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Exploring The Role of AI News Anchors in Content Quality and Continued Audience Engagement in Oman

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ABSTRACT

This paper discusses how artificial intelligence news reporters influence the level of perceived content and viewer interest in Omani media. With increasing adoption of AI anchors, it is now important to learn how audiences perceive and use these technologies. Drawing on expectation confirmation theory, the study suggests a conceptual framework examining perceived intelligence, novelty, information quality, and trust as predictors of continuance intention and consumer interest in AI-based news content. The research used a structured questionnaire to gather the data, which consisted of 465 valid answers, and was analyzed with the help of partial least squares structural equation modeling (PLS-SEM). The results show that perceived intelligence, perceived novelty and trust are significantly used in the quality of information and continuance intention. The mediating role of continuance intention is also influenced by these factors albeit indirectly on consumer engagement. Information quality and continuance intention are serial mediators between perceived intelligence, perceived novelty and trust to continuance intention. The consumer engagement variance is explained in 70% by the proposed model. The research adds to the growing body of literature on AI-driven media by explaining the processes by which AI anchors impact long-term audience interest in underexplored areas.

Keywords: *AI News Anchors; Content Quality; Audience Engagement; Media Innovation; Oman*

INTRODUCTION

The rapid development of artificial intelligence (AI) has significantly altered the production of digital content and interaction with the audience in the modern media context. Among the key ones, there has been the introduction of AI news presenters AI-driven virtual presenters that are meant to appear like humans in terms of speech patterns, facial expressions, and emotions. With the help of advanced machine learning and generative measures, AI anchors are deployed to convey news and information with the goal of contributing to efficiency, consistency, and engagement of audiences [1]. With the increasing familiarity of audiences with digital and automated media formats, the nature of the impacts of these technologies on perceptions of quality of content and engagement has become a research issue of critical concern.

In the Middle East and, specifically, in Oman, there has been a faster pace of AI technology adoption over the last few years. The National Program of Artificial Intelligence and Advanced Digital Technologies, which is in line with the Oman Vision 2040, shows the strategic nature of Oman in regard to digital transformation. Within the media industry, AI technologies are applied to news broadcasting and other communications with the population, such as AI anchors to spread the election results and information in multiple languages. Regardless of such developments, there is limited empirical studies that explore the perceptions and interaction of audiences in Oman with AI anchors. It is also due to the extended use of AI that the government of Oman has been able to share with the population the outcomes of Shura elections in real time [2]. To enhance the visuality of the elections in the eyes of the population, the Ministry of Interior itself in cooperation with a London based generative AI company referred to as Yepic also joined the supplementary efforts. This technique has worked successfully in producing multilingual, big and quality scale films in minutes with just a single shot. The firm has also succeeded in creating customized avatars to symbolize the community of Oman, to update the people about the election outcomes (Figure 1).

Figure 1. AI anchor presenting the Shura election's results. *Source: Oman's Ministry of Interior (2023)*

The existing research on the topic of AI in journalism and media communication defined both the opportunities and challenges in terms of automation, such as trust, credibility, and quality of the content [3, 4]. It has been highlighted that perceived intelligence, novelty, and trust are significant factors influencing user perception of AI-based systems and how these factors affect the continued use and use of these systems. But much of this literature has been carried out in the Western or East Asian settings and little focus has been made on culturally unique settings like in Oman. In addition, content quality, continuance intention or engagement has frequently been explored independently in the literature, but the literature has not explored the relationships between them or their interactions within a coherent theoretical framework [5].

To fill these gaps, this research focuses on the expectation confirmation theory and analyzes the influence of the main aspects of AI as an anchor, such as perceived intelligence, perceived novelty, and trust, on the quality of information, continuance intention, and consumer interest in the Omani media. By shedding light on the pathways of how AI anchors affect long-term audience attention, the study aims to elucidate the processes whereby AI anchors can be involved in maintaining attention on the audience; a gap that is yet to be filled in both the local and global studies.

In line with this, this study will primarily focus on how AI news anchors can influence content quality and continued interest among the audience in Oman. In particular, the research questions that the study discusses are the following:

RQ1: How do the AI anchor features (perceived intelligence, perceived novelty, and trust) affect the quality of information?

RQ2: How much continuance intention is affected by AI characteristics of anchors?

RQ3: What can be done to use AI anchor features to improve consumer interest in news information?

The questions answered by the study provides input to the growing body of literature on AI-based media through extending the expectation confirmation theory to a little-known cultural setting. In practice, the results can inform media organizations, policy makers and players who are interested in implementing AI anchors in a manner that can improve the quality of content, audience trust, and the sustained interest of the audience in Oman and other such markets.

LITERATURE REVIEW

Artificial Intelligence Anchors in the Newsroom

The incorporation of artificial intelligence (AI) has been increasing as technology continues to transform dramatically. The literature review in this paper presents the multifaceted aspects of how artificial intelligence anchors enhance the quality of the content and maintain audience engagement. The enhancing role of artificial intelligence is analyzed using expectation confirmation theory (ECT) as the theoretical basis to interpret the engagement of the audience and the quality of information. The key characteristics related to the artificial intelligence anchors analyzed include perceived intelligence (PI), perceived novelty (PN), trust (TR) in artificial anchors, and their implications for the quality of the content and the engagement of the audience.

