Feeling Economy, Artificial Intelligence, and Future Jobs
A Systematic Literature Review

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Abstract: The Feeling Economy, related to tasks that involve emotions or feelings, studies the impact not only on the economy but also on society, influencing areas such as employment, marketing, education, politics, governance, and ethics. This study is the first systematic and bibliometric literature review to investigate the current state of knowledge on this topic, considering the emergence of artificial intelligence (AI). This review followed the PRISMA method using the VosViewer computer program. The thematic analysis of the 21 chosen studies resulted in the extraction of three key research themes: (1) characterization of multiple AI; (2) response of employees and clients/consumers to multiple intelligences; and (3) effects of AI on job skills and tasks. The results of this study allow for a greater and more detailed understanding of how the Feeling Economy has developed and been studied. The possibility of significant change, like jobs, stands out, with increasing emphasis on skills related to feeling, empathy, and emotional intelligence. There will also be practical implications for political and business decision-makers for understanding the changes necessary to thrive in the Feeling Economy, considering the replacement of human tasks by AI and exploring human/AI complementarity and integration. One proposes a future research agenda.

Keywords: Feeling economy, Artificial intelligence, Mechanical AI, Thinking AI, Feeling AI.

1 Introduction

Feeling economy, a promising new scientific area, is defined as "… an economy in which the total employment and wages attributable to feeling tasks exceed the total employment and wages attributable to thinking or mechanical tasks" (Huang et al., 2019, p.44). The main reason for the emergence of the Feeling Economy is the advancement of artificial intelligence (AI), as a field of study focused on creating software or machines that reproduce the cognitive abilities of human intelligence and perform tasks usually performed by humans (Russell & Norvig, 2010). Since AI is designed to imitate human intelligence, it, therefore, can do (perform mechanical tasks), think (perform thinking tasks), and feel (perform feeling tasks), just like human beings or better (Rust & Huang, 2021).

For this reason, given that AI has started to carry out many tasks in current jobs, there have been more studies on the topic (Pereira et al., 2023). Among the broad topics related to human resource management, most articles concentrate on the impact of AI on jobs, particularly concerning the future of work and technological unemployment (Pan & Froese, 2023).

It is ironic that the entire discussion once again turns to the question of replacing human workers with "machines", given that the argument goes back more than two centuries when several prominent economists from the era of the Industrial Revolution debated technological unemployment (Steuart, 1767; Mortimer, 1772).

While some contend that technological change has permanently eliminated certain jobs while creating others in their place (for example, the transition from coachmen to drivers with the advent of the automobile), others argue that sufficiently advanced AI systems can perform all tasks more efficiently and cost-effectively than humans (e.g., Atack et al., 2019).

However, although such a negative outlook is not necessarily likely, recent economic studies have examined how automation (including AI) increases unemployment (Acemoglu & Restrepo, 2020), inequality (Mokyr et al., 2015), reduces wages (Lordan & Neumark, 2018; Acemoglu & Restrepo, 2020), and causes technological substitution (Lu et al., 2018; Prettner & Strulik, 2020).

One of the most cited studies in the media is by Frey and Osborne (2017), which argues that automation and AI will lead to significant job losses. However, according to Willcocks (2020), the study has several limitations, namely the fact that it does not carry out any analysis of the jobs that are likely to be created by changes in work and technology and the fact that it focuses on work and professions and not in activities and tasks.

Thus, as in Frey and Osborne (2017), most pessimistic studies that estimate job losses due to AI focus on jobs rather than breaking them down by tasks and activities, leading to a misunderstanding of the likely effects of AI (Willcocks, 2020). Therefore, to obtain a more realistic view of this issue, the big challenge is to analyze the tasks and activities of each profession or job and what changes in employment underlie the links between AI and the skills and abilities of employees.

One assumes that jobs typically involve three types of tasks or intelligence levels required by AI: mechanics, thinking, and feeling and that AI can replace human employees in the tasks they are best at (Huang et al., 2019). Mechanical tasks refer to performing routine, repetitive work with minimal learning requirements. Thinking tasks require analyzing, acquiring knowledge, and making autonomous decisions based on data. Feeling tasks involve feeling, responding to emotions, communicating, and having more interpersonal behavior. Thus, like machines and robots have taken over mechanical tasks, AI performs thinking tasks better, while feeling tasks seem more difficult for AI to perform (Huang et al., 2019; Rust & Huang, 2021).

Many tasks that previously required human intelligence are now automated through AI as machines are trained to "think". However, automating emotional intelligence proves more challenging, which currently constitutes the human worker's competitive advantage over machines. This process in which AI quickly takes over a more significant share of thinking tasks leaves human intelligence focused on the "Feeling Economy" (Huang et al., 2019; Rust & Huang, 2021).

The Feeling Economy is an economic perspective in which the total number of jobs and wages related to emotional tasks is more significant than those attributable to thinking tasks or mechanical tasks (Huang et al., 2019). Tasks that involve interpersonal interaction, empathy, and emotional involvement (e.g., interacting with individuals within and outside the organization, or building and keeping relationships and influencing or selling) are of greater importance than thinking tasks and mechanical tasks, both for managers and employees as well as consumers (Rust & Huang, 2021). As a result, employment and wages will increasingly depend on these tasks, which could cause an upheaval in the current social order (Huang et al., 2019; Rust & Huang, 2021).

Literature in this area is taking its first steps, which suggests the need for more scientific studies to understand what this field can provide for the future of jobs. This gap in the literature stands out because although research on AI accumulates daily, the only systematic reviews of the literature closest to this area that we were able to identify address limited and specific fields, such as the impact of AI on public employment and public policies (Reis et al., 2021b); and about the various modes of autonomous intelligent defence systems in the defence industry (Reis et al., 2021a).

However, we have not found any literature review focusing on the Feeling Economy. Therefore, an integrated discussion needs to be improved considering this bold and potentially controversial direction that society is taking on how AI changes the dynamics of jobs; it reconfigures work routines, work processes, and skills and how workers perceive these changes and respond by altering how they work. In this context, this systematic literature review seeks to contribute to filling these gaps in research results on the Feeling Economy. More specifically, it aims to identify changes like work and emerging skills, new forms of work, and new jobs and present an integrated assessment of the problems and findings of the primary individual studies about the Feeling Economy.

Inspired by these thoughts, the research question arises: What is the current state of knowledge about the Feeling Economy, considering the emergence of AI? The following section will describe the methodology used to fulfill this article's objectives and answer the formulated research question.

2 Methods

To carry out the systematic literature review, we chose the PRISMA method (Moher et al., 2009) because it helps to synthesize academic literature in a precise and reliable way, as it implies the adoption of a transparent and reproducible set of phases that allow researchers to enhance the overall quality of the review process (Brereton et al., 2007). This type of review is beneficial and relevant to integrate studies on emerging topics such as the one we propose to investigate because the breadth and depth of work on a topic can be explored and understood, enabling the evaluation of the work's validity and quality or, conversely, revealing weaknesses, inconsistencies, and contradictions, and also gaps that can be identified (Paré et al., 2015; Xiao & Watson, 2019).

The research protocol addressed the following question: What is the current state of knowledge about the Feeling Economy, considering the emergence of AI? Based on this question, we designed a search protocol that we applied to the following databases: Academic Search Premier, EBSCO Databases, Business Source Complete, Science Direct, Web of Science, IEEE Xplore Digital Library, Wiley Interscience, Sage, Scopus, Elsevier, and Taylor and Francis. Thus, the Boolean sentence was as follows: (AI OR "artificial intelligence") AND ("feeling econ*"). The search on all terms indicated in the full text of the articles was carried out in September 2024.

First, one removed the duplicate documents (68 articles). Next, we present the inclusion and exclusion criteria.

Inclusion criteria: all the articles written in English, without temporal restrictions, that deal with the 'Feeling Economy' as an economic concept linked to the role of AI.

