Tese de Doutoramento

MOBILE ADVERTISING EFFECTIVENESS VERSUS PC AND TV, USING CONSUMER NEUROSCIENCE

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D. José Ramón Porto Pedrido

Titulo da tese: Mobile advertising effectiveness versus PC and TV using consumer neuroscience

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To my family

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Finally, I encourage students who are thinking about doing their PhD to go ahead, don't doubt, it's a wonderful experience that will enrich you as a person and scholar.

RESUMO

Considerando a importancia cada vez maior dos móbiles na vida das persoas e o avance das técnicas de investigación a través das neurociencias das condutas do consumidor, (*consumer neuroscience*), este estudo analiza o modo de mellorar a eficacia da publicidade nos móbiles.

Nos derradeiros 20 anos a publicidade trasladouse de medios tradicionais a medios dixitais, o que supón a dia de hoxe mais do 58% do investimento total a nivel mundial. Nestes medios o investimento concéntrase actualmente no teléfono móbil, que xa supón un 68% do total. Unha das razóns fundamentais é que os consumidores están cada vez mais tempo (case 7h.) a navegar pola rede co seu móbil e un 63% do consumo de contido é vídeo.

Tanto investigadores como empresas, están de acordo en que o "*engagement*" é unha boa variable para medir a eficacia da publicidade. Os métodos tradicionais baseados en enquisas teñen algunhas limitacións. Esta Tese Doutoral utiliza "*consumer neuroscience*" como complemento da investigación tradicional de enquisa para medir, mediante o "*engagement*", a eficacia da publicidade no móbil en formato vídeo fronte ao PC ou a TV.

Os resultados suxiren que é mellor utilizar un único algoritmo para todos os experimentos en "*consumer neuroscience*", xa que métricas iguales ou similares de diferentes algoritmos non están correlacionadas.

Cando se compara o efecto da publicidade en móbil con PC ou TV, a carga cognitiva e maior en móbil que en PC ou TV, polo que suxerimos que os anunciantes deben desenvolver anuncios que teñan menos texto e poucas imaxes para non incrementar a carga cognitiva. Tamén recomendase utilizar o formato de vídeo en pantalla completa como o "*interstitial*".

Os resultados tamén mostran que a atención é maior en PC ou TV que no móbil, se ben non podemos concluír que a maior tamaño de pantalla a atención sexa maior, xa que a atención en PC e maior que en TV; tampouco que a atención aumenta cun menor tamaño de pantalla. Estes resultados están na mesma liña con Babiloni (2019) que postula que a atención é maior en PC que na TV.

Finalmente, a utilización de vídeos en formato de pantalla completa pode que reduza o efecto do tamaño da pantalla comparando con PC ou TV, xa que noutras métricas como intensidade emocional ou a percepción da intrusividade, por parte do consumidor, no se atopan diferencias significativas.

Palabras clave: Móbil, *engagement*, *consumer neuroscience*, *neuromarketing*, publicidade dixital, eficacia publicidade móbil.

RESUMEN

En los últimos 20 años la publicidad se ha movido de medios tradicionales a medios digitales, realizándose en estos ya más del 58% de la inversión en publicidad a nivel mundial. En estos medios la inversión se concentra, los últimos años, en los teléfonos móviles que acaparan actualmente el 68% del total. Una de las razones fundamentales es que los consumidores están cada vez más tiempo (casi 7h. actualmente) navegando en internet a través de su móvil, siendo vídeo el 63% del consumo de contenido.

Tanto investigadores como empresas, están de acuerdo en que "*engagement*" es una buena variable para medir la eficacia de la publicidad. Los métodos tradicionales que se basan en las encuestas tienen algunas limitaciones. Esta Tesis Doctoral utiliza "*consumer neuroscience*" como complemento de la investigación tradicional para medir, a través del "*engagement*", la eficacia de la publicidad en móvil en formato video comparándola con la de PC y TV.

Los resultados sugieren que es mejor utilizar un único algoritmo para todos los experimentos en "*consumer neuroscience*" ya que métricas iguales o similares de diferentes algoritmos no se correlacionan.