Expectation Confirmation Theory

This theory includes the components perceived intelligence, perceived novelty, continuance intention, trust, consumer engagement, and satisfaction, and it applies to a wide range of systems, including AI anchors [7-9]. According to Huang and Yu (2023), the role of perceived intelligence, perceived novelty, and trust in AI anchors has a huge impact on the quality of content generated and on the continuation of audience engagement [10].

In the process of social adoption for AI news anchors, we believe that users will subconsciously compare their thoughts before and after watching the videos of AI news anchors and thus generate individual satisfaction. We thereby retained three variables of the ECM namely, continuance intention, quality of content, and consumer engagement and combine them with the core characteristics of AI news anchors such as perceived intelligence, perceived novelty, and trust to establish the theoretical model of the mechanism underlying users' willingness to continue watching AI news anchors [7-9].

Considering the characteristics of AI news anchors through the ushue of the expectation confirmation model (ECM), various factors like perceived intelligence, perceived novelty, continuance intention, and trust contribute to the sustained attention, which ultimately represents an individual's intention to continue using new applications (continuance intention). The table below describes the objectives, design, and key findings of studies using expectation confirmation theory models on artificial intelligence news. The keywords for this topic were confirmation expectation theory, artificial intelligence news anchors, media, and news.

Research Model and Hypothesis Development

Based on the expectation confirmation model (ECM) and the characteristics of AI, the proposed model consists of perceived intelligence (PI), perceived novelty (PN), continuance intention (CI), trust (TR), information quality (IQ), and consumer engagement (CE), which are defined in Table 3. The hypotheses in the conceptual model are composed of both original hypotheses from the ECM and new hypotheses developed from the extant literature.

Table 3. Definitions of the constructs

Construct	Definition	Reference
PI	The cognitive nature of AI assistants' perceived intelligence is considered to impact the evaluations of users regarding the usefulness and performance of AI assistants, focusing on their efficiency.	[11]
PN	Users' evaluation of AI news anchors' novelty.	[12]
TR	Users' cognitive trust and emotional trust for AI news anchors.	[12]
IQ	Users' evaluation of the quality of news broadcast by AI anchors.	[13]
CI	Continuance intention is referred to as the overall willingness of the user to continuously utilize AI.	[14]
CE	The extent to which users' initial expectations about AI news anchors have been met after they watch videos of AI anchors.	[15]

AI Anchor Characteristics and Consumer Engagement

Perceived intelligence (PI), perceived novelty (PN), and trust (TR) are key factors driving consumer engagement with AI news anchors. Perceived intelligence reflects how users evaluate an AI system's competence, behavior, and communication skills [10, 16]. Higher PI fosters confidence in AI agents and positively influences user engagement by enhancing cognitive, emotional, and behavioral involvement [17-21]. Perceived novelty represents users' perceptions of AI systems as innovative, unique, or surprising, which satisfies their innate desire for new experiences [22]. Novelty positively impacts consumer satisfaction and engagement by stimulating curiosity, attention, and repeated interaction [17, 20, 21, 23, 24]. Novel AI news experiences, such as adaptive presentation and interactive features, reinforce engagement through expectation confirmation. Trust encompasses cognitive trust, based on the logical evaluation of accuracy and professionalism, and emotional trust, based on comfort and security in AI-mediated interactions [25]. Trust plays a critical role in AI news consumption by reducing uncertainty and enhancing reliance on AI anchors as credible sources [17, 18, 26, 27]. Expectation confirmation theory explains that meeting initial user expectations increases trust, which in turn strengthens engagement across cognitive, emotional, and behavioral dimensions [28]. We propose the following hypotheses:

(H1a): Perceived intelligence of AI anchors has a significant influence on user engagement regarding the news.

(H1b): Perceived novelty of AI anchors has a significant influence on user engagement regarding the news.

(H1c): Trust in AI anchors has a significant influence on user engagement regarding the news.

AI Anchor Characteristics and Information Quality

Research indicates a strong relationship between the perceived intelligence (PI) of AI anchors and information quality (IQ). Intelligent content that explains information comprehensively encourages viewers to engage cognitively, enhancing consumer engagement [29]. Perceived intelligence users' subjective evaluation of an AI anchor's competence, reasoning, and communication skills serves as a cue for credibility and information reliability, aligning with expectation confirmation theory (ECT). When users' expectations about an AI anchor's intelligence are confirmed, they rate the information as higher in quality [10]. Empirical evidence supports both direct and mediated relationships between perceived intelligence and information quality.

Perceived novelty (PN) also influences information quality. Novelty attracts attention, increases engagement, and enhances perceived usefulness, consistent with the Technology Acceptance Model (TAM) and the Information Systems Success Model [31]. Studies show that novel content improves perceptions of credibility, engagement, and informational value [10, 27]. In AI news contexts, perceived novelty is associated with higher ratings of clarity and engagement, suggesting a direct effect on IQ [32]. Trust (TR) is another key determinant of IQ in AI-mediated news. Trust reflects audience confidence in AI anchors' accuracy and sincerity, and it directly shapes evaluations of informational quality. According to ECT, trust influences how users compare outcomes with expectations, affecting satisfaction and perceived IQ [17]. Empirical studies show that higher trust leads to greater acceptance of content and improved perceptions of accuracy, credibility, and relevance [18, 19, 29, 33]. Hence, we propose the following hypotheses:

(H2a): Perceived intelligence of AI anchors has a significant influence on the information quality of the news.