Exclusion criteria: all the articles that did not fully align with the scope and boundaries of the study, namely the use of the expression 'feeling economy' without being the study concept, such as "feeling economy hill" or "feeling economy stuck" (33 articles); the presence of the expression "feeling economy" only in the article references (47 articles) with no consequences for the studies in question; and even when the expression is in the body of the article with the correct meaning, its non-use in a theme focused on the Feeling Economy (60 articles). Thus, 140 articles were eliminated after this verification, leaving only 22 for thematic and bibliometric analysis.

Considering that other relevant articles for our study could be published outside the chosen databases or our Boolean search, we used cross-referencing (two articles) and the Elicit researcher assistance program (two articles), which allowed us to identify four more articles. Thus, the selection process identified 26 publications for review. The number of studies that were identified, excluded, included, and selected at each stage of the systematic literature review selection phase is shown in Figure 1.

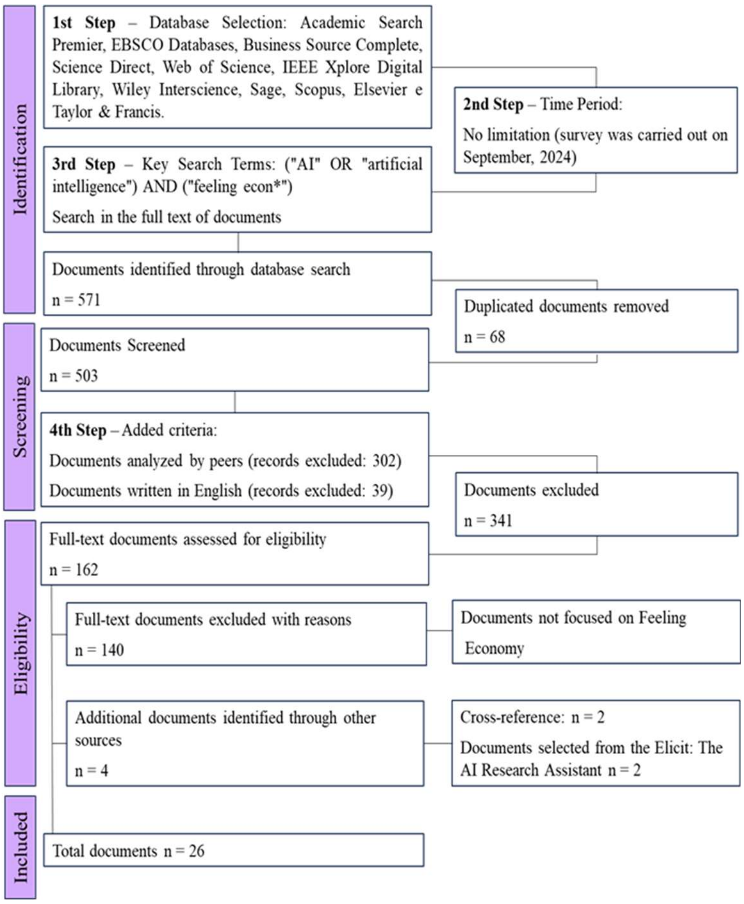

Figure 1 Flow diagram of articles search.

Bibliometrics, first introduced by Pritchard (1969), has demonstrated effectiveness as a quantitative analysis tool of scientific production and has played an increasingly important role in Library Science or Information Science (Milojević et al., 2011). Bibliometric methods are based on a quantitative approach that complements meta-analysis and structured qualitative literature reviews. They direct the researcher to the most influential works, objectively mapping the research and allowing them to support their conclusions with aggregated bibliographic data (Zupic & Čater, 2015). Understanding the evolution of publications and citations is one of the principles of bibliometric analysis that we will analyze in the next section. To this end, we conducted an analysis of bibliographic coupling, the co-citation network, and the keyword co-occurrence network using the VOSviewer software version 1.6.18 with the aim of building and displaying bibliometric maps, as well as identifying thematic groups and their reference networks (van Eck & Waltman, 2010; Waltman et al., 2010; Perianes-Rodriguez et al., 2016). We found that, by coincidence, all articles are from the Web of Science database, which allowed us to use the VOSviewer software safely. Furthermore, all articles are from magazines classified by the Chartered Association of Business Schools (CABS).

3 Findings

3.1 Bibliometric analysis

Selected publications include research articles (21 articles), three literature reviews, one conference paper and one editorial. Regarding the number of publications, the first two articles appeared in 2018, followed by 2019 with one article and 2020 with three articles. Since then, the annual number of publications has been increasing, reaching five publications in 2021, representing 19.23% of total publications, and in 2022, nine registered publications, representing 34.62% of total publications. Four articles were published in 2023, and until September 2024, only two articles were published. Regarding the number of citations, we found that the two articles from 2018, as they were precursors on the topic, stand out from the rest in terms of number of citations, with 2,078 citations, representing 60.44% of the total citations. In the top five, there are four articles from M.-H. Huang and R. T. Rust with 57.8% of the total citations. Table 1 shows the publications per year, ordered by the number of article citations, the average per year, and its percentage in the sample.

The 26 selected publications have 3,438 citations, representing an average of 132 citations per article. Figure 2 shows the evolution of the number of citations and publications of the 26 documents from 2018 to September 2024. Citations have increased significantly, consistently every year, reaching a maximum number in 2023 of 880 citations. The evolution of the number of citations, in general, has been in line with the evolution of the number of publications and reflects the emerging nature and growing interest in the topic under investigation, given that more than half of the documents were published in the last three years. Therefore, these data demonstrate that academic interest has been gradually growing and highlight the topic's popularity, relevance, and timeliness. The year 2024, as it was yet to end, did not allow us to draw definitive conclusions about the most recent developments.

Table 1 Number of citations for each article.

Author and Year	Citations WoS	Percentage in the sample	Citation average / Year
Huang and Rust (2018)	1,124	32.69%	187.33
Wirtz et al. (2018)	954	27.75%	159
Huang and Rust (2021b)	351	10.21%	117
Huang and Rust (2021a)	322	9.37%	107.33
Huang et al. (2019)	190	5.53%	47.5
Youn and Jin (2021)	105	3.05%	35
Jaiswal et al. (2022)	101	2.94%	50.5
Schepers et al. (2022)	55	1.60%	27.5
Pantano and Scarpi (2022)	42	1.22%	21
Shepherd and Majchrzak (2022)	27	0.79%	13.5
Bagozzi et al. (2022)	23	0.67%	11.5
Kipnis et al. (2022)	21	0.61%	10.5
Giraud et al. (2022)	20	0.58%	20
Vorobeva et al. (2022)	17	0.49%	8.5
Esmaeilzadeh and Vaezi (2022)	16	0.47%	8
Huang and Rust (2024)	12	0.35%	12
Huang and Rust (2022)	11	0.32%	5.5
Reis et al. (2021b)	10	0.29%	5
Vorobeva et al. (2023)	10	0.29%	10
Patulny et al. (2020)	8	0.23%	2
Reis et al. (2021a)	7	0.20%	2.33
Saßmannshausen et al. (2022)	4	0.12%	4
von Richthofen et al. (2022)	4	0.12%	2
Do et al. (2023)	2	0.06%	2
Chaturvedi et al. (2024)	1	0.03%	1
Kalateh et al. (2021)	1	0.03%	0.33

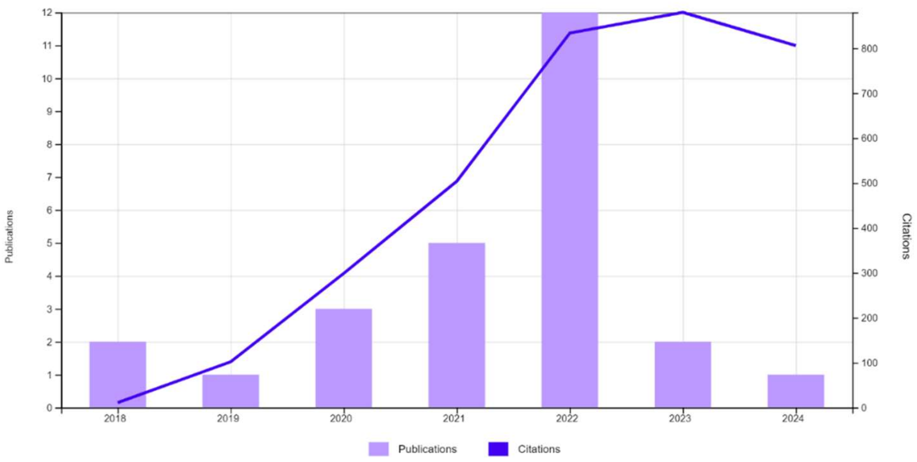

Figure 2 Evolution of publications and citations.

