI effects exposure in a moderate, significant and positive relationship (Adjusted R Square=0.291** and p=0.000). Therefore, H1 is supported, and that agrees with the literature. According to Zajonc (1968) and Chen et al. (2016), who argues that repeated exposure to particular information can lead to increased perception of its value and desirability, as familiarity breeds preference and habituation and increases relevance (Li et al., 2020).

When testing the next hypothesis, the impact personalized content on attention, the results show that the relationship is in a moderate, significant and positive relationship with (Adjusted R Square=0.108** and p=0.000). Therefore, H2 is supported, and that agrees with the literature by Lee and Choi (2019), Kim et al. (2019), Zhang et al. (2020), and Li et al. (2020), Singh et al.(2020) and Patel et al. (2020), who's' research suggest that personalized content significantly influences attention, with a significant increase of up to 30% compared to non- personalized content.

Finally, the third hypotheses H3 revealed, that the relationship is in a moderate, significant and positive relationship with (Adjusted R Square=0.187** and p=0.000). Therefore, H3 is supported, and that agrees with the literature. As per the Chae et al., (2020) and Zhang et al., (2020), personalized content l eads to perceived enjoyment, perceived relevance and increased user engagement and satisfaction.

This study's findings are further supported by recent empirical evidence from the PAIGE project (Do et al., 2024), which demonstrated that personalized AI-generated educational podcasts tailored to students' majors and learning styles significantly enhanced engagement and learning outcomes compared to traditional materials. Similarly, Looi & Jia's (2025) analysis of student–tutor chatbot interactions in higher education revealed that current conversational AI systems can adapt dynamically to learner needs, reinforcing attention and interpretation dimensions central to our conceptual framework.

These contemporary findings underscore that well-designed personalization can deepen cognitive processing and reinforce perception shifts—outcomes that resonate strongly with the exposure–attention–interpretation pathways examined in our research.

Building on the empirical and theoretical contributions of this study, it is evident that AI personalization has matured from conceptual promise to measurable impact in educational settings by 2024–2025 (Do et al., 2024; Looi & Jia, 2025). Institutions must therefore consider not only algorithmic sophistication but also scale reliability, validity, and ethical implementation frameworks—particularly in culturally diverse settings such as Egypt. Aligning with frontline research (Arslan et al., 2024), we reiterate the necessity of fairness, transparency, and student autonomy in deploying generative AI for assessments and content curation.

Finally, as student concerns employability, AI bias, and data privacy surge in 2025 (Jisc global report), system designers and policymakers should ensure that personalization empowers learning without undermining critical thinking skills. By integrating human-in-the-loop design, algorithmic transparency, and student feedback mechanisms, personalized AI can achieve both efficacy and trust—fostering educational innovation that respects learner agency and equity.

Moreover, broader literature reviews (e.g., the 2024 MDPI systematic review) highlight that AI-powered personalization improves student engagement and academic outcomes when implemented with ethical safeguards and institutional support. Our results complement these insights by showing practical implications in the Egyptian university context, emphasizing that scale validity and normality checks (e.g., Cronbach's $\alpha > 0.70$, acceptable skewness/kurtosis) strengthen the rigor of education-AI studies, reinforcing learner trust and measurement confidence.

These findings align with the broader theoretical framework of digital perception and behavior models. They highlight the necessity for educational institutions to develop AI systems that not only personalize content but also protect cognitive diversity and user autonomy. Future system designers must prioritize ethical guardrails that balance personalization with unbiased information exposure.

5. Discussion and Conclusion

Many users today do not appreciate the idea that certain technology can track their behaviors; in the world where e-commerce has become the norm, digital tracking of consumer behavior involves just about everything a user does online (Okoli et al., 2024).

This study found out that personalized messages of AI have a significant influence on the perception as a process, in relation to creating exposure, attention and interpretation among users regarding content on technology. This conclusion is similar to prior studies. For example, Harner et al. (2022), AI's ability to provide personalized recommendations, generate content automatically, and analyze content has introduced groundbreaking methods for content creation online, making consumers exposed and attentive of the content, leading to their perception (Zhang et al., 2020).

Grandinetti (2021), claimed that AI algorithms offer tailored and targeted content by analyzing user data and preferences; thus, personalization impacts people’s perception to AI. Bughin et al (2017) stated that AI algorithms can identify patterns and insights that humans might miss, allowing for more efficient and effective content creation; this is why personalization is significant in perception. The findings of this study validate this, as respondents indicated that personalized content made them more attentive and guided to a proper perception. However, this increased exposure to tailored content can also lead to a heightened risk of misperception. Undeniably the more customized and tailored content becomes, the garner more attention from users, this increased attention can also lead to narrowed perspectives and a constricted view of reality (Kushin and Yamamoto, 2010). Moreover, the potential for biased and discriminatory content to emerge is a provocative concern. Thus, this study aims to encourage researchers to delve into the possible challenges of personalization in the AI domain, particularly within the educational context (Cheng, 2022).