(H2b): Perceived novelty of AI anchors has a significant influence on the information quality of the news.

(H2c): Trust in AI anchors has a significant influence on the information quality of the news.

AI Anchor Characteristics and Continuance Intention

Continuance intention (CI) reflects users' willingness to repeatedly consume content on AI-mediated platforms and underpins audience retention, loyalty, and ongoing engagement [10]. In AI news contexts, CI is influenced by users' perceptions of intelligence, novelty, and trust in AI anchors. Perceived intelligence (PI) users' assessment of an AI anchor's cognitive capabilities, reasoning, accuracy, and adaptability positively predicts CI. Intelligent AI anchors enhance users' confidence, reduce cognitive effort, and reinforce expectation confirmation, leading to satisfaction and repeated usage [17, 34]. PI also fosters trust and perceived control, further strengthening CI in information-intensive news environments. Perceived novelty (PN) the perception of AI anchors as innovative, unique, and distinct from traditional media also drives CI. Novelty stimulates curiosity, intrinsic motivation, and enjoyment, sustaining repeated use beyond initial adoption [10, 35-37]. Novel AI features, such as virtual avatars, synthetic voices, and adaptive content, maintain user interest and reinforce expectation confirmation, strengthening long-term continuance. Trust (TR) in AI anchors is a critical predictor of CI, reflecting users' confidence in system reliability, competence, transparency, and integrity [19, 38]. Trust reduces the perceived risk of misinformation or errors, supports expectation confirmation, and encourages users to integrate AI anchors into routine news consumption [17]. Therefore, we propose the following hypotheses:

(H3a): Perceived intelligence of AI anchors has a significant influence on the continuance intention of users regarding news.

(H3b): Perceived novelty of AI anchors has a significant influence on the continuance intention of users regarding news.

(H3c): Trust in AI anchors has a significant influence on the continuance intention of users regarding news.

Information Quality and Consumer Engagement

Information quality has been widely recognized as a key determinant of consumer engagement in digital and AI-mediated environments, including AI news anchors. Information quality typically encompasses dimensions such as accuracy, relevance, timeliness, completeness, and clarity of information provided to users [31].

Empirical evidence from previous studies consistently supports a positive relationship between information quality and consumer engagement. Drawing on the Information Systems Success Model, DeLone and McLean (2003, 2016) proposed that information quality directly influences user engagement and continued interaction with digital systems. Accordingly, several studies have hypothesized that information quality has a positive effect on consumer engagement, particularly in AI-driven and automated content platforms [4]. In digital journalism contexts, high-quality information delivered by automated agents has been shown to increase users' cognitive and affective engagement by reducing uncertainty and enhancing trust in AI-generated news.

Prior studies indicate a significant relationship between information quality and consumer engagement in the context of AI anchors. According to expectation confirmation theory (ECT), users form initial expectations regarding the accuracy, relevance, credibility, and timeliness of information delivered by AI anchors. When these expectations are confirmed through high-quality information, users experience satisfaction and positive evaluations, which enhance their cognitive, emotional, and behavioral engagement [17]. The results show that information quality has a significant positive effect on consumer engagement, indicating that users are more likely to interact with, trust, and continuously engage with AI anchors when the information provided meets or exceeds their expectations [42]. This finding is consistent with the Information Systems Success Model, which emphasizes information quality as a critical determinant of user engagement and continued usage [31]. Therefore, we propose the following hypothesis:

(H4): Information quality has a significant influence on consumer engagement regarding the news.

Continuance Intention and Consumer Engagement

Prior research presents mixed evidence regarding the relationship between continuance intention (CI) and consumer engagement (CE) in AI-mediated environments. Continuance intention reflects users' willingness to repeatedly interact with AI anchors, whereas consumer engagement encompasses cognitive, emotional, and behavioral involvement, such as attention, interaction, and emotional attachment. Drawing on expectation confirmation theory (ECT) and extensions of the Technology Acceptance Model (TAM), several studies suggest a positive direct relationship between CI and CE, whereby users who intend to continue using AI anchors exhibit higher levels of engagement through repeated exposure, interaction, and parasocial bonding [17, 23, 27]. Similar findings in livestreaming and virtual influencer research indicate that sustained usage intention fosters familiarity and immersion, which, in turn, enhances engagement [44].

However, a growing body of research challenges the assumption that CI directly translates into engagement. Empirical studies of AI-based and utilitarian systems reveal that continuance intention often leads to habitual or passive consumption, rather than active engagement [45]. In AI news contexts, users may intend to continue using AI anchors for efficiency and convenience without demonstrating emotional or interactive involvement, resulting in a non-significant CI–CE relationship [45]. This intention–behavior gap suggests that CI may explain system retention but not higher-order engagement outcomes [46].

Human–AI interaction research further indicates that engagement is driven more strongly by experiential and affective factors such as social presence, anthropomorphism, emotional expressiveness, and narrative richness than by cognitive intention alone [41]. Additionally, habit formation in automated systems weakens the influence of intention on behavior, as repeated use becomes routine rather than motivationally driven [46]. Consequently, CI and CE may operate as parallel but distinct post-adoption outcomes rather than sequentially linked constructs in AI-mediated news environments.