As for the most used newspapers (Table 2), we found that, with eight articles published (47.96% of total citations), the JOURNAL OF SERVICE RESEARCH leads, followed by the JOURNAL OF SERVICE MANAGEMENT (28.13%) with two publications. It is also important to highlight that the JOURNAL OF THE ACADEMY OF MARKETING SCIENCE only presents one published article, but it is included in the top 5 of the most cited articles, representing 9.37% of the total of citations. As these are the most representative journals, it is also noteworthy that the 26 articles in the sample were published in 16 different journals, with other research fields, from economics, management, marketing, psychology, engineering, and technology.

Another relevant aspect, also shown in Table 2, is the notoriety of the journals. One chose the classification carried out by the ACADEMIC JOURNAL GUIDE 2021, which shows that two articles have a rating of 4*, nine articles have a rating of 4, four articles have a rating of 3, and five articles are rated 2.

Table 2 Most important journals in the sample.

Journals	No. articles	CABS ranking	% Citations	Editor
Journal of Service Research	8	4	47.96%	Sage
Journal of Service Management	3	2	28.13%	Emerald
California Management Review	2	3	5.56%	University of California Press
Journal of Marketing	1	4*	0.35%	Sage
Journal of Business Venturing	1	4	0.79%	Elsevier
The International Journal of Human Resource Management	1	3	2.94%	Taylor and Francis
Ergonomics	1	3	0.12%	Taylor and Francis
Current Issues in Tourism	1	2	0.29%	Taylor and Francis
Computers in Human Behavior	1	2	3.05%	Elsevier

Finally, Figure 3 shows the most prolific countries regarding published documents, considering the authors' affiliations. Documents authored by researchers from institutions in multiple countries are assigned to various locations, resulting in a total publication count per country that exceeds the total number of records. The United States leads in this field, with 15 publications, followed by Taiwan with eight, Portugal with five, and the United Kingdom and Germany with three. Other countries, such as Australia and India, have two publications, and Italy, Israel, France, Qatar, Singapore, Spain and the

Netherlands have one. Thus, the number of publications in the sample is only 26, with the researchers interested in this topic from different latitudes, especially in developed countries.

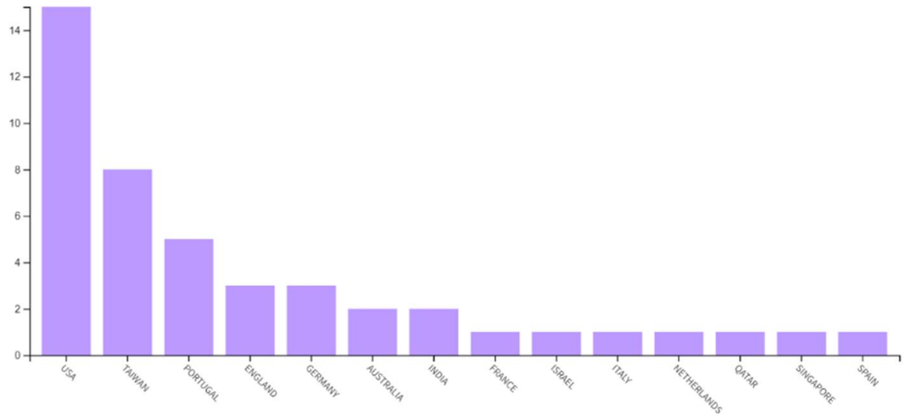

Figure 3 Documents by country.

Bibliographic Coupling measures the relationship between two articles based on the number of references they both cite (Figure 4). It is especially suitable for analyzing relationships and bringing together topics from academic articles (Zupic & Čater, 2015). Co-citation Analysis measures the relationship between two articles based on the number of publications appearing to have been cited concomitantly. Since the 1970s, co-citation analysis has been adopted as a standard and is prominent in bibliometric analysis (Small, 1973). This analysis is beneficial because if specific references simultaneously cite a set of articles, it suggests common ideas among these articles. These shared concepts represent a particular knowledge domain's central themes and intellectual structures (Leydesdorff & Vaughan, 2006). The use of this bibliometric method, combined with network analysis (Newman et al., 2009; van Eck & Waltman, 2019), made it possible to support the study of the co-citation network of cited references, which define coherent research areas, classifying and grouping scientific articles based on their common cited references (Griffith et al., 1974). Network theory was used for the graphical mapping of co-citation analysis, and the determination of thematic groups was carried out using the methodology adopted by Waltman et al. (2010). Cluster analysis was conducted using the VOSviewer software, a tool for building and visualizing bibliometric networks.

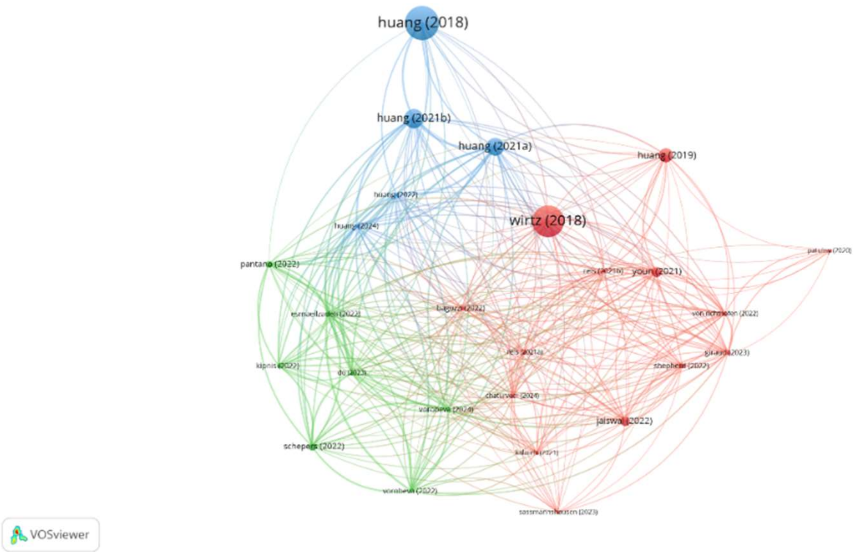

Figure 4 Bibliographic coupling.

Figure 5 shows the formation of three thematic groups generated in the VOSviewer software, each represented by a different color. The lines represent the interactions of co-citations between authors, with the thickness of the "nodes" being proportional to the number of citations each author receives. As the focus of our study is the Feeling Economy, the following thematic groups were identified:

• thematic group 1 (blue color) – characterization of multiple AI;

• thematic group 2 (green color) – response of employees and clients/consumers to multiple AI; and

• thematic group 3 (red color) – effects of AI on job skills and tasks.

