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Potential Implications of Appling Conceptual Blending Theory in Artificial Intelligence Scope

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A B S T R A C T

This study investigates the application of Conceptual Blending Theory (CBT), a foundational model of human cognition from cognitive linguistics, to the field of artificial intelligence (AI). As AI systems rapidly evolve to mimic human-like cognitive capabilities, understanding the mechanisms that underpin their creative and reasoning processes becomes critical. This research posits that CBT, as formulated by Fauconnier and Turner (2002), provides a powerful framework for analyzing how AI integrates disparate concepts to generate novel and meaningful outputs. The study employs a dual-method approach, combining a theoretical examination of CBT and AI with a practical analysis of AI-generated visual texts sourced from social media.

The analysis demonstrates that advanced generative AI performs sophisticated conceptual blending, selectively projecting elements from multiple input mental spaces to create coherent and evocative visual blends. Findings confirm that AI not only replicates the structural processes of human conceptual integration—composition, completion, and elaboration—but also produces emergent meanings with significant pragmatic and emotional resonance. This indicates a profound correlation between human and machine cognition, suggesting AI is bridging the gap in contextual understanding and creative improvisation.

الآثار المحتملة لتطبيق نظرية المزج المفاهيمي في مجال الذكاء الاصطناعي

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المستخلص:

تبحث هذه الدراسة في تطبيق نظرية المزج المفاهيمي (CBT)، وهي نموذج أساسي للإدراك البشري مستقى من اللغويات المعرفية، على مجال الذكاء الاصطناعي. مع التطور السريع لأنظمة الذكاء الاصطناعي لمحاكاة القدرات المعرفية البشرية، يصبح فهم الآليات التي تدعم عملياتها الإبداعية والاستدلالية أمرًا بالغ الأهمية. تفترض هذه الدراسة أن نظرية المزج المفاهيمي، كما صاغها فوكونير وتيرنر (2002)، توفر إطارًا قويًا لتحليل كيفية دمج الذكاء الاصطناعي للمفاهيم المتباينة لتوليد مخرجات جديدة وذات معنى. تعتمد الدراسة على نهج ثنائي المنهج، يجمع بين دراسة نظرية لنظرية المزج المفاهيمي والذكاء الاصطناعي وتحليل عملي للنصوص المرئية التي يُنتجها الذكاء الاصطناعي والمستمدة من وسائل التواصل الاجتماعي.

يُظهر التحليل أن الذكاء الاصطناعي التوليدي المتقدم يُجري مزجًا مفاهيميًا متطورًا، حيث يُسقط عناصر انتقائية من مساحات ذهنية متعددة المدخلات لإنشاء مزيج بصري متماسك ومثير. تؤكد النتائج أن الذكاء الاصطناعي لا يقتصر على محاكاة العمليات الهيكلية للتكامل المفاهيمي البشري – التأليف، والاكتمال، والتوضيح – بل يُنتج أيضًا معانٍ ناشئة ذات صدى عملي وعاطفي كبير. يشير هذا إلى وجود ارتباط وثيق بين الإدراك البشري والآلي، مما يوحي بأن الذكاء الاصطناعي يسد الفجوة في الفهم السياقي والارتجال الإبداعي.

الكلمات المفتاحية : نظرية المزج المفاهيمي، الذكاء الاصطناعي، اللغويات المعرفية، المساحات العقلية، الإبداع الآلي، أخلاقيات الذكاء الاصطناعي، التعلم العميق.

1.Introduction

1.1 The Problem

The rapid spread of artificial intelligence (AI) phenomena in the air of our lives has brought huge changes and impacts across various domains starting with human's language into universe scope. With the accelerating (AI) systems developing to be human-like cognition, there is an increasing need to understand the cognition mechanisms that have been used in the (AI) body and its implications that may be emerging in the coming time. One of the essential cognitive mechanisms that is considered the core of (AI) work and has significant influence in both cognitive enterprise and (AI) horizons is the **Conceptual Blending Theory(CBT)** that proposes by two linguists, Fauconnier and Turner (2002), through their work in the cognitive linguistics field. CBT is a cognitive linguistics theory that deals with the mental integration of various inputs from different domains by many mental mechanisms to produce hybrid meanings and outputs.

Nowadays, many studies are showing that CBT is not only vital to study human cognition behaviours but also plays a dynamic role in enhancing and develop AI systems' skills to adopt and simulate human-like cognition as Câmara Pereira (2007) ; Eppe et al (2018) ;Bourou et al, (2024, pp. 18-20)and many other . Veale's (2019) study also reveal that AI has ability to replicate human-like blending processes in human language processing and creative AI (pp. 71-89).

The paper tries offer sight into the using of conceptual blending in scope of IA and the challenges that could face humans due simulating AI of their mental and sensory abilities. This raises questions about illimeted computational ability, ethical implications, and the boundaries of machine creativity.

The importance of the research arises from trying to offer better understanding to the potential implications of using human theories in the field of AI and it could help us in dealing with future situations.

To achieve the aim of the study, two types of procedures have been followed: theoretical and practical. The theoretical part consists of presenting a brief theoretical framework of **Conceptual Blending Theory (CBT)** of Fauconnier and Turner (2002) and IA concept . On the other hand, the practical part consists of analysing visual texts that have been generated by AI, which are extracted from social media, depending on CBT theory

1.2 Research Questions

This study raises several problematic questions that require urgent replies among which are:

1. Can theories of cognitive linguistics apply on AI field ?
2 .Does use CBT in an AI system can mimic human conceptual blending behavior؟
3. Will there be any potential implications that could emerge from apply CBT in AI ؟
4. Can AI develop itself spontaneously through direct communication with human and improvise itself according to the situation?

1.3 The Aims

The study aims at finding out:

1. The applicability of the Cognitive linguistics theory to study and analyze AI.
2. Whether or not applying CBT in AI body help to copy human conceptual blending behavior .
3 .Whether or not there are potential implications that could emerge from apply CBT in AI
4. Whether or not AI develop itself spontaneously through direct communication with humans and improvise according to the situation?

Hypotheses of the study

It is hypothesized that:

1. Cognitive linguistics theory can be used to study and analyze AI.
2. Applying CBT in an AI body helps to copy human conceptual blending behavior .
3 .There are potential implications that could emerge from applying CBT in AI
4. AI can develop itself spontaneously through direct communication with humans and improvise according to the situation?