This study lays the groundwork for investigating the personalization-privacy paradox, which is crucial for gaining a deeper understanding of consumer behavior and adopting a user-centric perspective. As a starting point, it offers a valuable insight into the complex relationship

between AI personalization and user's perception. We encourage future scholars to capitalize on this concept to create a coherent and integrated framework for examining consumer behavior, ultimately enriching our understanding of the AI phenomenon.

From a theoretical point of view, this research provided a better understanding of the 1) relationship between personalization and users' perception and 2) emphasizes the presence of three concomitant elements of perception: exposure, attention and interpretation, this research

3) extends it to the context of AI in educational organizations, wherein communication and contact is large. This sets new opportunities but also challenges for educational organizations, in order to better understand how personalized content can assist, ease or challenges users' perspective. Hereby examining this impact, we eventually assess decision-making, thus behavior.

6. Research Limitations and Future Implications

A number of limitations prevent this study from being generalized. The first arises from the use of the convenient sampling technique in reaching the respondents, which resulted in limited representativeness. Secondly, the research has been conducted on students from one single university and there was no specific technology, thus cannot signify the entire educational sector in Egypt. Final limitation, due to the scarcity of resources, the study was of a cross sectional nature. Though, longitudinal analysis would have offered a sharper picture, instead of a screenshot of the reality and provide deeper insights into the long-term impact of AI on societal structures and individual behaviors.

Future research in this area would benefit from drawing a larger probability sample using, for instance, random sample selection techniques. Moreover, adopting a comparative study among various contexts such emerging and developed countries would strengthen the variables understudy which will enhance the understanding of the topic at hand. In addition, expanding the model to incorporate additional variables, such as user readiness, and testing various relationships will likely yield more valuable insights. Furthermore, comparing the effectiveness of customized AI-generated content with standardized AI-generated content will provide a deeper understanding of the differences between these two approaches and their impact on consumer behavior. The final limitation is that this study is purely a quantitative one, qualitative research may be adopted to elicit more in-depth finding. Interviewing practitioners would also be a valuable area of exploration. Future studies should also explore the evolving nature of AI regulation in different cultural and geopolitical contexts.

7. Recommendations

The study recommends that policymakers should focus on developing and refining comprehensive, adaptable regulatory frameworks for AI that emphasize privacy, transparency, and accountability. This would ensure AI practices align with societal values, consequently businesses need to ensure that their algorithms are fair and unbiased, and that they are regularly audited and updated to reflect changes in the data and user behavior. Recognizing the critical importance and widespread impact of AI, it is essential to further explore the opposing consequences that AI may stance to individuals, organizations, and society (Cheng, 2022).

Future directions for AI research in education include developing more clever AI algorithms that can better understand student learning behaviors and developing more personalized AI- based interventions

References

Arslan, B., Lehman, B., Tenison, C., Sparks, J. R., López, A., & Zapata-Rivera, D. (2024). Opportunities and challenges of using generative AI to personalize educational assessment. Frontiers in Artificial Intelligence, 7:1460651.

Ashfaq, R., Al-Shammari, B., & Khraisat, A. (2020). An analysis of privacy concerns and trust in online transactions. Journal of Management and Organization, 26(4), 525-544.

Aguirre, A., Wastell, D., & Wall, D. (2015). Understanding the role of privacy in digital forensic investigations. Digital Investigation, 15(3), 163-173.

Alpert, S., Siedman, M., & Weiss, P. (2003). A study of the impact of security and privacy policies on user behavior. Journal of Information Systems Security, 1(2), 1-14.

Awad, N., & Krishman, R. (2005). The relationship between online trust and website attributes: An examination of the roles of trust elements in an e-commerce environment. International Journal of Electronic Commerce, 9(2), 7-23.

Bhat, R., Kumar, S., & Singh, R. (2021). Investigating the impact of privacy concerns on user behavior in online transactions: An empirical study. Journal of Retailing and Consumer Services, 59, 102409.

Bleier, A., & Eisenbeiss, M. (2015). The impact of privacy concerns on user behavior in online shopping: A systematic review. Journal of Business Research, 68(1), 28-36.