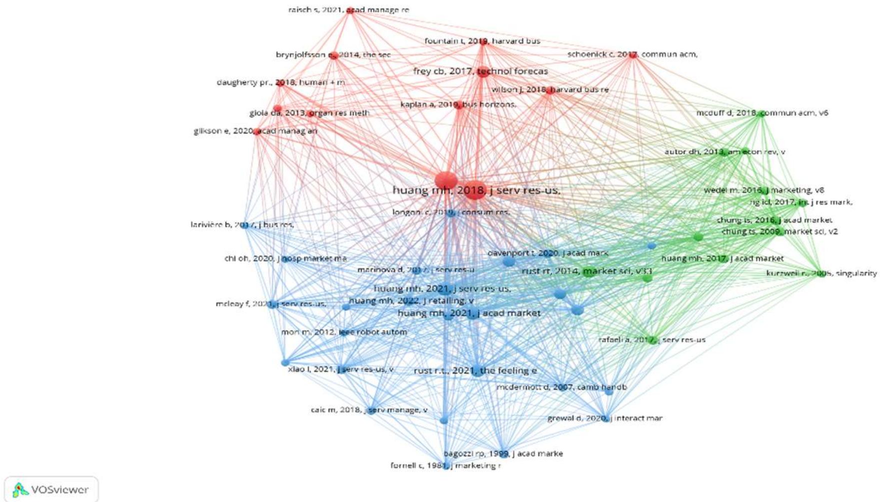

Figure 5 Co-citation network.

We built a co-occurrence network of authors' and editors' keywords to complement our research and reinforce this nomination. The co-occurrence of two keywords represents the number of publications in which both appear together in the keyword list (van Eck & Waltman, 2019). This analysis was also carried out using the VOSviewer tool, defining a minimum of two occurrences for each keyword. In the keyword network generated by VOSviewer, the distance between two knowledge domains signifies the strength of their connection; a greater distance indicates a weaker connection between the items. The size of an item reflects its frequency of occurrences, and the colors represent the different knowledge domains grouped by VOSviewer. Thus, a co-occurrence network was created with 52 items, 428 links, and three thematic groups (Figure 6). The terms "artificial intelligence" and "feeling economy" were used to define bibliographic research and are naturally more prominent in this network. The former has 22 occurrences and a total link strength of 126; the latter has six occurrences and a total link strength of 27. Worthy of note is also the keyword "feeling AI," which appears with four occurrences, a total connection strength of 38, which, as it is a word close to "feeling economy," justifies the fact that it has values lower than the "artificial intelligence." Other keywords worth highlighting on the network included mechanical AI, thinking AI, robots, replacement, augmentation, automation, technology, and future.

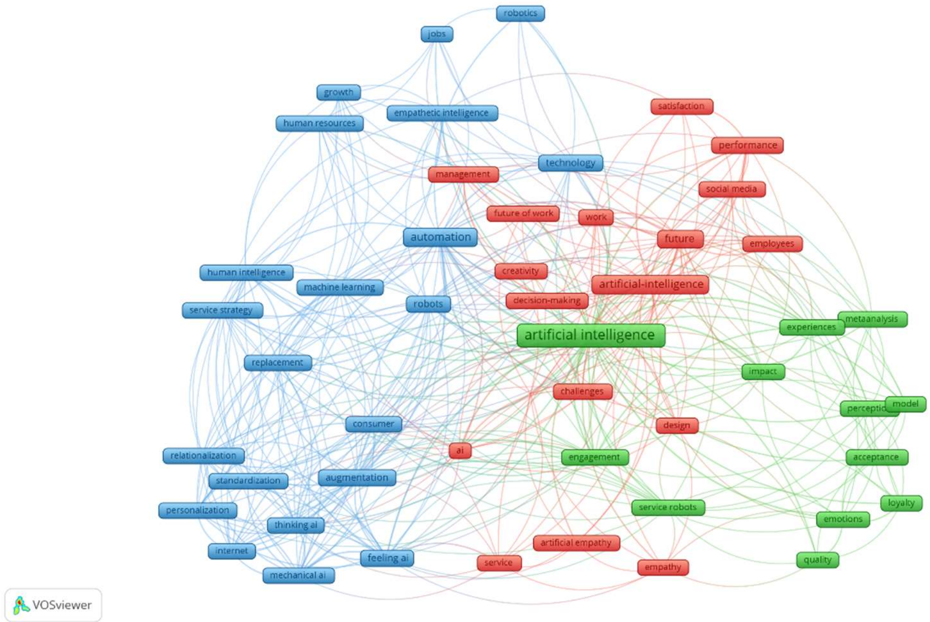

Figure 6 Co-occurrence of keywords.

3.2 Thematic analysis

Based on the results presented above and the thematic analysis of the 26 articles, each cluster was characterized by listing the topics and set of central ideas of each one. The three clusters identified are not balanced in terms of published articles; since the characterization of multiple AI (cluster 1 – blue) contains four publications, the response of employees and clients/consumers to multiple AI (cluster 2 – green) has seven publications, and the effects of AI on job skills and tasks (cluster 3 – red) includes ten publications.

3.2.1 Cluster 1 – characterization of multiple AI

The four studies in this thematic group have the same authors and are conceptual articles in common (Table 3).

Table 3 Blue cluster articles.

References and countries	Theories and models	Objectives	Main results and conclusions
Huang and Rust (2024). Taiwan	Theory of Emotions; Theory of mind; Machine theory of mind; Theory of empathetic	Develop a process designing an AI-powered customer service experience, which begins with precise emotion detection, followed by the generation of empathetic responses, assistance in emotional regulation, and ultimately the creation of a meaningful emotional bond with the customer.	The identified challenges emphasize the technological hurdles that engineers must overcome by applying a framework of marketing principles to the development and study of the "caring machine." These include ensuring the accuracy of emotion recognition by validating it against marketing-based emotion theories using diverse emotional signals and methodologies, leveraging prompt engineering to improve Generative AI's comprehension of emotions, employing "response engineering" to tailor emotion management recommendations, and strategically integrating Generative AI to foster emotional connections that enhance both customer emotional well-being and customer lifetime value.
Huang and Rust (2022). Taiwan	Multiple AI perspective	See if AI is making consumer decisions, complementing, and replacing human customers, or even being the customer. Propose ways to serve AI customers better.	The prevalence of AI clients is growing and expected to become even more widespread in the future. Reverse engineering is likely to prove unsuccessful in comprehensively understanding AI clients. An approach akin to the study of human consumer behavior would be more beneficial in this regard.
Huang and Rust (2021a). Taiwan	Feeling Economy; Multiple AI perspective	Develop a framework to strategically plan AI integration in marketing, aiming to maximize its advantages. Provide a systematic approach to identify research gaps that inform practical and strategic research in AI marketing.	Multiple AI is applied in research, strategies, and marketing actions to help professionals use AI efficiently. With the rapid advancement of AI, it will be able to take on various thinking tasks in marketing, including, eventually, emotional functions. However, due to the lack of a fully-fledged feeling AI, marketers turn to machine AI and thinking AI to handle emotional tasks.
Huang and Rust (2021b). Taiwan	Feeling Economy	Develop a strategic framework for using mechanical, thinking, and feeling AI in customer engagement, incorporating considerations pertaining to the nature of the task, service offering, strategy, and service process.	Use mechanical AI for routine and repetitive tasks; thinking AI for data-driven tasks, analysis and prediction; and feeling AI for experience-centric, emotional functions that require interaction and communication. In the current state of technology, mechanical services are best performed by mechanical AI, thinking services by thinking AI and human intelligence, and emotional services are still best suited for execution by human intelligence.
Huang and Rust (2018). Taiwan	AI job replacement theory	Understand when, how, and at what scale AI should deliver services, how this integration will reshape service delivery, and the professional skills required. Develop a theory about AI replacing jobs.	The theory outlines four critical intelligences for service tasks: mechanical, analytical, intuitive, and empathetic. It suggests a sequential replacement of jobs by AI, starting with mechanical tasks, followed by analytical, intuitive, and empathetic tasks. The progression of AI across these intelligences presents opportunities for novel human-machine integration in service delivery but also poses a significant threat to human employment.