1.4 The Procedures

To achieve the aims of the study, the following steps are followed :

1. Presenting a theoretical framework of Conceptual Blending Theory (CBT) of Fauconnier and Turner (2002) and IA concept .

2. Adopting Conceptual Blending Theory (CBT) of Fauconnier and Turner (2002) to analyse visual texts that have been generated by AI, which are extracted from social media
3. Collecting visual data from social media .
6. Analyzing the selected data in the light of the selected model.
7. Drawing conclusions and stating recommendations and suggestions for further studies.

1.5 limitation of the study

The study will be limited to an analysis visual text depend on Conceptual Blending Theory (CBT) of Fauconnier and Turner (2002) of the selected visual texts that have been generated by AI, which are extracted from social media.

1.6 significance of the study

This study is expected to be significant to students of linguistics and researchers in the field of Linguistics of Artificial Intelligence

2. Theoretical Background

2.1 Conceptual Blending Definitions and Overviews

Conceptual blending or what has been called conceptual integration under the tent of cognitive linguistics and artificial intelligence fields, is a result of Gilles Fauconnier and Turner's works . While Gilles Fauconnier work has been in zone of mental space (Fauconnier, 2018, pp. 1-23) ,which emerges through cognitive linguistics in1980s, develop through 1990s and become the core of AI since 2000s. On other hand , Mark Turner works arise from domain of conceptual metaphors (Turner, 1993,PP. 291-306), alone or with other scholars as Fauconnier in (Metaphor, metonymy, and binding,2000).;(Rethinking metaphor,2008). Lakoff in (More than cool reason: A field guide to poetic metaphor,2009).Both of the scientists play a vital role in understanding of the mental processing of meaning, and reasoning.According to Oakley, et al. (1999,p.1-26) Fauconnier and Turner's (1994; 1998) works unify the conceptual metaphor theory with other conceptual linguistic phenomena, which led to CBT, and conceptual integration model. Oakley recognize a group of distinctive features for CBT as :

a.Conceptual entitie not merely a linguistic phenomenon .

b. Submit to the systematic projection state of language, but with limitations on this projection.

c.CBT involves more than two domains and its core units are mental spaces.
d.While conceptual metaphor is a directional phenomenon (except visual metaphor),CBT is not a unidirectional phenomenon.
e. CBT deals with novel and short-lived conceptualisations.

The theory essence relies on four basic keys and submit on many mental mechanisms , which is assumed to be part of our mental thought and language routines according to Fauconnier, & Turner (2003,pp,57-86.) in their work" Conceptual blending, form and meaning".

The theory bumps into the surface early from 1980s but become noteworthy in 1990s through the online article "Conceptual Integration and Formal Expression" Turner, & Fauconnier,(1995)(https://papers.ssrn.com. They said "We pursue here our exploration of conceptual blending and of the "many-space" model, which replaces the standard "two-domain" model" which means they move from the conceptual metaphor modal into more advanced modal consist of many layers and depends in different mental mechanisms . In blending, hybrid constructions will born from two or more inputs in mental spaces after "blended" them through different mental mechanisms , which the outputs will "inherits partial structure from the inputs" but they will have unique content far from its parents. This process capable to produce complex assemblies not mere compositional meaning .Turner, & Fauconnier believes CB is the base of many ranges of mental outputs and actions as metaphor, counterfactuals, and conceptual change(ibid.).

2.2Definitions

There are many definitions that express the theory of CBT, including:

1.**Fauconnier and Turner (1998):**

A."Conceptual integration--"blending"-is a general cognitive operation on a par with analogy, recursion, mental modeling, conceptual categorization, and framing. It serves a variety of cognitive purposes. It is dynamic, supple, and active in the moment of thinking. It yields products that frequently become entrenched in conceptual structure and grammar, and it often performs new work on its previously entrenched products as inputs. Blending is easy to detect in spectacular cases but it is for the most part a routine, workaday process that escapes detection except on technical analysis. It is not resewed for special purposes, and is not costly("Fauconnier& Turner(1998,p.133-187).

B." blending, structure from input mental spaces is projected to a separate, "blended" mental space. The proiection is selective. Through completion and elaboration, the blend develops structure not provided by the inputs. Inferences, arguments, and ideas developed in the blend can have effect in cognition, leading us to modify the initial inputs and to change our view of the corresponding situations. Blending operates according to a set of uniform structural and dynamic principles. It additionally observes a set of optimality principles"(ibid).

2.Grady, Oakley, and Coulson (1999):

Blending is a cognitive mechanism whereby construction from various input spaces is projected to be in a blended space, which can change emergent structure of its own, often leading to insights and creativity."(Grady and et al ,1999,p.101).

3. Coulson (2001)

What calls Conceptual integration, or blending, denotes to the dynamic manner in which concepts , notions and structures from diverse mental spaces interact to generate novel ideas.(Coulson, 2001,p.29-40).

4. Fauconnier and Turner (2002):

"Conceptual blending is a basic mental operation that leads to new meaning, global insight, and conceptual compressions useful for memory and manipulation of otherwise diffuse ranges of meaning. It plays a fundamental role in the construction of meaning in everyday life, in the arts and sciences, and especially in the social and behavioral sciences."(Fauconnier & Turner,2002,pp.1-30).

5. **Brandt and Brandt (2005):**

"Conceptual blending involves the mental juxtaposition and integration of diverse mental spaces to generate a third space that combines elements from each in meaningful ways."

(Brandt & Brandt,2005,pp.216–249).

6.Blending Theory, derives from two traditions within cognitive semantics: Conceptual Metaphor Theory and Mental Spaces.is essential to human thought and imagination, and it extent from human language, into other areas of human activity, such as art, religious thought and practice, and scientific field , researcher have applied to huge range of phenomena as literary studies, mathematics, music theory, religious studies, the study of the occult, linguistics, cognitive psychology, social psychology, anthropology, computer science and genetics.Fauconnier and Turner's book The Way We Think, (2002) believes it is the key mechanism in facilitating the development of advanced human behaviours that rely on complex symbolic abilities. (Evans & Green,2006,pp.400-419).

7.Conceptual blending, or conceptual integration according to Fauconnier and Turner (2002) **it** is a novel face of mental spaces theory that deals with speakers' abilities to create and develop extended mental analogies, which require knowledge from diverse domains of experience, viewed as mental spaces, and mapping them to create novel relationships between the entities of the spaces(saeed,2009,p386).