Cuando se compara el efecto de la publicidad en móvil con PC o TV, la carga cognitiva es mayor en móvil que en PC o TV, por lo que sugerimos que los anunciantes deben desarrollar anuncios con menos texto y pocas imágenes que no incrementen esta carga. Se recomienda utilizar formato de vídeo en pantalla completa como el "*interstitial*".

Los resultados también muestran que la atención es mayor en PC y TV que en móvil, si bien no podemos concluir que a mayor tamaño de pantalla la atención será mayor, ya que la atención en PC es mayor que en TV; tampoco que la atención aumenta con un menor tamaño de pantalla. Estos resultados están en línea con Babiloni (2019) que postula que la atención es mayor en PC que en TV.

Finalmente, la utilización de videos en formato de pantalla completa puede que reduzca el efecto del tamaño de la pantalla comparando con PC o TV, ya que en otras métricas como la intensidad emocional o la percepción de intrusividad, por parte del consumidor, no tienen diferencias significativas.

Palabras clave: Móvil, *engagement, consumer neuroscience, neuromarketing*, publicidad digital, eficacia publicidad móvil.

ABSTRACT

During last 20 years advertising has been moving from traditional to digital media, meaning more than 58% of total ad spending worldwide and concentrate in last years in mobile 68% of spend. One main reason is that consumers spent more time on mobile (almost seven hours per day actually) in internet and basically with video content that suppose 63% from total content.

All actors in the advertising industry, publishers, advertisers and researchers and marketers point engagement as a good variable to measure advertising effectiveness. Traditional methodology to measure advertising effectiveness is based in surveys. This research use consumer neuroscience as a complement of traditional research with survey to measure using engagement mobile advertising effectiveness with video ads compare to PC or TV.

Findings suggest that it is better to use one algorithm for all the consumer neuroscience experiments, given that equal or similar metrics do not correlate in different algorithms.

When comparing the advertising effect in mobile versus PC or TV, cognitive workload is higher in mobile than PC or TV so we suggest that practitioners should take care when designing advertising that not contribute to increase this workload. Ads in mobile should be with less text in big size font that are easy to read and few images that communicate main message.

Results show that attention is higher in PC and TV than in mobile, but we cannot assume that the higher the screen size is attention is higher as we see that PC has better attention than TV. This doesn’t mean also that attention increase with lower screen size. Results are in line with Babiloni (2019) that attention is higher in PC than in TV.

Finally, the use of video ads full screen in mobile may reduce the effect of screen size comparing with PC or TV, as other metrics like arousal or perception of intrusiveness, by the consumer, has no significative differences.

Keywords: Mobile, engagement, consumer neuroscience, neuromarketing, digital advertising, mobile advertising effectiveness.

RESUMO EXTENDIDO

Nos derradeiros 20 anos a publicidade trasladouse de medios tradicionais a medios dixitais, o que supón hoxe en día máis do 58% do investimento total en publicidade a nivel mundial.

Dende mediados dos anos 90, anos nos que se realizaron os primeiros anuncios *online*, a maior parte da publicidade dixital desenvolveuse en PC, a pesares de que na última década o líder absoluto é o móbil, que abarca actualmente o 68% do investimento en internet e segue a crecer. Un dos motivos fundamentais deste crecemento é que os consumidores están cada vez mais tempo (actualmente case sete horas ao día) a navegar en internet co seu móbil. Isto supuxo a aparición de novos formatos en móbil e o desenvolvemento de novas estratexias especificas para este dispositivo: publicidade baseada na localización xeográfica do móbil; persoalización dos anuncios baseada en datos dos usuarios; voz e audio nos móbiles, publicidade sincronizada no móbil co consumo que esta facendo nese momento o usuario, ou finalmente a publicidade incentivada no teléfono que, aínda que tivo o a súa orixe nas aplicacións de xogos para móbil, estase a trasladar a todo tipo de aplicacións ou á navegación en páxinas *webs* .