Huang and Rust (2018) start from the point of view that AI is designed to have the capabilities and abilities of humans. Huang and Rust (2018) initially distinguish four intelligences from the literature on human intelligence and AI: mechanical, analytical, intuitive, and empathetic. Later, when presenting the Feeling Economy theory, Huang et al. (2019) combined analytical AI with intuitive AI and called it thinking AI to align with the tasks performed by humans and emulated by machines. Intuition was more difficult for computers to emulate than analytical thinking. Still, AI is developing rapidly with intuitive thinking, so making this distinction would no longer make sense (Huang et al., 2019). They also changed the name of empathetic AI to feeling AI, which aligns with the theory's name, establishing the paradigm of three levels of AI intelligence: mechanical, thinking, and feeling intelligence (Huang et al., 2019). We find service robots within the scope of mechanical intelligence and current technologies such as remote sensing, automatic translation, classification algorithms, and clustering and dimensionality reduction algorithms (Huang & Rust, 2018, 2021a, 2022).

In thinking intelligence, we find the execution of more complex tasks that are still systematic, consistent, and predictable, encompassing problem-solving and the discovery of significant data patterns as a basis for personalization (Huang & Rust, 2021b). Machine Learning is one of the most used AI analytics applications, but text mining, speech recognition, and facial recognition also fall into this category (Huang & Rust, 2021a). The intuitive subtype of thinking AI can creatively adjust to new situations; that is, it can learn and adjust its behavior through a comprehensive comprehension of the context. (Huang & Rust, 2018, 2021b). This approach is used for more detailed and adaptive personalization as it attempts to replicate the human brain through a virtual neural network (Huang & Rust, 2021b). Deep Learning and neural networks are current methods of thinking intuitive AI processes data. Some current intuitive applications for decision-making are IBM Watson (AI platform for business), expert systems (e.g., AlphaGo, Libratus), and recommendation systems (e.g., Netflix, Amazon, Spotify) (Huang & Rust, 2018, 2021a, 2022).

Feeling intelligence refers to the ability to identify, understand, and relate to other people's emotions and then act accordingly, responding emotionally appropriately and influencing the emotions of others (Huang & Rust, 2018, 2024). It represents a machine capable of experiencing emotions and feelings or, at minimum, simulating feelings, emotions, and behavior. a machine that can feel or, at least, behave as if it had feelings, learning and adapting with experience based on context and individual-specific data as its defining characteristic (Huang & Rust, 2018, 2021b). Current technologies that include AI applications, chatbots, and virtual agents, as well as applications employing natural language processing to interact (e.g., Alexa, Cortana, Siri), are examples of feeling AI, as they simulate emotions and interact, although they still a similar way to thinking AI. On the other hand, more advanced applications, such as the chatbot Replika and the humanoid robot Sophia from Hanson Robotics, use speech recognition technology, recurrent neural networks, personalized hardware, and automatic emotion recognition (Huang & Rust, 2018, 2021a, b). Recently Huang & Rust (2024) investigated the potential of Generative AI (GenAI) to facilitate customer progression throughout the customer care journey, and they identify GenAI as the most advanced iteration of feeling AI currently available.

3.2.2 Cluster 2 – response of employees and clients/consumers to multiple AI

The second thematic group involves a set of studies that analyze and try to understand how employees and clients/consumers respond to multiple AIs. To achieve this, its authors mostly use empirical research methods, precisely five quantitative and one qualitative (Table 4).

Table 4 Green cluster articles.

References and countries	Theories and models	Objectives	Main results and conclusions
Do et al. (2023). USA		Design and validate a scale that measures the concept of "empathetic creativity," which refers to the ability to demonstrate creativity in the application and execution of empathetically intelligent skills during service interactions.	Highlights the importance of empathetic intelligence as a key dimension of human intelligence that frontline employees must cultivate to sustain a competitive advantage. Recommend that frontline employees, especially those working in high-contact professional services, demonstrate empathetic creativity in their interactions with customers.
Vorobeva et al. (2023). Portugal	Feeling Economy; Mediation model.	Analyze customer reactions in the tourism and hospitality sector to different AI replacement approaches (augmentation versus replacement) compared to the exclusive use of human employees. Investigate how these approaches impact acceptance, satisfaction and ease of use of AI-based services.	Augmentation is preferred over complete AI replacement in the tourism and hospitality industry because customers favor augmented service providers. The absence of emotion-related characteristics in AI diminishes customer service acceptance, leading to the perception that AI is less enjoyable and more challenging to use compared to human service providers.
Esmaeilzadeh and Vaezi (2022). USA	Feeling Economy; Theories of consciousness	Present a theory of AI consciousness and propositions about conscious AI, its relationship to feeling AI, and how it affects service delivery.	The theory posits that consciousness emerges from the co-creation of language between two agents and the shared understanding of symbol meanings. Conscious AI enables empathy, which, coupled with AI awareness, can enhance service delivery outcomes.
Kipnis et al. (2022). UK	Community Philosophy Method, LEGO® Serious Play®, and Design Thinking; Grounded Theory.	Investigate the perceptions of consumers with disabilities regarding the potential utility of robots in long-term care, as well as the factors that may influence their acceptance, particularly those related to vulnerability.	At all mechanical and thinking AI levels, participants imagined that robots' capabilities could contribute to their well-being. Regarding feeling AI, participants suspect that robots can exhibit cognitive and behavioral empathy but recognize that affective and moral empathy is the exclusive prerogative of humans. Thus, for the foreseeable future, care remains a human responsibility.

Pantano and Scarpi (2022). UK	Theories about Human Intelligence; Theory of emotions; Social perception theory; Social interaction theory.	Examine the degree to which AI systems can possess multiple intelligences and investigate whether different intelligences evoke varying emotional responses in consumers.	Intelligence classifications used for human intelligence can serve as a theoretical basis for understanding AI. Human-like AI intelligences can be diverse, with some AIs exhibiting multiple dominant intelligences. Consumer reactions to AI intelligence vary, expressing different emotions with different intensities and levels of emotional attachment and satisfaction.
Schepers et al. (2022). The Netherlands	Feeling Economy; Emotion appraisal theory.	Know how customers respond to robots with different intelligences: mechanical, thinking, and feeling.	Each category of intelligence (mechanical, thinking, and feeling) can elicit positive emotions in customers. The most prominent effects are observed in robots equipped with advanced levels of feeling AI.
Vorobeva et al. (2022). Portugal	Feeling Economy; Social comparison theory.	Investigate the distinct effects of various service-related tasks (cognitive versus affective) on employees' emotions and behaviors.	When exposed to AI, service employees exhibit heightened negative emotions, diminished self-perceived capability, an increased apprehension regarding potential replacement, predict lower performance, and perform worse on thinking tasks than feeling tasks.
Wirtz et al. (2018). Singapore	Role theory; Uncanny Valley theory.	Examine the prospective role of service robots in future contexts and advocate for a research agenda within the field of service research.	Compares the attributes and functionalities of service robots with those of frontline employees, aiming to elucidate the types of service tasks that robots are poised to dominate, areas where human presence will be predominant, and scenarios where humans and robots are expected to collaborate.

There are also two conceptual articles, one of which addresses the three intelligences of AI (Wirtz et al., 2018) and another on the paradigm of consciousness in AI (Esmaeilzadeh & Vaezi, 2022). The first examines consumers' perceptions, beliefs and behaviors related to service robots (Wirtz et al., 2018), in line with the AI multiple intelligences perspective of Huang and Rust (2018), presenting a model of acceptance of a service robot, taking into account the level of complexity of cognitive/analytical (thinking) and emotional/social (feeling) tasks. These authors concluded that robots would increasingly provide services whose cognitive/analytical tasks had little need for social interaction. In contrast, they considered that if emotional/social tasks were more complex, then customers would prefer a level of social interaction, which it seemed unlikely that robots could achieve, which would leave these services in the human sphere. However, Wirtz et al., (2018) point out that, in complex cognitive/analytical tasks, human service providers feel more comfortable with AI's support. Two more articles empirically corroborate the study by Wirtz et al. (2018) on customer responses to the three forms of intelligence in service robots (Kipnis et al., 2022; Schepers et al., 2022). In one of them, through five quantitative studies, Schepers et al. (2022) discovered consistent evidence that service robots featuring thinking and feeling AI stimulate positive emotions in customers. In contrast, with mechanical AI, positive emotions are less clear (Schepers et al., 2022). In another qualitative study (Kipnis et al., 2022), participants reflect on concepts of long-term care robots equipped with sophisticated AI capabilities, spanning mechanical, thinking, and feeling dimensions. About feeling AI, they conclude that this capacity does not seem to be achieved because, although participants imagine that robots are capable of, at least, exhibiting cognitive empathy (understanding the factors that contribute to a person feeling better) and behavioral empathy (performing acts beneficial and therapeutic), they acknowledge that robots cannot experience and express affective empathy (being forced to act based on emotional solid responses) and moral empathy (genuine compassion), two essential components required to achieve a genuine sense of "being cared for".