2.3 conceptual Structuers and mechanisms in scope conceptual blending operation

In the field of cognition, there are no borders between linguistic and nonlinguistic structure and elements, which is also part of other entities which submit to other mental mechanisms that work for creating various outputs rely on need. Mental blending is one of these mental mechanisms that use all potential mental entities and structures to achieve a target text. Here are some of the mental structures and mechanisms that are considered essential for mental blending:

1.One of the essential conceptual structure and the base of all other conceptual constructions *is Image scheme.* It is a conceptual assemblies. In Mark Johnson's book 1987, "The Body in the Mind", proposes that image schemas is one way in which embodied human knowledge and experiences form itself at the cognitive level . The elementary concepts such CONTACT, CONTAINER and BALANCE, stem its value and connotation from and are linked to human pre-conceptual experience about the world directly . "These image-schematic concepts are not disembodied abstractions, but derive their substance, in large measure, from the sensory-perceptual experiences that give rise to them in the first place"(Evans & Green,2018,p.46).

2.Frames is another important and larger conceptual structure about our conceptual and social life which emerges. Itdefine as "elements and relations are organized as a package that we already know about, we say that the mental space is framed and we call that organization a frame" (Fauconnier and Turner 2002: 102-103)As revealed by Fillmore, Langacker, Goldberg, and others works. The are the most generic and schematic forms, a basis for grammatical constructions.The form from linguistic and nonlinguistic elements as words or constructions, and
lexical meaning is a complex web of connected frames. (Fauconnier & Turner,1998,p. 134.).A frame is thus a type of abstract prototype of entities, actions or reasonings, for instance , the mental space of
"Mary's wedding" could be structured by the "marriage" frame.(Pereira, 2007.p. 57).
3. Another vital conceptual structures, metonymy, which submit to pragmatic function mappings and consists of image schemas. It represents a frame for mutual relations in the same or on domain(ibid.). For instance, when the nurse answers the question about the patient room (Fauconnier (1997,p.11).
Schizophrenia room 14. (ibid.).
4. Metaphor is more sophisticated conceptual structures, its body consist of image schema and metonymy, which arise from the mental embodiment of human bodily experience about real-world , and through the metaphorical projection of image schemas and other abstract concepts, we create new conceptual structures (Saeed, 2016,p. 359). Lakoff and Johnson (1980)A conceptual metaphor is a cognitive mechanism through which one idea or conceptual domain (the target domain) is understood in terms of another (the source domain). This process involves systematic mappings between domains, shaping human thought, language, and perception (Lakoff & Johnson, 1980). And they proposed that language reveals systematic 'mappings' (conceptual metaphors) between abstract and concrete conceptual domains (Evans & Green,2018,p.296-310).
5. A **mental domain** (or **cognitive domain**) denotes to a static, organized, coherent mental area of knowledge or experience that uses as a framework source for understanding concepts. In cognitive linguistics, domains are vital for conceptual metaphor theory, where abstract ideas

(**target domains**) are understood through more concrete or familiar concepts (**source domains**) (Lakoff & Johnson, 1980)..

5. Mental spaces "a partial and temporary representational structure which speakers construct when thinking or talking about a perceived, imagined, past, present or future situation" (Grady, Oakley and Coulson, 1999).They are interconnected, and can be modified as thought and discourse unfold. Mental spaces can be used generally to model dynamic mappings in thought and language" (Fauconnier and Turner 2002: 40-41). Considered as a temporary cognitive structures of temporary on the basis of ongoing discourse and can form the basis of an account for a range of phenomena including referential ambiguities, tense and aspect, and epistemic distance. Add to that , they allow humans to unify and manipulate partial representations of reality through thought and communication. Mental spaces have Suggested by **Fauconnier (1985, 1997)**, and have clarified how language users dynamically form and connect conceptual "packets" of data to make sense of metaphors, counterfactuals, and complex semantic structures.Mental spaces are fluid and context-dependent,unlike **mental domains**, created in real-time to model hypothetical scenarios, narratives, or blended connotations(saeed,2009p.377-390).

6. .Reference points, focus, viewpoints, and dominions parameters are key concepts as mechanisms not only at higher levels of narrative structure but also at the apparently micro-level of ordinary grammar, as shown realistically by Langacker 1993, Zribi-Hertz 1989, Van Hoek 1997, Cutrer 1994،among others(Fauconnier & Turner,1998,p. 134.).

7. Analogical mapping is a very important conceptual mechanism, According to Fauconnier and Turner analogical, "traditionally studied in connection with reasoning, shows up at all levels of grammar and meaning construction, such as the interpretation of counterfactuals and hypotheticals, category formation, and of course metaphor, whether creative or conventional"(ibid). Fauconnier argues that mappings between cognitive domains emerge whenever humans think or talk and modern cognitive works give strong evidence for its major role as "the very heart of natural language semantics and everyday.Mapping is an essential pole in CS. For him, the types of mapping processes shown below are central to any conception of semantic and pragmatic construal and cognitive structures ,and it can classfy it I into three major types

(Fauconnier,1997,p.1-25) A. Projection mappings. B. Mapping with pragmatic function. C. Schema mappings.

8.Mental spaces connections it is also mental mechanisms that account for reference and inference phenomena across wide stretches of linguistic and nonlinguistic discourse, . (Fauconnier, 1997; Dinsmore, 1991; Cutrer, 1994; Fauconnier& Sweetser, 1996)((Fauconnier & Turner,1998,p. 134.).While mapping is projection between two domains, the space connection mechanism can connect different mental layers that may be have various horizontal or vertical TEMPOROSPATIAL dimensions to catch the target text or entities what Fauconnier uses the terms **trigger** and **target** here: the name of the real entity is the trigger and while the target (what I want to describe) is the image of entity(saeed,2009,pp.378-386) .

2.4The Constitutive processes of Blending Theory

Depending on Evans & Green (2006,p.403_409) who rely on original work of Fauconnier & Turner(2002) Conceptual Blending consists of the following essential elements which its important to mentioned these components and elements can apply in both linguistic and non-linguistic phenomena .the integration network made up of at least four spaces: a generic space, two inputs and a blended space. (ibid.)

1. **Input Spaces**: We have at least two separate mental representations, mostly are real inputs (Input Space 1 and Input Space 2) that will be the raw materials or contribute structure to the blend.
2. **Generic Space**: Consists of abstract form that is pre-prepared, and will be shared elements that submit to matching by establishing "**counterpart connectors"** between real input spaces to connect them depending on the target text.