A publicidade no móbil enfróntase a unha serie de problemas importantes: "*Banner blindness*", que fai referencia a que os usuarios non prestan atención aos anuncios; "*ad-blocking*", software que bloquea a aparición dos anuncios mentres o usuario navega por internet; fraude publicitario con *clicks* ou impresións falsas e, tamén, o tamaño da pantalla, que e moito mais pequena comparada coa do PC ou da TV.

Moitos académicos suxiren que a publicidade no móbil debe ser diferente da publicidade en PC ou TV para aproveitar as súas características especificas e únicas, como a xeo localización, a persoalización ou a maior interacción, e mitigar algúns dos problemas mencionados anteriormente.

Os datos mais actuais confirman que a tendencia dos últimos anos na navegación por internet a través do móbil ven liderada, en gran medida, polo consumo de vídeo, que supón xa un 63% do consumo total a nivel mundial. Isto supón que o SMS, que foi o primeiro formato de publicidade, e o *banner* que e o principal formato de publicidade dixital, vaian decrecendo en beneficio de novos formatos para o móbil como os "*interstitial*", "*native*" ou vídeo.

Esta tendencia a un maior consumo de vídeo no móbil xerou una maior demanda das empresas a definir novas estratexias e formatos de comunicación nos móbiles, un maior gasto en publicidade dixital para móbil e a necesidade de coñecer como se pode medir, para determinar a súa eficacia en comparación coa publicidade tradicional.

A comunidade académica, coñecedora desta necesidade, desenvolveu grandes liñas de investigación nos diferentes aspectos desta materia e, mais concretamente, na eficacia da publicidade dixital. Esta Tese Doutoral intenta contribuír á análise e mellora da medición da eficacia da publicidade dixital en móbil e comparala coa doutros dispositivos, como PC o TV, para propoñer melloras.

Tanto os investigadores como as empresas coinciden en que o "*engagement*" é una boa variable cara a medición da eficacia da publicidade, polo que desenvolvéronse diferentes modelos de "*engagement*" para a dita medición baseados nas súas dimensións. Un dos modelos mais recoñecidos é o de Dessart (2016) que establece tres dimensións do "*engagement*": cognitiva, emocional e de comportamento. Tradicionalmente, a medición da eficacia da publicidade dixital baséase en métricas tales como *clics*, tráfico á *web*, tempo en pantalla, etc., as cales non reflicten correctamente a medición da súa eficacia, xa que unicamente utilizan a dimensión do comportamento do "*engagement*" e non teñen en conta as outras dúas dimensións.

Os métodos tradicionais para medir a eficacia da publicidade baséanse en enquisas que, segundo os académicos, teñen algunhas limitacións que a "*consumer neuroscience*" contribúe a solucionar, complementar ou minimizar.

O 95% das decisións relacionadas coas compras fanse a un nivel subconsciente. As técnicas de "*consumer neuroscience*" permiten entrar no subconsciente dos consumidores para captar e analizar a actividade cognitiva, a atención e as respostas emocionais que os consumidores teñen ante estímulos de *marketing* como os anuncios das marcas.

Tanto os académicos como a industria da publicidade están investigando dende fai anos coas tecnoloxías de *consumer neuroscience* para comprender o efecto que a publicidade ten no subconsciente dos consumidores e poder medir a súa eficacia. Tradicionalmente estas tecnoloxías divídense en dous grupos:

- Técnicas que miden o CNS (Sistema nervioso central): son tecnoloxías que miden os cambios eléctricos ou metabólicos da actividade neuronal. Entre estas atópanse fMRI, EEG e MEG.

- Técnicas que miden o PNS (Sistema nervioso periférico): Son o *Eye-tracking*, FEA, GSR, Electro miografía facial, ou os test de asociación implícita.

Cada unha de estas tecnoloxías ten unha serie de vantaxes e desvantaxes, que as fan máis adecuadas en función das necesidades da investigación concreta. As empresas de desenvolvemento de software teñen dispoñibles diferentes solucións baseadas nestas tecnoloxías e hoxe en día moitos investigadores utilizan varias delas de forma conxunta.