In this context, Do et al. (2023) underscores the importance of empathetic intelligence for frontline employees (FLEs) to remain competitive. Specifically, it suggests that FLEs in high-contact professional services should exhibit empathetic creativity during customer interactions. As services shift from being standardized to more personalized and relational, FLEs must prioritize tasks requiring emotional intelligence, critical thinking, and customer engagement – areas where they outperform robots. Furthermore, Vorobeva et al. (2023) conducted three studies in the tourism and hospitality sector that demonstrate that customers react and accept an augmented service that combines humans and AI better than a service provided by AI alone, which is congruent with Huang and Rust's (2018, 2021a) Feeling Economy framework. Similar results appeared with the employee response study, in which Vorobeva et al. (2022) illustrated that attitudes towards AI replacement are contingent upon the characteristics of the tasks involved. Particularly, in the context of AI presence, service workers exhibit heightened negative sentiments, perceive themselves as less proficient, express increased apprehension regarding AI substitution, report diminished perceived competence, and display inferior performance in cognitive tasks related to emotional engagement (Vorobeva et al., 2022).

In this cluster, two more studies expand the structure of Huang and Rust (2018, 2021a). In one of them, Pantano and Scarpi (2022) provide a new guideline for developing AIs capable of better imitating human abilities, classifying five types of AI:

- Logical-mathematical intelligence (ability to solve complex problems through logical reasoning);
- Social intelligence (ability to comprehend emotions and engage in interactions with humans);
- Visual-spatial intelligence (spatial perception and comprehension);
- Linguistic-verbal intelligence (capability to comprehend human language and replicate it for communication with humans); and
- Processing speed intelligence (the capacity to swiftly and efficiently accomplish straightforward, repetitive tasks).

They highlight that recent AI-based services can generate and convey emotions, and various types of AI evoke distinct emotional responses in consumers. The findings indicate that consumers react differently to different AI intelligences, exhibiting varying emotions with different intensities and levels of emotional attachment, satisfaction, and intention to continue using AI. Specifically, logical-mathematical and visual-spatial intelligence increases positive emotions but does not decrease negative emotions. On the other hand, processing speed reduces positive emotions but does not increase positive emotions. Only social intelligence impacts both positive and negative emotions (Pantano & Scarpi, 2022). The other study, which is conceptual, expresses that in order for AI to progress to the next level, it is necessary to develop capabilities such as empathy, creativity, and metacognition, and this will only be possible through the consciousness paradigm (Esmaeilzadeh & Vaezi, 2022). Consciousness in AI is an emergent phenomenon that predominantly arises when two machines collaboratively develop a language, enabling them to recall and communicate their internal states and manipulate symbols across temporal variations. Mindful AI can drive better service delivery outcomes by enhancing the customer experience, facilitating broader adoption, and ensuring greater accountability. This paradigm can facilitate introspection, self-learning, and potentially the progression from AI to machine superintelligence (Esmaeilzadeh & Vaezi, 2022).

3.2.3 *Cluster 3 – effects of AI on job skills and tasks*

The third thematic group identified involves a set of studies that attempt to discover the effects of AI on job skills and tasks. Six articles are conceptual, four are qualitative, and three are quantitative. Table 5 characterizes the articles belonging to this thematic group.

Table 5 Red cluster articles

References and countries	Theories and models	Objectives	Main results and conclusions
Chaturvedi et al. (2024). India	Feeling Economy; Social exchange theory; Uncanny Valley theory.	Explore the role of empathetic artificial companions in understanding and addressing consumers' emotional needs through affective computing.	Identify three key capabilities—conversational, functional, and emotional—that influence customer perceptions of AI companions. Address challenges, such as declining user engagement over time, and introduce the "social alienation paradox," complicating their integration into marketing models. Recommend a hybrid design of AI companion capabilities to enhance marketing performance and foster deeper customer relationships throughout the customer journey.
Saßmannshausen et al. (2022). Germany	Mental models; Trust models; Feeling Economy.	Conduct a comprehensive and systematic review to identify all previously studied factors that influence human trust in technology-driven counterparts.	Advocate for technology development that prioritizes human trust, aligning with cycles of technology creation and human-centered design. As we transition to a "feeling economy" where decisions are emotion-driven, trust will become crucial in human-AI interaction, especially given the rise of artificial general intelligence.
Giraud et al. (2022). France	Feeling Economy; Grounded theory	Unveil the impact of AI implementation on the evolution and adaptation of managerial skills within organizations.	The findings indicate that AI is likely to enhance most managerial skills, with only a few being replaced or unaffected. The results also emphasize the importance of prioritizing technical and non-technical managerial skills to ensure the successful implementation of AI.
Bagozzi et al. (2022). USA	Technology acceptance model; Feeling Economy.	Explore how AI can transform the services economy into a Feeling Economy.	Eventually, the emotional benefits provided or driven by AI are expected to increase economic productivity and improve people's well-being.
Jaiswal et al. (2022). India	Theories of dynamic ability, neo-human capital, and AI job replacement.	In the AI-driven era, identifying the crucial skills to upskill employees ensures they thrive, remain employable, and remain competitive.	AI will quickly take over mechanical intelligence tasks shortly. Analytical tasks will be more difficult for AI to imitate. Intuitive and empathetic tasks will be even more difficult for AI to replicate.
Shepherd and Majchrzak (2022). USA	Basic machine learning AI model; Feeling Economy.	Explain how AI can be combined with entrepreneurship and explore the possibilities of this potential super tool by directing its use towards productive processes and results.	Entrepreneurs can use AI to augment their decisions and actions to seek opportunities for productive gains. The ways AI can enhance entrepreneurship require future work of theory building, theory elaboration, theory testing, and empirical theorizing.
von Richthofen et al. (2022). Germany	Feeling Economy.	Know what changes have been noticed by knowledge workers who have started working with AI applications and what factors they consider conducive to the development and implementation of AI.	Transformations related to the implementation of AI in knowledge work include the transition from manual and repetitive tasks to those that require reasoning and empathy, the emergence of novel tasks and roles, and the acquisition of new skills and/or skill requirements. The conditions conducive to developing AI systems necessitate leadership support, participatory change management, and efficient knowledge integration.