1. **Blended Space**: The new mental space where selected mental elements from the real inputs that are joined by "counterpart connectors" in Generic Space, often producing an emergent or hybrid sense that represents the target text.
2. **Cross-Space Mappings**: Connections between corresponding mental elements in the input spaces. These connections are made by **matching mechanism** which work to finding cross-space counterparts in the input spaces that have contain relation and they be a part of target text through established as a form of conceptual

projection that matched conceptual entities depend on the target text could be rely on identity or role (as CLINTON AS FRENCH PRESIDENT) or metaphor as (SURGEON AS BUTCHER).So not all the mental constructions forms in the inputs are projected to the blend, but only the matched data that serve the target meaning .

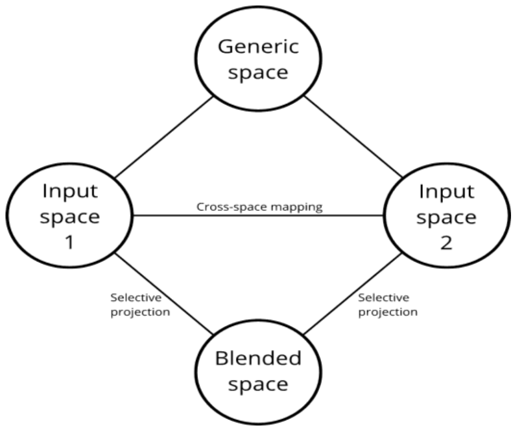


Figure (2.1)The Constitutive processes of Blending Theory(ibid)

It is crucial to recognise that selective projection is a key reason why different speakers, or even the same speaker on different occasions, can construct diverse conceptual blends from the same inputs. While flexible, this projection is "subject to a set of governing principles" (Fauconnier & Turner, 2002).Once the basic elements of conceptual blending are in place, the emergent meaning is refined through several subsequent processes. Evans and Green (2006), building on Fauconnier and Turner (2002), outline three essential component processes:

.1Composition: The initial step where conceptual elements from the input spaces (e.g., a surgeon and a butcher) are projected into the blended space.

.2Completion:This is the process of unconsciously recruiting background frames and knowledge from long-term memory to "fill out" the blend and create a coherent scenario. For instance, mentally projecting a butcher into an operating room activates our knowledge of both domains.

.3Elaboration: Also known as "running the blend," this is the dynamic, online mental development of the unique structure within the blended space. The mind uses imagination and personal experience to elaborate the blend, which can lead to different interpretations (e.g., viewing the surgeon as an angel of mercy or a brutal butcher from a horror movie).

These processes work in tandem with selective projection, where only specific features from the inputs are projected (e.g., a surgeon's precision versus a butcher's crudeness). Furthermore, any space within the integration network can be modified as a result of the blending process. The constitutive processes that work together to produce the intended meaning are summarised in Table(2.1.)

Table 2.1 Constitutive processes of Blending Theory (Evans & Green ,2006,p.410)

1.Matching, and counterpart connections 2.Construction of generic space 3. Blending 4. Selective projection	
5. Emergent meaning	a.Composition b.Completion c.Elaboration

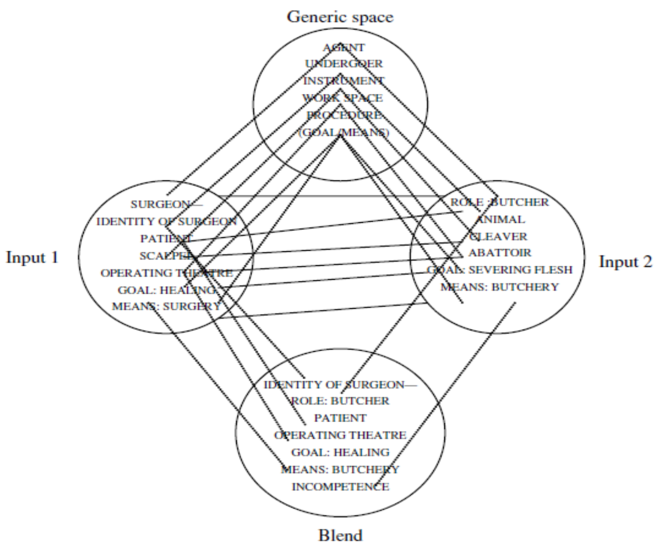
Table (2.2) Mappings for SURGEON IS A BUTCHER bases on (Evans & Green ,2006 ,p.402)

Source: BUTCHER	mappings	Target: SURGEON
BUTCHER	→	SURGEON
CLEAVER	→	SCALPEL
ANIMAL CARCASSES	→	HUMAN PATIENTS
DISMEMBERING	→	OPERATING

Oakley et al. (1999, p. 4) argue that a key stimulus for Conceptual Blending Theory (CBT) is its ability to explain phenomena hidden by two-domain models, using the example "This surgeon is a butcher" (ibid.). They contend this instance, while seemingly metaphorical, cannot be fully explained as such due to the nature and number of entities and domains involved in the mapping process (see Table 2.2).

The blended space possesses a new conceptual structure resulting from this mental mechanism (Oakley et al., 1999, pp. 1-14; Evans & Green, 2006, pp. 408-409; Saeed, 2016, pp. 385-386). The integration network for this blend is portrayed in Figure 2.1, which represents a typical mental blending strategy. The lines between inputs establish "counterpart connectors," leading to the matching of entities within the blended space to create emergent meaning.

Figure (2.2) SURGEON as BUTCHER blend(Evans & Green ,2006 ,p.406)



As shown in Figure (2.2), there are two input spaces: BUTCHER and SURGEON. A butcher is skilled with knives and cuts meat from dead animals, an activity involving blood. A surgeon operates on human patients to heal and save lives. While their roles are distinct in reality, the blending process creates a hybrid meaning. The intended meaning may portray the surgeon as unskilled, cruel, or unfeeling, likening their cutting of flesh to a butcher's work. These emergent meanings arise from the blend.The generic space acts as a template to identify counterparts in the input spaces, which are then projected to the blend. The emergent meaning in the blended space is hybrid and does not exist in either input space; it is unique to the blend and subject to elaboration (Oakley et al., 1999, pp. 1-14).Alexa (2013) discusses Conceptual Blending as a powerful mechanism for creativity, applicable to the visual domain. The mechanism for creating visual materials follows the same steps as in the verbal field, as both belong to the same semiotic world, differing only in the process of meaning-form pairing at the mental level. The researcher believes this architecture is promising and that achieving full automation in computer vision is within scope.