We propose the following hypothesis:

(H5): Continuance intention has a significant influence on consumer engagement regarding the news.

Mediation of Content Quality

Prior studies strongly support the proposition that information quality mediates the relationship between perceived intelligence (PI) of AI anchors and consumer engagement (CE) with news. Existing research strongly supports information quality (IQ) as a central mediating mechanism linking key user perceptions of AI news anchors namely, perceived intelligence, perceived novelty, and trust to consumer engagement (CE) with news content. Perceived intelligence (PI) reflects users' evaluations of an AI system's cognitive capabilities, such as accuracy, analytical ability, and contextual understanding [34]. However, PI alone does not directly drive engagement. Instead, intelligent system capabilities become meaningful to users when they result in high-quality informational outputs characterized by accuracy, relevance, clarity, and timeliness [31]. Empirical studies show that intelligent AI systems enhance perceived information quality, which increases trust; satisfaction; and ultimately, cognitive, emotional, and behavioral engagement with news content [41, 48]. This mechanism aligns with the DeLone and McLean Information Systems Success Model, which posits that system characteristics influence user outcomes indirectly through information quality [31]. Similarly, perceived novelty (PN) users' perceptions of AI anchors as innovative and distinct from traditional news delivery can attract attention and curiosity but does not sustain engagement on its own [35]. Prior research indicates that novelty enhances engagement only when it improves the perceived quality and informational value of content [36]. In AI news contexts, novelty signals advanced technological capability, leading users to expect higher-quality information. When these expectations are fulfilled, perceived information quality increases, which in turn drives deeper engagement behaviors such as sustained attention, sharing, and interaction [7]. In addition, trust in AI news anchors (TR) is closely intertwined with information quality in shaping engagement. Research shows that information quality enhances trust in AI anchors, which subsequently increases satisfaction and continuance intention precursors to engagement behaviors [10]. Therefore, we propose the following hypotheses:

(H6a): Information quality mediates the association between perceived intelligence and consumer engagement regarding the news.

(H6b): Information quality mediates the association between trust in AI and consumer engagement regarding the news.

(H6c): Information quality mediates the association between perceived novelty and consumer engagement regarding the news.

Mediation of Continuance Intention

Recent research highlights continuance intention (CI) as a crucial mediating mechanism linking users' perceptions of AI news anchors to consumer engagement behaviors such as repeated viewing, sharing, and commenting. CI reflects users' willingness to sustain interactions over time, transforming cognitive and affective evaluations into observable engagement [10]. Perceived intelligence (PI) users' assessments of an AI anchor's accuracy, reasoning ability, and professionalism have been shown to enhance engagement indirectly through CI by fostering trust and satisfaction [10, 49]. However, this mediating effect is context-dependent; repetitive or emotionally flat content may weaken the PI → CI → engagement relationship [27]. Similarly, perceived novelty (PN) can stimulate curiosity and encourage repeated interaction, thereby strengthening CI and engagement. Yet excessive or poorly aligned novelty may reduce satisfaction and continuance intention, particularly among users with limited experience with AI news anchors [10]. Therefore, we propose the following hypotheses:

(H7a): Continuance intention mediates the association between perceived intelligence and user engagement regarding the news.

(H7b): Continuance intention mediates the association between trust in AI and user engagement regarding the news.

(H7c): Continuance intention mediates the association between perceived novelty and user engagement regarding the news.

In conclusion, the proposed model and assumptions are depicted in Figure 2.

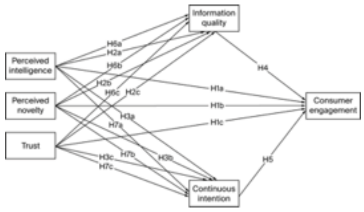

Figure 2. The proposed conceptual model

METHODS

Statistical Analysis Tools

Data were analyzed with two statistical packages SPSS (version 26) and SmartPLS 4. The demographic features of the respondents (age, gender, years of work experience, and education level) were analyzed using SPSS. Initial data screening and cleaning were also carried out using it to guarantee completeness, accuracy and appropriateness to be used in further analysis. The Partial Least Squares Structural Equation Modeling (PLS-SEM) was done using SmartPLS 4. This software was used to assess the measurement and structural models, test the hypotheses that are put forward and to analyze mediation and moderation effects. The PLS-SEM was suitable because the research had a predictive aim and a number of latent constructs were to be assessed using several measures.

Structural Equation Modeling

The use of Structural Equation Modeling (SEM) helped analyze the connections between the research constructs and also test the hypotheses of the research. SEM fits well the analysis of complex model and multivariate latent variables that includes measurement items and it allows measuring the measurement and structural relationships simultaneously [51].

In this research, the PLS-SEM method was implemented with the SmartPLS 4 because it was selected based on its application in prediction-based research and the possibility of complex models with mediating and moderating relationships. The SEM analysis was conducted in two stages. To determine the validity and reliability of the constructs, the measurement model was tested. This involved the analysis of internal consistency reliability and construct validity. Second, structural model was evaluated in order to test the hypothesized relationships of latent variables.