Kalateh et al. (2021). Portugal	Feeling Economy; Smart Industry; Model conceptual "Feeling Smart Industry"	Evaluate the importance of human-centered characteristics, specifically empathetic and emotional skills, in the new era of the economy and industry.	They introduce an innovative conceptual model, "Feeling Smart Industry", for the growing era of the feeling economy, integrating emotive skills with smart industry and digitalization. Instead of simply adapting to new technologies and digitalization, they propose an approach focused on effective personalization, highlighting the importance of the human dimension in jobs and everyday life.
Reis et al. (2021a). Portugal	Feeling Economy; Model by Vagia et al. (2016)	Categories and characterize the modes of autonomous intelligent defence systems in the defence industry according to the various levels of warfare, different types of decisions, and artificial intelligence.	Autonomous intelligent systems can be categorized into three modes, correlating with the three types of AI: mechanics for fully independent operations, thinking for partially autonomous operations, and feeling for operations with more excellent decision-making and human intervention.
Reis et al. (2021b). Portugal	Feeling Economy; AI job replacement theory.	Present conceptual evidence on the influence of AI on public employment and its impact on public policies, based on the theory of job replacement by AI by Huang and Rust (2018).	In the public sector, different levels of intelligence in service tasks can be replaced by AI. Currently, it is appropriate to retain and reskill the existing human workforce while preserving the personalization of public services rather than considering automating tasks that require intuitive or empathetic skills.
Youn and Jin (2021). USA	Relationship theory in consumer research; Personality theory.	They are examining the effects of the type of relationship (virtual assistant versus virtual friendship) consumers develop with AI-enabled chatbots.	The perception of brand personality and para-social interaction influences multiple dimensions of customer relationship management—virtual friend chatbots with feeling AI induce more vital para-social interaction than virtual assistant chatbots with thinking AI.
Patulny et al. (2020). Australia	Emotional capital theory.	An updated research agenda on "emotional economies" is proposed, referring to economies increasingly characterized by creating, extracting and exploiting labor and emotional products. This transformation is facilitated and embodied by rapid advances in AI.	Evidence indicates that AI will supplant numerous forms of human labor, retaining only those services that necessitate technologically irreplaceable, emotion-centered soft skills for human workers. Some literature suggests a remote likelihood that AI could even replace emotional labor, although this has been considered unlikely for many years. It is predicted that emotions will become essential commodities and central to future economies.
Huang et al. (2019). Taiwan	Feeling Economy.	Examine the impacts of AI on tasks and employment, and elucidate the implications for managerial practices.	Emotional tasks within human occupations are experiencing a growing significance and are forecasted to surpass cognitive tasks by 2036. Furthermore, remuneration for emotional tasks is exhibiting a swifter rate of growth compared to cognitive tasks. To protect their jobs, workers can improve their feeling and empathy skills. Educators, researchers, managers, and companies will use this trend to succeed.

Huang et al. (2019) are seminal in introducing the "Feeling Economy," in which AI increasingly performs thinking and analytical tasks. Human workers become progressively more oriented toward interpersonal, empathetic, and feeling tasks, such as interpersonal communication within and beyond the organization, fostering and sustaining interpersonal connections, and engaging in sales or influencing endeavors. They empirically revealed that, according to US government O*NET occupational data from 2006 to 2016, feeling tasks are becoming more significant than thinking or mechanical.

The correlation between total employment and average wages is progressively linked to feeling-oriented tasks, as wages within these domains are exhibiting faster growth compared to those within cognitive-oriented tasks. The advent of the Feeling Economy will pose a threat to certain occupations while simultaneously reshaping others, yet it will also engender fresh and promising opportunities for managers, employees, consumers, researchers, educators, and businesses (Huang et al., 2019). Even within domains with constrained scope for automation, where human intervention remains imperative, such as in war strategies, Reis et al. (2021a) delineate three modalities of autonomous intelligent systems within the defense sector that interface with the three categories of AI. They conclude that in the most advanced mode, a heightened level of decision-making and human intervention (feeling AI) is requisite, transcending the two preceding modalities, which are inclined toward greater automation and are susceptible to eventual replacement by machines in the medium to long term (Reis et al., 2021a).

Also, Kalateh et al. (2021), when building a conceptual model that combines the characteristics of the Smart Industry with those of the Feeling Economy, argue that AI and new technologies will be responsible for carrying out thinking tasks and will afford managers and workers additional time to concentrate on team cohesion, interpersonal communication, and collaborative efforts aimed at enhancing employee performance. Thus, there will be more emphasis on human approaches to 'feeling' in the workplace and from the customer's perspective, raising the level of interest for workers with emotional skills, who will be more likely to find employment and receive higher wages. Therefore, emotional skills and tasks will be approached as having a fundamental role in the different sectors of the smart industry (Kalateh et al., 2021). In the same way, in the provision of services, Bagozzi et al. (2022) argue that in the Feeling Economy, empathy is crucial, and the prevalence of AI in the provision of services will boost the economy of high-tech services and high human contact. In this high-touch economy, with service delivered by AI, human employees, or both, AI can enhance customer service interactions and improve human employee well-being (Bagozzi et al., 2022). Likewise, analyzing how AI is affecting public employment, Reis et al. (2021b) posited that policymakers should preserve public sector positions necessitating empathetic and interpersonal aptitudes within human control. Consequently, they advocated for the retention and retraining of the current human workforce to sustain the personalized delivery of public services, rather than contemplating the automation of tasks demanding intuitive and empathetic capabilities (Reis et al., 2021b).

From a micro perspective, and based on case studies carried out in eight German entities engaged in the implementation or development of AI systems, von Richthofen et al. (2022) identified three significant transformations linked to the integration of AI within the realm of knowledge work: the transition from manual labor and repetitive duties to tasks necessitating reasoning and empathy; the inception of novel tasks and functionalities; and the evolution of fresh skills and/or skill prerequisites. In this sense, in another study to identify the fundamental abilities necessary for improving workers' qualifications, Jaiswal et al. (2022) conducted interviews with 20 seasoned professionals employed in multinational corporations within India's information technology sector. Their findings suggest that tasks associated with machine intelligence, such as basic statistics, are poised to be swiftly assumed by AI in the near future. Analytical tasks, encompassing data analysis and technology-driven digital skills, are expected to demand more effort for AI to replicate. Intuitive tasks, including complex cognitive processing, decision-making, continuous learning, as well as empathetic tasks like communication, interpersonal relations, and leadership, are anticipated to present significantly greater challenges for AI to emulate (Jaiswal et al., 2022). Similar results can be observed at the managerial level, where, as noted by Giraud et al. (2022), the majority of managerial skills are expected to be augmented by AI. However, certain skills, such as those related to information gathering and automatable, repetitive tasks, may be replaced, while others, such as leadership and imagination, are likely to remain unaffected.

In the same direction, Patulny et al. (2020) proclaim that technology will supplant numerous current forms of human labor, leaving only service-oriented tasks, interpersonal skills, and emotionally labor- intensive roles that are technologically irreplaceable for humans to undertake. However, the prospect of AI supplanting emotional labor is deemed remote, albeit proponents suggest this is improbable for the foreseeable future (Patulny et al., 2020). However, some applications already do this, and the first advances in AI in the Feeling Economy are chatbots (Youn & Jin, 2021). Youn and Jin (2021) selected satisfaction with the chatbot relationship as one of the factors to assess the impact of relationship type on para-social interaction and brand personality. They found that a chatbot, as a virtual friend with empathically intelligent AI-oriented towards the feeling task, will induce more vital para-social interaction in comparison to a chatbot serving as a virtual assistant, with analytical AI-oriented towards the thinking task. Another area of application is artificial intelligence companions. Chaturvedi et al. (2024) analyzed market offerings and identified three key capabilities: conversational, functional, and emotional. Functional capabilities arise from Mechanical AI and Thinking AI, emotional capabilities stem from Thinking AI and Feeling AI, while conversational capabilities are shaped by Generative AI and Feeling AI. Notably, empathetic chatbots like Luka's Replika and Microsoft's Xiaoice are capable of recognizing and responding to users' emotions.

Therefore, the escalating significance of the feeling and emotional data sectors, alongside media platforms and digital representations, is anticipated to position feelings and emotions as pivotal commodities within forthcoming economies (Patulny et al., 2020). Therefore, when discussing how AI applications can increase business success, Shepherd and Majchrzak (2022) suggest the integration of artificial intelligence with entrepreneurial endeavors and represent an opportunity to capitalize on the Feeling Economy. Entrepreneurship has the potential to contribute human touch, emotional intelligence, and the cultivation of high-quality relationships to complement AI and thus improve decision-making and make AI implementation more effective (Shepherd & Majchrzak, 2022). To ensure the success of these interactions, trust has emerged as the primary determinant. This is particularly critical when individuals depend on AI to accomplish their objectives in contexts that are vulnerable and potentially high-risk (Saßmannshausen et al., 2022).