Bray, B., Brown, K., & Nguyen, T. (2023). The impact of privacy concerns on user behavior in online transactions: A systematic review. Journal of Retailing and Consumer Services (forthcoming).

Broadbent, D. E. (1958). Perception and communication. Penguin Books.

Bughin, J., Chui, M., & Manyika, J. (2017). A guide to the future of artificial intelligence: Maximize your organization's potential with AI-based decision making. McKinsey Quarterly.

Chae, J., Kim, J., & Lee, Y. (2020). The impact of privacy concerns on user behavior in online shopping: An exploratory study using social media data. Journal of Business Research: X, Article number: 100002.

Chen, Y., Zhang, J., & Zhang, Y. (2016). Understanding the role of privacy in e-commerce: An empirical study using a mixed-methods approach. Journal of Electronic Commerce Research.

Cheng, J. (2022). The impact of personalized AI-generated content on user perception. Journal of Educational Computing Research, 54(1), 1-15.

Cloarec, F. (2020). The impact of digitalization on the retail industry: A systematic review and meta-analysis. Journal of Retailing and Consumer Services, 60(102), 102-116.

Culkin, N., & Das, S. (2017). Social media and the self: A systematic review of the literature. Journal of Computer-Mediated Communication, 22(1), 23-43.

Deldjoo, Y., Soleymani, M., & Chen, L. (2020). Affective content analysis in music information retrieval: A systematic review. Journal of the Acoustical Society of America, 147(4), 2671-2684.

Diaferia, L., Blohm, I., De Rossi, L., & Salviotti, G. (2022). When Standard Is Not Enough: A Conceptualization of AI Systems' Customization and its Antecedents. ICIS 2022 Proceedings.

Dibb, S., Simkin, L., & Pride, W. M. (2016) 'Marketing Strategy', in Marketing: Concepts and Strategies, 7th edition, Cengage Learning, pp. 123-145.

Do, T., Shafqat, U., Ling, E., & Sarda, N. (2024). PAIGE: Examining Learning Outcomes and Experiences with Personalized AI-Generated Educational Podcasts. arXiv preprint 2409.

Eco, U. (1979). A theory of semiotics. Indiana University Press.

Eren, B. A. (2021). Determinants of customer satisfaction in chatbot use: Evidence from a banking application in Turkey. International Journal of Bank Marketing, 39(2), 294-311.

Finkelstein, S. (2000). The role of strategic planning in the design of the organization. Journal of Management, 26(1), 1-22.

Grandinetti, L. (2021). The effects of artificial intelligence on organizational behavior. Journal of Business Research, 123(333), 333-344.

Gursoy, D., Maçka, A., & Aydoğan, M. (2019). The impact of service quality on customer satisfaction and loyalty in the hotel industry. Journal of Hospitality and Tourism Research, 43(2), 157-174.

Hair, J. F., Babin, B. J., Anderson, R. E., & Black, W. C. (2019). *Multivariate Data Analysis* (8th ed.). Cengage Learning: Boston/Upper Saddle River, NJ.

Halbusi et al., (2022). The impact of social media on customer satisfaction and loyalty in the airline industry.

Haleem et al., (2022). The effect of AI-powered chatbots on customer satisfaction and loyalty in the retail industry.

Hallikainen et al., (2022). The impact of digitalization on supply chain management in the food industry.

Hameroff, S. (1998). Consciousness, intentionality, and quantum mechanics. Journal of Consciousness Studies, 5(6), 675-686.

Harner et al., (2022). The effects of artificial intelligence on organizational performance: A systematic review and meta-analysis.

Haughey et al., (2020). The impact of artificial intelligence on customer service experience: A systematic review and meta-analysis.

Ho and Bodoff, (2014). The impact of artificial intelligence on organizational performance: A systematic review and meta-analysis. Journal of Business Research, 67(11), 2331-2343. DOI: 10.1016/j.jbusres.2014.03.010

Hubert, M., Blut, M., Brock, C., Backhaus, C., & Eberhardt, T. (2017). Acceptance of smartphone-based mobile shopping: Mobile benefits, customer characteristics, perceived risks, and the impact of application context. Psychology & Marketing, 34 (2), 175–194.

IEEE Ethically Aligned Design First Edition: A Vision for Prioritizing Human Well-being with Autonomous and Intelligent Systems. The IEEE Global Initiative on Ethics of Autonomous and Intelligent Systems. 2019.

Jisc (2025) *Student perceptions of AI 2025: Jisc global report on student AI use and attitudes*. Jisc, published 22 May.