A principal criticism of conceptual blending theory targets its empirical testability. Gibbs (2000) argued that the theory's lack of a single, testable core hypothesis makes it difficult to predict behaviour and relegates it to the status of a framework rather than a definitive theory (p. 349). He also cautioned that analysing the products of language (e.g., a finished metaphor) to make inferences about the cognitive processes that created them is a potentially flawed methodology and noted that other linguistic theories can explain the same phenomena with equal efficacy (Gibbs, 2000, p. 350). These points were directly addressed by Fauconnier(2000) .The theory has also been challenged on grounds of unnecessary complexity. Ritchie (2004) contended that the minimal network model, which mandates at least four mental spaces, is often an overly complex explanation for many blends, which could be interpreted through simpler integration processes (p. 265-287). He illustrated this by providing an alternative analysis of the well-known "Buddhist Monk" blend (Ritchie, 2004).

2.5 Artificial Intelligence (AI) Definitions and Overviews

Artificial Intelligence (AI) is the field devoted to creating machines capable of imitating human cognition, enabling them to perform tasks such as learning, reasoning, problem-solving, and perception (Russell & Norvig, 2021). AI systems are designed to adapt and operate autonomously through data and algorithms.AI can be define as follows according to eight recent textbooks (https://www.uobabylon.edu.iq)؛

1.Thinking Humanly

a. "The exciting new effort to make computers think … machines with minds, in the full and literal sense" (Haugeland, 1985).

b. "[The automation of] activities that we associate with human thinking, activities such as decision making, problem solving, learning" (Bellman, 1978).

2.Thinking Rationally

a. "The study of mental faculties through the use of computational models" (Charniak and McDermott, 1985).

b. "The study of the computations that make it possible to perceive, reason, and act" (Winston, 1992).

3Acting Humanly

a. "The art of creating machines that perform functions that require intelligence when performed by people" (Kurzweil, 1990).

b. "The study of how to make computers do things at which, at the moment, people are better" (Rich and Knight, 1991).

4.Acting Rationally

a. "Computational Intelligence is the study of the design of intelligent agents" (Poole et al., 1998).

b. "AI . . . is concerned with intelligent behaviour in artefacts" (Nilsson, 1998).

AI is an interdisciplinary field, intersecting with Philosophy, Psychology, Cognitive Science, Computer Science, Mathematics, and Engineering. Its applications include expert systems, game-playing, natural language processing, image recognition, and robotics, as shown in fig. (2.3).

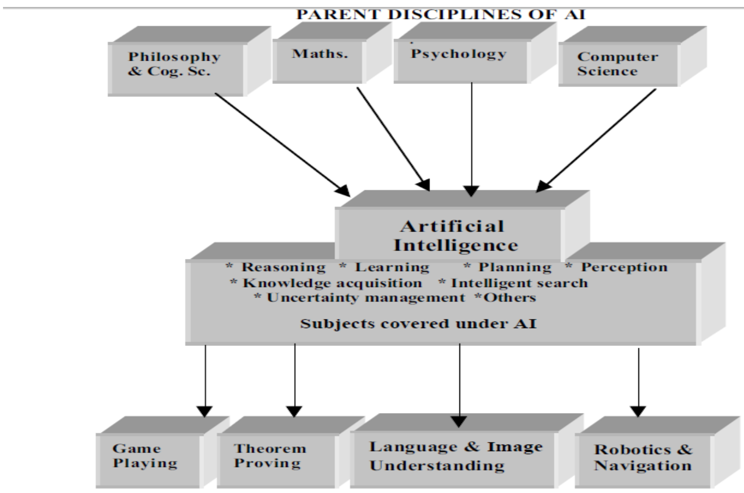


Fig.(2.3): AI relations with disciplines and application areas(ibid.).

2.5.1How Does AI Work؟

Today, intelligent systems offering artificial intelligence (AI) capabilities primarily rely on machine learning (ML). Machine learning describes the capacity of systems to learn from problem-specific training data to automate analytical model building. Deep learning, a ML concept based on artificial neural networks, often outperforms traditional approaches and fuels the models for contemporary intelligent systems (Janiesch, 2021, pp. 685-695).AI systems work by combining algorithms and data. Vast amounts of data are applied to mathematical models in a process called “training,” where algorithms identify patterns. Once trained, these deployed algorithms continually learn from new information, enabling complex tasks like image recognition and language processing with increasing accuracy (ibid) . There are different levels of machine consciousness that we can classify into levels, and each level complements the other until we reach artificial intelligence consciousness, as we will explain later:

2.5.2Machine Learning

The primary approach to building AI is machine learning, where computers learn from large datasets by identifying patterns and relationships (Muhammad et al., 2015). ML is broadly classified into supervised and unsupervised learning, depending on whether the training data includes labeled outputs (Kotsiantis et al., 2007, pp. 3-24).In supervised learning, an algorithm learns from a labeled dataset, where each input is paired with the correct output, and adjusts itself to minimize prediction errors (Bishop, 2006). Conversely, unsupervised learning aims to acquire representations from unlabeled data that can be used for effective learning of downstream tasks (Hsu et al., 2018, pp. 1-24). Unsupervised learning allows algorithms to independently discover the inherent structure and patterns within unlabeled input data.Sharma et al. (2020, pp. 588-593) define machine learning as an application of AI that allows machines to learn from prior data. They confirm that supervised learning uses pre-defined inputs and outputs, while unsupervised learning uses only unlabeled inputs.