4 Discussion

According to Huang and Rust (2018), AI is developing predictably from mechanical intelligence through analytical and intuitive thinking intelligence and reaching the current empathic or feeling intelligence. They also stated that the replacement of man by machines depends on the complexity of the task and not on the level of the function, first replacing the simplest intelligence tasks (mechanical and analytical thinking) and then those of greater complexity (intuitive thinking and feeling). Huang and Rust (2021a) clarified that the attribution to a specific intelligence is not based on the utilization used but rather on the purpose for which it is used. For example, facial recognition is considered thinking AI when it is used to identify someone. Still, it is also feeling AI when it is used to discover someone's emotional state from their facial expression.

Another essential aspect to highlight is that feeling AI is still at an early stage of development, as it analyses data acquired from two-way interactions such as chatbots or social bots. This data, which can be considered emotional, is not read by the thinking AI used in these conversational platforms, as it needs more contextual and individual-specific data (Huang & Rust, 2021a). Therefore, Youn and Jin (2021) distinguish the feeling chatbot from the thinking chatbot, a virtual assistant.

AI will not necessarily replace humans, but it can complement them, being a solid point for companies, as this could increase productivity (Shepherd & Majchrzak, 2022). Huang and Rust (2021b) developed the notion of collaborative AI, in which humans and AI will perform some tasks, and both will work as a team. Currently, this means that only mechanical AI can be used when tasks are more repetitive. When tasks are more data-driven, the likelihood that analytical thinking AI can solve the task without human intervention is also high. Suppose tasks are more intuitive, emotional, and empathetic, requiring communication and experience-based solutions. In that case, it is less likely that AI will be able to solve the task successfully without human intervention. Thus, through the establishment of a symbiotic relationship between humans and machines, human intelligence stands to be enhanced by the collective intelligence of machines (Vorobeva et al., 2023).

The development of AI increases the risk of replacing human work, which could lead to people's negative feelings compared to AI's capabilities (Vorobeva et al., 2022), as well as lower performance on thinking tasks than on feeling tasks. Consequently, as AI applications assume a greater array of tasks, the necessity for human employees diminishes, leading them to converge more on feeling tasks (Jaiswal et al., 2022). This risk of replacing humans with AI justifies the need to improve people's communication, interpersonal, and emotional intelligence skills so that they can continue in the job market (von Richthofen et al., 2022). This development could increase wages for people in the Feeling Economy (Huang et al., 2019).

Jobs and wages depend more on interpersonal, empathetic and feeling tasks. In that case, it also appears that consumers are increasingly oriented towards relationships and feelings and, consequently, present more emotional needs (Huang et al., 2019). Thus, companies are increasingly incorporating different types of AI into providing services and interacting with their customers through, for example, conversational interfaces managed by AI (Huang et al., 2019; Huang & Rust, 2021b; Schepers et al., 2022). Therefore, it is essential to understand that various AI intelligences awaken different emotions and provoke different consumer reactions. However, more is needed to know about this. Only Pantano and Scarpi (2022) showed that AI is configurable, describable and measurable and that consumers react differently to multiple AI, revealing positive emotions (excitement, happiness, enthusiasm, inspiration and pride) and negative ones (anger, fear, anxiety, shame and sadness) across varying intensities, levels of emotional attachment, satisfaction, and propensity to continue using AI. The other existing studies are about consumer responses to service robots that incorporate different types of AI (Wirtz et al., 2018; Kipnis et al., 2022; Schepers et al., 2022). Generally, each type of intelligence (mechanical, thinking and feeling) can stimulate customers' positive emotions and boost service robots' acceptance.

Now, analyzing the case of employees, only Vorobeva et al. (2022) analyzed how AI affects work results depending on the type of task performed. It will be essential to enhance understanding of the impacts of AI on the labor ecosystem. More specifically, investigate potential variances in employee responses when AI fully replaces or partially replaces human work.

Finally, all studies were done on AI from a supply perspective, except a theoretical work by Huang and Rust (2022). However, it is also crucial to study AI from a demand perspective, i.e., as a customer, advising humans on their purchases (e.g., using augmented reality and virtual reality to show houses to customers), replacing itself as a human customer, (e.g., chatbots that make marketing calls autonomously and more efficiently than humans) and being customers themselves (e.g., Google Duplex and other platforms that work as AI agents for human customers). In these cases, the study of AI will be in line with the Feeling Economy.

Analyzing the thematic groups makes it possible to identify a future research agenda (Table 6).

Table 6 Future research based on clusters' themes.

Clusters	Research agenda
Characterization of multiple AI	What categorization method yields the most insightful understanding of feeling tasks? How do we characterize the new algorithms and models that will be able to collect and process multimodal emotional data? Is a further sub-classification of feeling AI necessary? Given the possibility of conscious AI, what will change in characterizing multiple AI? Given the possibility of a conscious AI, how do we define the limits of AI applications in each type of intelligence? What laws, regulations, and policies about ethics and morals should be implemented in each type of intelligence, including the privacy of those involved?
Response of employees and clients/consumers to multiple AI	How do consumers react to the standardization of AI-enabled services? Based on a neuroscientific approach, what is the range of consumer emotional responses to the Feeling AI? What are consumers' emotions' frequency, intensity, and persistence when faced with different AI? How do customers accept AI-based services, considering different framings of AI (fully versus partially replacing human tasks)? How can AI be integrated into human-AI employee teams? What factors contribute to the success and failure of these teams? What determines the acceptance of such teams by employees and customers? How do different framings of AI (fully versus partially replacing human tasks) distinctly impact employees' feelings and behavior when performing thinking tasks vs feeling tasks? What discriminatory behaviors might AI engage in, and how does it impact employee feelings and behavior? What role does the upward and downward social comparison that AI triggers in employees?
Effects of AI on job skills and tasks	What is the advancement of the Feeling Economy across various sectors and occupations? What are the mechanisms underlying changes in the intelligence composition of jobs, and how do jobs transform in the Feeling Economy? How can we retrain and redeploy unskilled service workers displaced by machine AI? Given that the prospect of upskilling or reskilling all low-skilled service workers is improbable, it is imperative to consider the future implications for those individuals whose skills become obsolete and who are unable to acquire new competencies? What skills are needed to adapt to the emerging Feeling Economy, considering the different sectors of activity and types of jobs? What policies should governments follow to provide that workers of today and tomorrow have the necessary skills to remain competitive and avoid being laid off because of AI? How should the educational system prepare students for the Feeling Economy? What effects do demography (for example, the ageing of the population) and population density have on jobs in the Feeling Economy? Will conscious AI be capable of taking on management roles, directing human employees and creating new agency dynamics?

5 Conclusion

This study included the first bibliometric and systematic review of the literature on the current state of knowledge about the Feeling Economy, considering the emergence of AI. It concludes that there are three dominant lines of research: (1) the characterization of multiple AI, (2) the response of employees and clients/consumers to multiple intelligences, and (3) the effects of AI on job skills and tasks. This article acts as a contribution to systematizing existing literature in this field, allowing us to intuit the possibility of a significant change in future jobs and the skills needed for humans to work with AI collaboratively. The current emphasis on jobs where thinking tasks predominate will inevitably decrease in the future as AI increasingly takes over these tasks. This trend is already well known and means that human workers tend to be valued in terms of employment and salaries in tasks with a greater emphasis on empathy, feeling and emotional intelligence.

In practical terms, the results of this systematic review can help organizational leaders and government officials to discover which new tasks and functions, as well as new employee skills, will be considered critical to prosper in the emerging Feeling Economy. Furthermore, it will be essential to reflect on the replacement of human work by AI and the multiple possibilities for human/machine integration and complementarity.

The limitations of our study are related to the possibility of existing interesting grey literature that needed to be captured by our revision. Nevertheless, the PRISMA protocol permits the inclusion of pertinent articles, thereby minimizing the negative effects of this exclusion. Another arises from the selection of filters, for example, the fact that only articles in English are selected. The fact that few empirical studies on the Feeling Economy related to AI opens a vast window of opportunity to deepen this literature shortly, particularly regarding the research agenda proposed in this article.

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