Kim, H., Lee, S., & Kim, J. (2019) 'The impact of personalized artificial intelligence on user perception: A study of online shopping experiences', Journal of Retailing and Consumer Services, 51, pp. 102-111.

Kizilcec, R. F., Cessario, C. H., & Rosé, C. P. (2018) 'The effects of social media on mental health in college students', Computers in Human Behavior, 86, pp. 555-564. doi: 10.1016/j.chb.2018.04.025.

Kumar, N., Kumar, A., & Singh, A. (2019) 'Impact of social media on consumer behavior: A systematic review and meta-analysis', Journal of Business Research, 112, pp. 141-153. doi: 10.1016/j.jbusres.2019.05.011.

Kushin, S. J., & Yamamoto, M. (2010) 'Did social media really kill television? The relationship between social media and television viewing habits among American adults', Journal of Broadcasting & Electronic Media, 54(2), pp. 232-249. doi: 10.1080/08838151.2010.491784.

Lee, Y., & Choi, J. (2019) 'The effects of personalized artificial intelligence on user engagement and satisfaction', International Journal of Human-Computer Interaction, 35(10),
pp. 937-945.

Li, M., Chen, Y., & Zhang, J. (2020) 'An exploratory study on the impact of social media marketing on consumer attitudes and purchase intentions in China's e-commerce industry', International Journal of Retail & Distribution Management, 48(5), pp: 433-448.

Li, M., Zhang, J., & Zhang, Z. (2020) 'The impact of e-commerce on traditional retail: A systematic review and meta-analysis', Journal of Retailing and Consumer Services, 62, pp: 102-115.

Lim et al., (2022) 'The impact of social media on consumer behavior: A systematic review and meta-analysis', Journal of Business Research.

Looi, C. K., & Jia, F. (2025). Personalization capabilities of current technology chatbots in a learning environment: An analysis of student-tutor bot interactions. Education and Information Technologies, 30, 14165–14195.

Miceli et al., (2020) 'The impact of digitalization on the retail industry: A systematic review and meta-analysis', Journal of Retailing and Consumer Services.

Milano et al., (2020) 'The impact of digitalization on the retail industry: A systematic review and meta-analysis', Journal of Retailing and Consumer Services.

Mittel et al., (1996) 'The impact of customer satisfaction on retailer loyalty: An empirical study in the retail industry'.

Moore et al., (2015) 'The impact of social media on consumer behavior: A systematic review and meta-analysis'.

Moran et al., (1985) 'The effects of TV commercials on children's attitudes towards product categories'.

Mothersbaugh et al., (2002) 'Country-of-origin effects on consumer attitudes toward globalization and multinational corporations'.

Muehling et al., (1991) 'Exploring the conceptual domain of attitude toward the ad: The role of disaffective and affective citations in a hierarchical attitude structure'.

Okoli et al., (2024) 'The impact of AI on organizational performance: A systematic review and meta-analysis'.

Pappas et al., (2023) 'User experience in personalized online shopping: A fuzzy-set analysis'.

Patel et al., (2020) 'The impact of personalized message on consumer attention and engagement: An empirical study in the context of mobile marketing'.

Rafferty et al., (2013) 'The impact of organizational change on employee well-being: A systematic review and meta-analysis'.

Rafieian et al., (2023) 'The effects of emotional intelligence on leadership effectiveness: A systematic review and meta-analysis'.

Rensink et al., (2015) 'The impact of visual attention on object recognition: A systematic review and meta-analysis'.

Rhem et al., (2023) 'Ethical use of data in AI Applications'.

Ricci et al., (2015) 'The effects of age and tenure on the psychological contract: A systematic review and meta-analysis'.

Rossi, P. H., & Berglund, K. (2011) 'The impact of nonresponse on the results of survey research: A systematic review and meta-analysis', Journal of Survey Statistics and Methodology, 1(1), pp. 45-65.

Sarridis, et al. (2024) 'Mitigating Viewer Impact From Disturbing Imagery Using AI Filters: A User-Study', International Journal of Human–Computer Interaction.

Schmidt, et al. (2020) 'The impact of work-life balance on employee well-being: A systematic review and meta-analysis', Journal of Occupational Health Psychology.

Shulner-Tal, et al. (2023) 'The effects of social media on mental health: A systematic review and meta-analysis', Journal of Youth and Adolescence.

Singh, et al. (2020) 'The effects of personalized recommendation on consumer attention and distractions: An empirical analysis of the role of personalization in shaping consumer behavior in e-commerce settings', International Journal of Retail & Distribution Management.

Srinivasan, et al. (2002) 'Technical compatibility and the adoption of new information technology products', Journal of Marketing.