Validity and reliability were regarded as being very important to the quality of the research tool. Validity is the degree to which an instrument can measure what it is designed to measure whereas reliability is the relative measure of the uniformity of the measurement items. Even though the measurement items were based on the formerly tested scales [52], additional evaluation was required because of the novel research conditions and data. In this respect, reliability and validity were assessed at various levels of the analysis, such as in pre-test, pilot and the ultimate SEM assessment, as explained in the subsequent sections.

Sample Size

The determination of the sample size was based on the recommended statistical and methodological guidelines. In cases where the target population size is unknown, it is customary to use the formula by Cochran (2007) to estimate the minimum size of the sample that will be required in large population. The sample size of 385 respondents was obtained by using a 95% confidence level ($Z = 1.96$), a margin of error, and maximum variability ($p = 0.5$) [56].

$$n_0 = \frac{Z^2 pq}{e^2}$$

Cochran's formula to calculate sample size

where n0 is the sample size, e is the desired level of precision, p is the estimated proportion of an attribute that is present in the population, and q is 1-p. With 95% confidence probability, the Z score threshold is 1.96, $p < 0.05$ (two tailed) [56]. Israel [57] suggests an application of the formula where p=0.5 is used for maximum variability since the variability in the sample means is unknown [58]. The sampling variability of a statistic refers to how much the statistic varies from sample to sample and is usually measured by its standard error.

The calculation of the sample size according to [56] with 95% confidence probability, Z score 1.96, and p<.05 yielded:

$$Sample\,size = \frac{(1.96)^2 \times (0.5) \times (0.5)}{0.05^2} = 385$$

Besides this non-parametric statistical method, the requirements of the sample size were also considered within the PLS-SEM. One of the widely mentioned guidelines is the 10-times rule, according to which the lowest size of the sample should be ten times the upper bound of the number of structural paths to any latent construct in the model [52]. The upper limit of the number of arrowheads to a latent variable in the current research was six, which implied that the sample size was no less than 60 respondents.

In order to offer a stricter evaluation, statistical power analysis was carried out with the help of G*Power [48]. The level of significance assumed was a = 0.05, the medium effect size = f2 = 0.15, and statistical power = 0.95, and five predictors. According to these parameters, the sample size of 138 respondents was the minimal (see Figure 3).

The number of respondents used in this project was 190 which is more than 10-times rule and G*Power analysis recommends. It was thus deemed sufficient to provide enough statistical power and a good estimation of the PLS-SEM model [52].

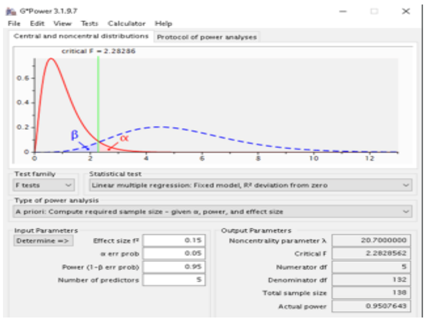

Figure 3. Using G*Power to calculate minimum sample size

Data Collection Procedures

The survey was conducted at the period of September 2025 through the use of a structured online, self-administered questionnaire. The survey was aimed to the news and social media audience members, journalists and the media and AI professionals. The questionnaire contained an introduction section that stated the intention of the study and assured anonymity and confidentiality of the responses given by the respondents.

There were 600 questionnaires which were sent, 501 of which were returned making the response rate to be about 90 percent. This number of 501 responses was considered complete and worthy of analysis. This is a large enough sample to meet the minimum sufficient size suggested by PLS-SEM, both the 10-times rule [59] and the guidelines on the statistical power of the test calculated using G*Power [48].

RESULTS

SmartPLS 4 was used to carry out partial least squares structural equation modeling (PLS-SEM), which aims to maximize the explanatory capacity (i.e., R2) of the endogenous latent variables and is suitable for theoretical prediction and exploratory research.

Demographic Characteristics

The demographic profile of the study reveals a predominantly local sample, with Omani nationals representing 100% of the participants. The gender distribution is relatively balanced, with males making up 52.3% and females representing 47.7% of the total group. Age-wise, the population is largely concentrated in the younger to middle-aged brackets, as 20.6% are between 18 and 24 years old, 50.3% are between 25 and 34 years old, and 25.2% are between 35 and 44 years old. Older demographics are less well represented, with 3.7% in the 45-54 age range and only 0.2% aged 55 years and above. Educationally, the participants are highly qualified; while 1.9% have a high school education and 14% hold a diploma, the majority have attained higher degrees, including a bachelor's degree at 50.5%, a master's degree at 28.8%, and a Doctorate at 4.7%.

Reflective Measurement Model Assessment

The assessment of the reflective measures entails an examination of internal consistency reliability, convergent validity, and discriminant validity. The initial run of the measurement model reveals seventeen items (17) with outer low loading values between 0.621 and 0.7. These items were analyzed first and deleted if removing the item led to a significant increase in AVE or Composite Reliability (CR) above their respective thresholds (0.5 for AVE, 0.7 for CR). The "One-at-a-Time" rule was followed by deleting the single lowest item, then the PLS algorithm was re-run, and the results were checked. Removing one low item will cause the loadings of the remaining items to increase and consequently to increase in AVE and CR. A total of four items from the consumer engagement (CE) construct were deleted as their removal led to a significant increase in both Average Variance Extracted (AVE) and Composite Reliability (CR). The final 8-item scale satisfies the threshold for convergent validity (AVE > 0.50) while maintaining the conceptual integrity of the construct.