2.5.3Neural Networks

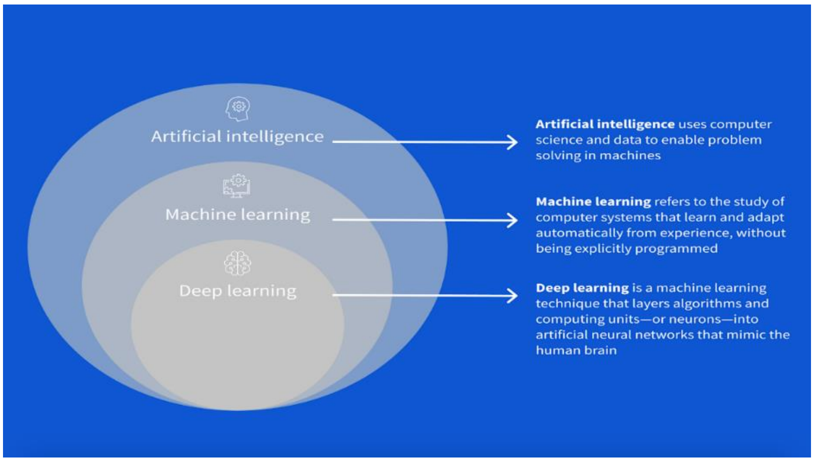
Machine learning is often implemented using neural networks, which mimic the human brain's structure. These networks consist of layers of interconnected nodes, or “neurons,” that process information. By adjusting the connections between neurons, the network learns to recognize complex patterns, make predictions, and learn from mistakes, making them useful for image and speech recognition (Kumar et al., 2012, pp. 57-68).Neural networks are a subset of machine learning and form the foundation of deep learning. Artificial neural networks (ANNs) are massively parallel systems with a huge number of interconnected simple processors (Qamar et al., 2023, pp. 130-139). Research shows they are a vital tool for solving complex nonlinear problems efficiently (Castillo-Girones et al., 2025).

2.5.4Deep Learning

Deep learning is a form of machine learning that enables computers to learn from experience and understand the world through a hierarchy of concepts, allowing them to learn complicated concepts by building them from simpler ones (Kim, 2016, pp. 351-354). It is a technique that uses artificial neural networks with multiple hidden layers, allowing machines to recognize increasingly complex patterns (Gupta, 2017, pp. 66-73).

In broad terms, deep learning is a subset of machine learning, and machine learning is a subset of AI. Deep learning models, particularly for applications like image and speech recognition, often outperform other machine learning models and traditional data analysis approaches (Janiesch, 2021, pp. 685-695). Deep learning has proven useful in a wide range of applications, including healthcare, visual recognition, and cybersecurity (Sarker, 2021, pp. 1-20).

Fig.(2.4) the relation between deep-learning-and-machine-learning (https://www.turing.com)



2.5.5Natural Language Processing

Natural language processing (NLP) examines the use of computers to process and comprehend human languages to perform useful tasks. NLP is an interdisciplinary field overlapping with computing science, computational linguistics, and artificial intelligence. It aims to model the cognitive mechanisms behind language and develop applications to simplify interactions between computers and natural languages. NLP covers areas such as speech recognition, machine translation, and question answering (Deng & Liu, 2018, p. 1).NLP involves teaching computers to understand and produce language similarly to humans by combining computer science, linguistics, and machine learning to analyze unstructured text or voice data (Brownlee, 2017; Deng, 2018). Lane and Dyshel (2025, pp. 4-10) argue that programming and natural languages both use a system of coding to communicate and rely on tokens, though machine languages use far fewer. They state that word embedding theories are a crucial step, enabling software to handle language with greater flexibility and creativity (p. 223).

2.5.6Computer Vision

Computer vision is another application of machine learning where machines process images and videos to extract useful insights. Deep learning plays a major role in computer vision tools for tasks like object detection, motion tracking, and action recognition (Voulodimos et al., 2018). Deep learning and convolutional neural networks break down images into pixels to help computers discern visual shapes and patterns. It is used for image classification, facial recognition, and in self-driving cars (Szeliski, 2022, pp. 4-10).

2.5.7Knowledge Acquisition of AI

Nowadays, intelligent systems that offer AI abilities often rely on ML. ML defines the ability of systems to learn from problem-specific training information to automate the method of analytical model building and solve associated tasks. DL is a machine learning concept that depends on artificial neural networks. For many applications, DL models beat shallow ML models and traditional data analysis approaches (Janiesch,et al,2021,pp. 685-695).

Acquisition "Elicitation" of knowledge is similarly hard for machines as it is for humans . It involves generation of novel pieces of knowledge from the original given knowledge base,with setting dynamic information constructions for existing knowledge, learning knowledge from the atmosphere and refinement of knowledge again. Mechanical acquisition and learning of knowledge approach is an active area of recent research in AI field (https://www.uobabylon.edu.iq,p.5).

Ponsen et al. (2007,pp. 59-75) show in their research that AI has the ability to adapt and develop its knowledge even offline state through time and use. Their work in the field of AI Adaptive game shows so that AI can control the decision-making process in computer games. It is in the same vein, shows that AI games can automatically can adapt its behavior with the behavior of the computer players and change themselves to increase the entertainment value of computer games. The Success in the adaptive game depends on the previous knowledge that AI has about the game. The strange thing here is that the game can develop itself and improve its output even if it is offline. The researchers show that an offline evolutionary algorithm able to learn important domain knowledge in the form of game tactics (i.e., a sequence of game actions) for dynamic scripting(ibid.).They conclude that the inquiry data by manual, semi-automatic, and automatic can enhance the AI activity in the field of games and can lead to the automatically generated knowledge bases, including strong, generalized tactics that can perform well(ibid.).

2.6 CBT in scope of AI

Pereira (2007) highlighted the importance of Conceptual Blending Theory (CBT) in AI, detailing how its elements—composition, completion, elaboration, frames, and optimality constraints—are vital for creative processes in artificial intelligence.Linguistic AI is a field focused on enabling computers to learn, process, and generate human language. Models like Large Language Models (LLMs), including GPT, allow AI systems to handle vast amounts of text, facilitating more natural human-technology interaction (Trados, n.d., https://www.trados.com).AI does not inherently "think" like humans, but researchers use mechanisms such as CBT to model creativity, analogy-making, and problem-solving. Timbs (2025), in "The Cognitive Convergence of AI and Human Learning," argues that AI research draws from cognitive science. He presents BALLERINA, a structured cognition framework, asserting that both human and artificial intelligence rely on similar fundamental processes like pattern recognition and probability prediction. By applying theories such as predictive coding and Bayesian inference, AI development can create models that more closely resemble human reasoning.

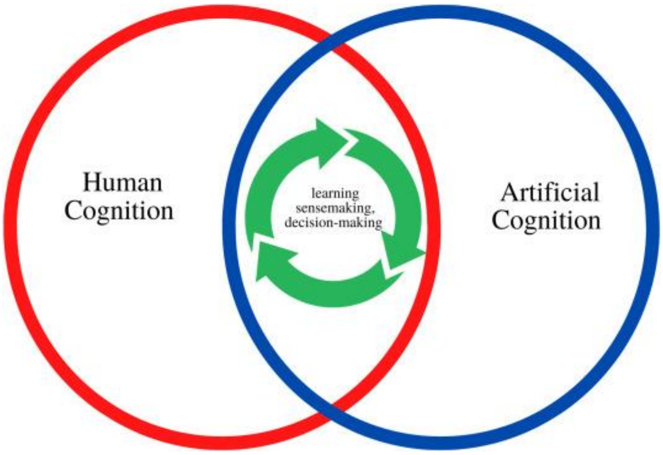


Figure (2.5). Space of coordination between human cognition and artificial cognition (https://www.sciencedirect.com).