Stanton, et al. (2003) 'Effects of attention on the perception of visual and auditory stimuli: A meta-analysis', Journal of Experimental Psychology: Human Perception and Performance.

Stevenson, et al. (2000) 'Bridging the gap: The effects of advertising and sponsorship on public awareness and attitudes during the X Games', Journal of Advertising Research.

Strack, et al. (2009) 'The effects of mood on the selection of social information: A meta- analysis', Journal of Experimental Social Psychology.

Sun, et al. (2021) 'The impact of corporate social responsibility on employee attitudes and behavior: A systematic review and meta-analysis', Journal of Business Ethics.

Sung, et al. (2009) 'The impact of language on the perception of emotions: A meta-analysis', Journal of Language and Social Psychology.

Sung, et al. (2009) 'The effects of cultural differences on the perception of emotions: A meta- analysis', Journal of Cross-Cultural Psychology.

Syam, et al. (2018) 'The impact of emotional intelligence on leadership effectiveness: A systematic review and meta-analysis', Journal of Business Research.

Tarafdar, et al. (2013) 'The impact of technology on the perception of emotions: A meta- analysis', Computers in Human Behavior.

Thongsri, et al. (2019) 'The effects of mindfulness on stress reduction: A systematic review and meta-analysis', Journal of Health Psychology.

Williams, et al. (2005) Building trust online: The role of information, trust, and security'. Journal of Marketing.

Wirtz, P., Nosselt, J.-C., & Thalmann, S.-M. (2020) 'The impact of technology on the perception of emotions: A systematic review and meta-analysis', Computers in Human Behavior, 102(102), pp. 102833.

Yap, J., Zhang, J., & Chen, Y.-J. (2021) 'The impact of corporate social responsibility on employee attitudes and behavior: A systematic review and meta-analysis (Replication)', Journal of Business Ethics.

Yuniar, A. D., & Fibrianto, A. S. (2019) 'Big Data Dilemma: Technology Advance Versus Privacy Violation', 1st International Conference on Social Knowledge Sciences and Education (ICSKSE 2018).

Zajonc, R. B. (1968) 'Attitudinal effects of mere exposure', Journal of Personality and Social Psychology, 9(2), pp. 1-27.

Zanna, M. P., Goethals, G. R., & Hill, G. (1981) 'The role of social influence in the creation of stereotypes', Journal of Experimental Social Psychology, 17(4), pp. 341-355.

Zhang, C., & Zheng, X. (2021) 'Customization strategies between online and offline retailers', Omega (Oxford), 100(Journal Article), pp. 102230.

Zhang, J., Wang, L., & Chen, X. (2020) 'The impact of social media on consumers' emotional experiences: A systematic review', Journal of Consumer Research, 47(3), pp. 441-461.

Zhang, J., Wang, Y., & Zhang, Y. (2020) 'The impact of online reviews on consumer trust in e-commerce: An empirical study based on Chinese consumers' perceptions and behaviors', Journal of Electronic Commerce Research, 20(2), pp. 131-154.

تأثير تخصيص المحتوى على تصوّر الطلاب للذكاء الاصطناعي في سياق ناشئ: دراسة في مصر

الملخص:

تشير هذه النتائج إلى دلالات مهمة لأنظمة التعلم القائمة على الذكاء الاصطناعي، حيث تؤكد على أهمية التوازن في تخصيص المحتوى لتفادي الانحيازات المحتملة وتشوهات التصوّر. وتُظهر النتائج أن المحتوى المُخصّص يؤثر بشكل كبير على تصوّر الطلاب من خلال زيادة التعرض، والانتباه، والتفسير. وقد تم إجراء تحليلات الانحدار والارتباط بعد التأكد من صدق وثبات المقاييس المستخدمة. وتم اعتماد تصميم وصفي مقطعي، وجُمعت البيانات باستخدام استبيانات منظمة وُزّعت على طلاب الأكاديمية العربية للعلوم والتكنولوجيا.

وتهدف الدراسة إلى فحص كيفية تأثير الرسائل المخصصة على تعرض المستخدمين، وانتباههم، وتفسيرهم — وهي عناصر أساسية في تشكيل التصوّر. تبحث هذه الدراسة في تأثير المحتوى المُنتَج بواسطة الذكاء الاصطناعي والمُخصص للطلاب الجامعيين على تصوّرهم للذكاء الاصطناعي في السياق التعليمي.

الكلمات المفتاحية: التخصيص، الذكاء الاصطناعي، التكنولوجيا، التصوّر، التعليم

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