Moving forward by examining the discriminant validity heterotrait–monotrait ratio of correlations (HTMT), the results show values higher than 0.90, suggesting that two or more of the constructs might be measuring the same thing (a lack of discriminant validity). In other words, they are too highly correlated to be considered distinct. While 0.85 is the strict/conservative threshold (suggested by Kline), Henseler et al. (2015) and Hair et al. (2022) state that 0.90 is acceptable for constructs that are conceptually very similar, as in the current case. To overcome this issue, items causing the overlap were identified by look at cross-loadings. If an item loads almost as highly on its own construct as on another construct, that item is "leaking" variance and will be deleted. The model is then re-run until (HTMT) values become less than 0.9. As a result of this process, six items were deleted (IQ03, PI02, PN01, TR02, TR04, and CI03).

The measurement model analysis proceeded again after deleting the excluded items and showed an acceptable result. As Table 5 depicts, the composite reliability (CR) values of all constructs are greater than the benchmark value of 0.70 [52], indicating internal consistency reliability. Convergent validity is supported, as the standardized factor loadings exceed the 0.70 cut-off [52] and the average variance extracted (AVE) is well above the 0.50 threshold [60]. Furthermore, Table 6 shows that the heterotrait–monotrait ratio of correlations (HTMT) is lower than the required threshold value of 0.9 [61] and confidence intervals do not include 1 [62], validating the discriminant nature of all constructs. Taken together, the results provide supportive evidence for the constructs' reliability and validity.

	CE	CI	IQ	PI	PN	TR
CE						
CI	0.773					
IQ	0.883	0.899				
PI	0.883	0.744	0.85			
PN	0.830	0.755	0.868	0.807		
TR	0.895	0.804	0.892	0.894	0.893	

Notes: CE—consumer engagement, CI—continuance intention, IQ—information quality, PI—perceived intelligence, PN—perceived novelty, TR—trust. Shaded boxes are the standard reporting format for HTMT ratios.

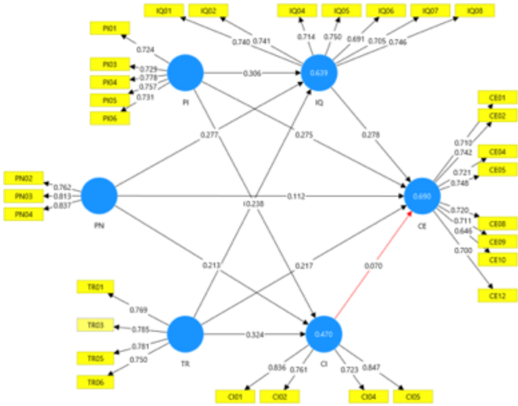

Figure 4. Results PLS path model estimation

Path Coefficients and Hypotheses Testing

In SmartPLS, the relationships between constructs can be determined by examining their path coefficients and related t statistics via the bootstrapping procedure with 10,000 re-samples.

Figure 5 and Table 7 show that ten hypotheses were accepted (H1a, H1b, H1c, H2a, H2b, H2c, H3a, H3b, H3c and H4) and one is rejected (H5). The following ten hypotheses were accepted:

H1a: Perceived intelligence of AI anchors has a significant influence on user engagement regarding the news (t value 7.81 at level of $p<0.01$); H1b: Perceived novelty of AI anchors has a significant influence on user engagement regarding the news (t value 2.635 at level of $p<0.01$); H1c: Trust in AI anchors has a significant influence on user engagement regarding the news (t value 5.651 at level of $p<0.01$); H2a: Perceived intelligence of AI anchors has a significant influence on perceived information quality of the news (t value 9.473 at level of $p<0.01$); H2b: Perceived novelty of AI anchors has a significant influence on perceived information quality of the news (t value 7.787 at level of $p<0.01$); H2c: Trust in AI anchors has a significant influence on the perceived information quality of the news (t value 8.812 at level of $p<0.01$); H3a: Perceived intelligence of AI anchors has a significant influence on the continuance intention of users regarding the news (t value 5.748 at level of $p<0.01$); H3b: Perceived novelty of AI anchors has a significant influence on the continuance intention of users regarding the news (t value 4.55 at level of $p<0.01$); H3c: Trust in AI anchors has a significant influence on the continuance intention of users regarding the news (t value 6.829 at level of $p<0.01$); and H4: Information quality of news has a significant influence on user engagement regarding the news (t value 4.209 at level of $p<0.01$).

The following hypothesis was rejected:

H5: Continuance intention has a significant influence on user engagement regarding the news (t value 1.374 at level of $p>0.05$).

Figure 5. Results of bootstrapping showing path coefficients and t values

Mediation Analysis

Mediation is when a third mediator construct intervenes between two other related constructs. Consider Figure 4.3 for a detailed illustration: a change in the exogenous construct Y1 causes a change in the mediator construct

Y2, which, in turn, results in a change in the endogenous construct Y3 in the PLS path model. The direct effects are the relationships linking two constructs with a single arrow Y1 → Y2. Indirect effects are those relationships that involve a sequence of relationships with at least one intervening construct involved in the Y1 → Y2 → Y3 sequence.