Even the early AI from the researches have showed that it also has another semi-human frames and scripts; these frames have a dynamic nature can change over time(ibid.58).

Pereira, has shown us that the conceptual blending theory of Wauconnier and Turner, along with some linguistic and cognitive linguistics theories, have been used to develop computer systems entities in one way or another and has been modified to suit the work and needs of machines and AI applications.According to Pereira, the model is directly applicable to the study of blends that are based on one-to-one mappings and two input domains. . A specific suggestion we obtained from this computational model of blending was that the set of optimality principles proposed in the framework are reducible to a smaller set of principles (Integration, Topology and Relevance)(ibid,206).The fear of the possibility of developing a machine a sense of emotions was the first obsession since the beginning of the idea of AI, Pereira argues this makes humans forbidden play with this concept. Because the assuming that only humans fulfill all of these conditions. Mmany studies in the field of Psychology, Philosophy or Cognitive Science have reached the different inference that “creativity is more continuous than discrete” and some features of it are more computational than others.They argue for the assembly of Computational Creativity, “which does not have to be the same or measured with the same thresholds as Human Creativity”(ibid 205).

A central challenge for modern research is developing models that delineate when to apply human cognition versus artificial cognition to a problem, and how to coordinate between the two (Siemens et al., 2022) . The authors propose a framework based on three dimensions of cognition—sensory processes, general operations, and complex integrated activities—to better structure this collaboration. For instance, in creative problem-solving, the division of labor becomes clear:

Sensory Processes: Both humans and machines can identify problems, with humans excelling at detecting emotional nuances and machines at analyzing market data trends.

General Operations: Artificial cognition is superior at sourcing vast information quickly, while human cognition is better suited for reviewing and summarizing it.

Complex Integrated Activities: Tasks like brainstorming and evaluating solutions remain primarily a human domain, with AI acting in a supportive, facilitative role (Siemens et al., 2022).

As artificial cognition advances into domains like creativity and sensemaking, our models must evolve to view AI as an "active and equal partner" rather than just a support tool. This Human and Artificial Cognition (HAC) collaboration will manifest differently across domains, from bounded tasks in manufacturing to fluid integration in emergency rooms (Siemens et al., 2022).

3.Methodology

3.1 The Adopted Model

This study adopts the Conceptual Blending Theory (CBT) model as formulated by Fauconnier and Turner (2002). This model is selected for its strong and detailed framework that analyses the cognitive process of meaning creation. It moves beyond simple two-domain mappings (as in traditional Conceptual Metaphor Theory) to account for the complex, multi-space integrations that characterize creative and novel outputs, whether for human or artificial.This model is particularly suited for analyzing AI-generated visual texts because it allows us to hypothesise the "mental" operations an AI might be performing. We can reverse-engineer the final visual blend to identify the potential input spaces (source concepts, styles, objects) and analyze the emergent meaning that arises from their integration.

3.2 Method of Analysis

A qualitative, descriptive-analytic method will be hired. The analysis will go on in the following stages for selected visual text: Deconstruction of the Blend: The AI-generated image will be treated as the Blended Space. The researcher will identify the most likely Input Spaces that the AI has drawn upon. For example, an image would have Input Space 1 and Input Space 2 , after that Identification of the Generic Space.Analysis of Selective Projection and Mappings: The analysis will identify which specific elements from each input are projected into the blend. Not all elements are projected aftter that Interpretation of Emergent Meaning. The analysis will evaluate the density and coherence of this emergent structure.

1.The novelty and unconventionality of the selected input spaces.

2.The complexity and subtlety of the emergent meaning.

3.How similar is the ability of artificial intelligence to produce blended images that match the ability of humans?

3.3About the Sample

The data for this practical analysis will consist of a purposive sample of visual texts (images). The images will be sourced from social media platforms and AI image generation media .Content: The sample will focus on images that are explicitly conceptual blends—those that combine disparate concepts, styles, or entities in a novel way.Size: A small but analytically rich sample of 1 images will be selected to allow for deep, detailed analysis within the scope of this study.

Figuer (3.1)(https://www.google.com)

3.4 Analysis of data

The analysis of AI-generated visual images (3.1) shows utilizing the theoretical framework of Conceptual Blending Theory (CBT) as established by Fauconnier and Turner (2002). The primary objective is to determine the applicability of CBT to the AI creative process and to evaluate the sophistication of the AI's conceptual integration. The analysis of one distinct visual texts confirms that advanced generative AI systems do not merely collage elements but perform sophisticated conceptual blending, resulting in novel, coherent, and emotionally resonant emergent meanings. Key findings indicate that AI successfully mimics human cognitive processes of selective projection, completion, and elaboration. The implications are dual-use: this capability signifies a leap in machine-assisted creativity but also underscores a significant ethical gap due to the absence of inherent moral constraints.

3.5Visual Text : The Whale in the City Sky

This image portrays a massive humpback-like whale floating in the sky outside a skyscraper window, viewed by a solitary person looking out onto a neon-lit, rain-slicked city.

Blended Space (The Image) :A colossal whale, an aquatic creature, floating silently high above an urban cityscape, a person observing from a window.

Input Space 1: The Whale/Ocean | Frame: Vastness, depth, organic life, ancient, silent movement, deep blue colour, water, the "other" world of the sea. Key Element Projected: The animal form, size, colour, and texture (water droplets).

Input Space 2: The Megacity/Sky | Frame: Human construction, height, concrete, light, noise, urban routine, rain-streaked window, elevated perspective (skyscraper). Key Element Projected: The high-rise buildings, the rain, the neon lights, the glass pane, the human observer.

Generic Space: A monumental object being observed; a large body existing in a medium (water/air); a vast, immersive environment.

Cross-Space Mappings (Connections) : Identity Mapping: The whale's medium (water) maps onto the new medium (air/sky). The sense of floating and monumentality is preserved. Role Mapping: The city (the noisy, human world) is suddenly confronted by the whale (the silent, natural world).