Based on the previous figure (Figure 6) there are two main relationships, the direct and indirect. According to Hair, Hult (63), these two relationships can be characterized into five types of mediating effects:

- Direct-only nonmediation—the direct effect is significant, but the indirect effect is not;
- No-effect nonmediation—neither the direct nor the indirect effect are significant;
- Complementary mediation—the indirect effect and the direct effect are both significant and point in the same direction;
- Competitive mediation—the indirect effect and the direct effect are both significant but point in opposite directions;
- Indirect-only mediation—the indirect effect is significant, but the direct effect is not.

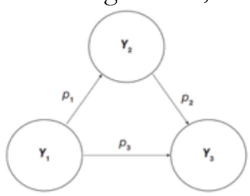

Figure 6. Mediation model

According to Hair, Hult (63) testing the type of mediation in a model requires running a series of analyses (Figure 7). This procedure relies on testing the significance of the indirect effect (p1.p2), then the direct effect (p3) to conclude the presence and type of mediation.

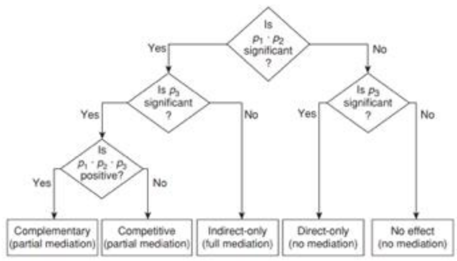

Figure 7. Mediation analysis procedure [63]

In the current model, perceived information quality (IQ) and continuance intention (CI) have the potential to operate as a mediator between the exogenous constructs (PI, PN, and TR) and endogenous constructs (CE). To begin the mediation analysis of IQ, the significance of the indirect effects is tested. The indirect effect from PI via IQ to CE is the product of the path coefficients from PI to IQ and from IQ to CE, as with the indirect effects from PN via IQ to CE, TR via IQ to CE. Mediation analysis of CI was tested the same way; PI via CI to CE, PN via CI to CE, and TR via CI to CE. To test the significance of these path coefficients' products, the bootstrap procedure was run with 10,000 bootstrap samples and the complete bootstrapping option turned on. The Bias-Corrected and Accelerated (BCa) Bootstrap and two-tailed testing with a significance level of 0.05 was activated [64]. The mediation analysis procedure focuses on the significance of the direct effects from PI to CE, PN to CE, and TR to CE. The results of the hypothesis testing (indirect and direct effect) are outlined in Table 8.

PI → IQ → CE: The results suggest that the indirect pathway that runs from perceived intelligence to consumer engagement through information quality ($\beta = 0.085$, $p < 0.01$) is significant. The direct effect ($\beta = 0.275$, $p < 0.01$) is also significant, revealing that information quality plays a complementary mediation role in the relationship between perceived intelligence and consumer engagement. Thus, H6a is supported.

PN → IQ → CE: The results suggest that the indirect pathway that runs from perceived novelty to consumer engagement through information quality ($\beta = 0.077$, $p < 0.01$) is significant. The direct effect ($\beta = 0.112$, $p < 0.01$) is also significant, revealing that information quality plays a complementary mediation role in the relationship between perceived novelty and consumer engagement. Thus, H6b is supported.

TR → IQ → CE: The results suggest that the indirect pathway that runs from trust to consumer engagement through information quality ($\beta = 0.090$, $p < 0.01$) is significant. The direct effect ($\beta = 0.112$, $p < 0.01$) is also significant, revealing that information quality plays a complementary mediation role in the relationship between trust and consumer engagement. Thus, H6c is supported.

PI → CI→ CE: The results suggest that the indirect pathway that runs from perceived intelligence to consumer engagement through continuance intention ($\beta = 0.017$, $p > 0.05$) is nonsignificant. However, the direct effect ($\beta = 0.268$, $p < 0.01$) is significant, revealing that continuance intention does not mediate the relationship between from perceived intelligence and consumer engagement. Thus, H7a is not supported. The relation in this case relies on the direct effect only between perceived intelligence and consumer engagement without any intervention of continuance intention.

PN → CI→ CE: The results suggest that the indirect pathway that runs from perceived novelty to consumer engagement through continuance intention ($\beta = 0.015$, $p > 0.05$) is nonsignificant. However, the direct effect ($\beta = 0.112$, $p < 0.01$) is significant, revealing that continuance intention does not mediate the relationship between perceived novelty and consumer engagement. Thus, H7b is not supported. The relation in this case relies on the direct effect only between perceived novelty and consumer engagement without any intervention of continuance intention.

TR → CI→ CE: The results suggest that the indirect pathway that runs from trust to consumer engagement through continuance intention ($\beta = 0.023$, $p > 0.05$) is nonsignificant. However, the direct effect ($\beta = 0.217$, $p < 0.01$) is significant, revealing that continuance intention does not mediate the relationship between trust and consumer engagement. Thus, H7c is not supported. The relation in this case relies on the direct effect only between trust and consumer engagement without any intervention of continuance intention.

The following Table 10 summarizes the hypotheses testing results of the current study.

Table 10. Summary of hypotheses testing

Hypothesis	Testing Result
H1a: Perceived intelligence of AI anchors has a significant influence on user engagement regarding the news.	Accepted
H1b: Perceived novelty of AI anchors has a significant influence on user engagement regarding the news.	Accepted
H1c: Trust in AI anchors has a significant influence on user engagement regarding the news.	Accepted
H2a: Perceived intelligence of AI anchors has a significant influence on the perceived information quality of the news.	Accepted
H2b: Perceived novelty of AI anchors has a significant influence on the perceived information quality of the news.	Accepted
H2c: Trust in AI anchors has a significant influence on the perceived information quality of the news.	Accepted
H3a: Perceived intelligence of AI anchors has a significant influence on the continuance intention of users regarding the news.	Accepted
H3b: Perceived novelty of AI anchors has a significant influence on the continuance intention of users regarding the news.	Accepted
H3c: Trust in AI anchors has a significant influence on the continuance intention of users regarding the news.	Accepted
H4: Information quality of news has a significant influence on user engagement regarding the news.	Accepted
H5: Continuance intention has a significant influence on user engagement regarding the news.	Rejected
H_{6a} Information quality mediates the relation between perceived intelligence and consumer engagement.	Accepted
H_{6b} Perceived information quality mediates the relation between perceived novelty and consumer engagement.	Accepted
H_{6c} Information quality mediates the relation between trust and consumer engagement.	Accepted
H_{7a} Continuance intention mediates the relation between perceived intelligence and consumer engagement.	Rejected
H_{7b} Continuance intention mediates the relation between perceived novelty and consumer engagement.	Rejected
H_{7c} Continuance intention mediates the relation between trust and consumer engagement.	Rejected

DISCUSSION

This paper analyzed the audience interest of AI-based news anchors through the perspectives of perceived intelligence, perceived novelty, trust, information quality and continuance intention in a PLS-SEM model. Based on the expectation-confirmation theory, the results provide detailed information about the cognitive and affective judgment of the audience on the news presentation by AI and the translation of these judgments into engagement. [68].

These findings reveal that perceived intelligence, perceived novelty, and trust are key drivers to consumer interactivity with AI news anchors. In terms of expectation-confirmation, this implies that the higher the AI systems are competent, innovative and reliable to the expectations of the users, the more the audience positively reacts and pays more attention to the content [13]. The concept of perceived intelligence is especially critical, especially when it comes to the news context, where they demand accuracy, coherence, and a sense of the context. The AI anchors are considered cognitively competent and hence legitimized as sources of information, which increases engagement.

The perceived novelty is also an important factor, and it means that the audience is sensitive to the innovative and distinct features of AI anchors. The observation is consistent with previous studies that indicate that novelty generates attention and curiosity, particularly in new technologies. But novelty is not enough; it works with trust, perception of intelligence, which shows that innovation should be supported with credibility in order to keep the engagement on a meaningful level [69].

One determinant of engagement and ratings of information quality was found to be trust. Trust in the media arena serves as a psychological process that minimizes the perception of risk and uncertainty. Trusting AI anchors encourages the audience to believe the information provided to them as truthful and valuable [70]. This adds strength to the claim that trust does not appear during the performance of systems but is a driving force influencing how audiences react to communication mediated by AI.

The results also indicate that perceived intelligence, novelty, and trust have a significant impact on perceived quality of information. It means that viewers evaluate the quality of information comprehensively, combining both content-specific properties and perceptions on a system level. Instead of assessing news content on its own, viewers seem to conclude the quality of information based on how competent and intentional the presented AI seems [71]. This observation builds on the expectation-confirmation theory by showing that the process of confirmation is not limited to system-use level but also content assessment in AI-based media conditions.

The quality of the information is a complementary mediating factor between the perception of the system and consumer engagement, and as such, it has a central role in the overall engagement process. Favorable attitudes towards AI anchors increase interest levels mainly by the ability of the audiences to rate the suitability, understandability and utility of the information presented. This points to the fact that even in technologically mediated situations, engagement is content based in essence [72]. The attraction to the AI systems can be achieved because of the novelty and intelligence; however, long-term engagement will be achieved because of the perceived value of the information presented [73].

Conversely, continuance intention failed to have a significant effect on consumer engagement, as well as mediate through system perception and consumer engagement. This result indicates that the use of AI news anchors can be more immediate and situational than prompted by the desire to use it over the long-term. Since the introduction of AI anchors in the news media is rather recent, the audiences might still lack a fixed behavioral intention, acting according to temporary assessments of the system performance and quality of its content [74]. These assumptions are based on conventional models of technology adoption and shows that continuance intention can be less significant in the initial or exploratory relationships with AI media technologies.

CONCLUSION

The work is relevant to the current body of AI-related research in journalism by analyzing how people respond to AI-assisted news anchors using the expectation-confirmation theory. The results show that perceived intelligence, novelty, and trust are main factors of engagement with information quality having a significant mediating factor. The findings highlight the fact that although AI technology may appeal to audiences with the help of innovativeness and the perceived ability, the long-term engagement is always determined by the perceived quality and trustworthiness of provided information. Theoretically, this paper applies the expectation-confirmation theory to the context of the AI-mediated news, and it focuses on how system perceptions impact the content judgments. In practice, the results can be used by media organizations in Oman and other countries to indicate that they should focus on transparency, reliability, and informational benefit when investing in AI news anchors instead of novelty. In spite of its efforts, the study has weaknesses in its cross-sectional design and situational orientation. Future studies might utilize longitudinal studies, cross-cultural comparisons or experiments to examine the audience-AI relationships in the changing media ecosystems.

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