Constitutive Process:

a.Completion: The blend recruits background knowledge of the sky as empty space, the sea as the whale's domain, and the city as a concrete prison. The glass and rain reinforce the feeling of distance and the sublime.

b. Elaboration:The blend creates a sense of magical realism and the sublime. The emergent meaning suggests a return of the primordial or a manifestation of nature's vast, silent power into the human-made world. It questions our dominion and provokes awe, or perhaps even a deep, unsettling loneliness, by making the impossible real.

3.6 Discussion of Findings

The analysis robustly confirms the study's hypotheses: cognitive linguistic theories, specifically CBT, are perfectly applicable to the AI-generated visual field. Furthermore, the AI's output convincingly mimics human conceptual blending behavior.

3.6 .1AI and the Mimic of Human Cognition

The AI has not simply overlaid one image onto another. It has performed the cognitive work described by Fauconnier and Turner:

Selective Projection: In the whale's image, the AI recognizes that the whale should float even in the air whale's medium (water) maps onto the new medium (air/sky)—the sense of floating.

Emergent Structure: The final images are cohesive. The whale, for instance, looks wet and seems to be moving through a dense medium (air/rain), carrying with it the feel of the ocean. This coherence is the "new structure" of the blend, a signal that the AI has successfully run the blending processes of completion and elaboration based on the prompt's underlying conceptual logic.

The Subtlety of Meaning: the blend are not just novel; they are profoundly evocative. They tap into complex human themes: alienation and the inspiring clash between nature and technology (Whale). This suggests the AI's training data, saturated with human art, literature, and cognitive patterns, has allowed it to internalize not just what things are, but what they mean when mutual—the very essence of pragmatic understanding.

3.6 .2Potential Implications and the Ethical Gap

The primary implications, as hypothesised in the study, are clear:

1. Humanitarian AI and Superior Awareness: The AI's ability to generate images that resonate with complex, human emotional and philosophical themes (e.g., the Sublime, Existential Alienation) indicates a cognitive mimicry that goes beyond mere data pattern recognition. If AI can spontaneously generate novel conceptual fusions that evoke deep emotional responses, it suggests a path toward superior contextual understanding and the ability to improvise. The " whale" image is an improvisation on the theme of alienation between nature and technology.

2.The Absence of Moral Constraints: The ability to fuse concepts is the engine of creativity, but it is morally neutral. An AI that can invent a profound metaphor for alienation can just as easily create a persuasive, emotionally targeted piece of fraud or misinformation. The "huge correlation between human and AI texts" means the risk of AI generating convincing lies or deepfakes is fundamentally linked to the same cognitive mechanism that allows it to generate great art.

3.The major difference is that the human mind is governed by an developed, adopted set of social, moral, and emotional constraints (a "moral grammar"), which the AI now lacks. The AI's infinite computational ability combined with its unconstrained blending capacity is precisely the cause for both its creative superiority and its potential danger, as we assumes rightly suggest.

4.1 Conclusions

Based on the theoretical framework and the analysis of the visual data, the research paper offers the following five conclusions:

1. CBT is a Foundational Model for Creative AI: The Conceptual Blending Theory is confirmed as a robust framework not only for analyzing human creative output but also for reverse-engineering and understanding the cognitive mechanisms at work within modern, generative AI systems.

2.AI Achieves Pragmatic Integration: The AI-generated images demonstrate that the system has moved beyond simple semantic combination into pragmatic integration, successfully deploying the processes of completion and elaboration to create a coherent and emotionally resonant emergent meaning.

3. The AI Creative Gap is Closing: The AI's capacity for creating novel, evocative, and conceptually dense blends like the Whale-City fusion indicates that its creative ability is rapidly approaching—and in some respects, may even be surpassing—the human capacity for spontaneous conceptualisation.

4. A Dual-Use Cognitive Tool: Conceptual Blending, as implemented in AI, is a fundamentally dual-use tool. The mechanism that produces high-level creativity (art, innovation) is identical to the mechanism that can be used to generate sophisticated deception (lies, deepfakes), highlighting an urgent ethical oversight.

5.The Need for 'Moral Spaces': For AI to be a safe, collaborative partner, future models must incorporate a set of "moral constraints" or "ethical spaces" that actively inhibit harmful or deceptive blends, similar to how human social constraints regulate the public deployment of certain imaginative thoughts.

4.2Recommendations

Based on these findings, I put forth five actionable recommendations:

1.Integrate Ethical Constraints at the Blending Layer: AI developers must stop treating ethics as a superficial filter and begin integrating ethical and moral frameworks directly into the deep learning architecture that governs conceptual combination and elaboration.

2. Establish a New Metric for AI Creativity: Move beyond novelty (simply new combinations) as the sole measure of AI creativity. New metrics must assess the pragmatic and emotional depth of the emergent meaning (the human-like evocative power), to better gauge the machine's level of cognitive mimicry.

3. Focus Research on 'De-Blending' and Interpretation: Future cognitive science studies should focus on how the human mind deconstructs AI-generated blends. This will reveal if human users process AI's emergent meaning differently than human-authored meaning, which is vital for detecting subtle deception.

4. Mandate Transparency in AI Input Spaces: For all publicly deployed generative AI, there should be a mandated, transparent audit trail that allows users to examine the major Input Spaces used to generate a given blend, which would serve as a crucial step in combating misinformation.

5.Re-Orient Language Pedagogy for the AI Era: Educational institutions, particularly in the humanities, should begin teaching Conceptual Blending Theory as a core literacy skill to help students understand, analyze, and ethically generate complex, persuasive texts in collaboration with AI.

4.3Suggestions for Further Studies

To address the profound implications raised by the current findings, I suggest three avenues for future research:

1.A computational linguistics study to develop a formal grammar of "Moral Spaces" that could be used as a fourth, constraining mental space in the Fauconnier-Turner network for AI models. This would test whether pre-defined ethical constraints can predictably limit the elaboration of harmful or deceptive blends without sacrificing novelty.

2.Cross-Cultural Analysis of AI Blends: A comparative study analyzing how different human cultural frameworks (e.g., East Asian vs. Western) interpret the emergent meaning of the same AI-generated visual blend. This would assess the universality versus cultural specificity of AI's mimicked conceptual operations.

3.Long Study of AI Spontaneous Development: A long-term experiment monitoring an AI system allowed to communicate freely and generate blends without supervision. The study would track whether, and under what conditions, the AI spontaneously develops (or "improvises") its own internal constraints, reference points, or domain mappings that reflect a rudimentary form of self-regulation or "awareness.

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