As tecnoloxías de "*consumer neuroscience*" usadas nesta Tese Doutoral son: EEG, que nos permite medir o estado cognitivo do suxeito; *Eye-tracking*, que nos permite medir a atención do suxeito; FEA, que nos permite medir o sentido das emocións, positivo ou negativo, utilizando a valencia; e GSR e HR, que nos permiten medir a excitación emocional do suxeito.

O principal problema para a medición da eficacia da publicidade, que manifestan tanto académicos como anunciantes, e a falta de métricas estandarizadas. Este problema ven agravado polos diferentes provedores de tecnoloxía, que utilizan diferentes algoritmos e métricas, que parece ser que non son comparables entre si e das que se descoñece en moitos casos a súa composición ou definición.

As métricas mais utilizadas para medir o "*engagement*" en *consumer neuroscience* poden dividirse en dous grupos, segundo que a dimensión sexa cognitiva ou afectiva:

- Métricas do "*engagement*" cognitivo:

    - Carga cognitiva, entendida como a medición do esforzo mental que fai unha persoa. Normalmente utilizase o EEG.
    - Atención, entendida como a primeira fase do recoñecemento. Normalmente utilizase o EEG, *Eye-tracking* ou FEA. Diferentes empresas que desenvolven software teñen métricas *ad-hoc* de atención, como *cognitive state* (*iMotions*) ou interese (*Neurologyca*).

- Métricas do "*engagement*" afectivo:
    - *Arousal*, que se define como a intensidade ou excitación emocional. Normalmente utilizase FEA, GSR, ou HRV.
    - Valencia, que se define como a aproximación ou rexeitamento ao estímulo medido a través das emocións. Normalmente utilizase FEA.

Esta Tese Doutoral utiliza "*consumer neuroscience*" como complemento da investigación tradicional de enquisa para medir, mediante o "*engagement*", a eficacia da publicidade no móbil en formato vídeo fronte ao PC ou a TV.

Baseándonos nas análises de investigacións previas e análises feitos por diferentes investigadores, consultoras e empresas da industria publicitaria, propoñemos as seguintes hipóteses divididas en dous grupos:

- Grupo de hipóteses 1: Analiza o "*engagement*" dos vídeos publicitarios comparando os métodos tradicionais coas técnicas de *consumer neuroscience*.
    - Hipótese 1a: Os resultados dos anuncios en vídeo correspondentes as dimensións cognitiva e afectiva do "*engagement*" do consumidor co uso de varios algoritmos (Facet e Kopérnica) de *consumer neuroscience* non están correlacionados.
    - Hipótese 1b: Existe unha correlación entre os resultados da medición da dimensión cognitiva e afectiva do "*engagement*" do consumidor a través dunha enquisa e dalgúns dos obtidos mediante os algoritmos de *consumer neuroscience*.
- Grupo de hipóteses 2: Analiza como os vídeos en móbil afectan as métricas de "*engagement*", carga cognitiva, atención, recordo da marca, intensidade emocional e valencia, comparándoos con outros dispositivos tales como PC e TV.
    - Hipótese 2a: A carga cognitiva dos anuncios en vídeo e maior en móbil que en PC ou TV.
    - Hipótese 2b: A atención aos anuncios en vídeo e maior en móbil que en PC ou TV.
    - Hipótese 2c: O recordo da marca en anuncios de vídeo e menor en móbil que en PC ou TV.
    - Hipótese 2d: A intensidade emocional en anuncios de vídeo e maior en móbil que en PC ou TV.

- Hipótese 2e: A valencia en anuncios de vídeo e mais negativa en móbil que en PC ou TV.
- Hipótese 2f: Os vídeos de móbil son mais intrusivos que os de PC ou TV.

Para a validación, ou non, de ditas hipóteses fíxose un experimento a partires dunha mostra de 60 participantes. Xeralmente nos estudos de *consumer neuroscience* participan entre 30 e 100 suxeitos, polo que a mostra está en liña con experimentos doutros investigadores. A técnica de mostraxe foi non aleatoria, empregando mostraxe de conveniencia. Os 60 participantes foron 27 homes e 33 mulleres con idades comprendidas entre os 20 e os 58 anos, cunha idade media de 28 anos.

O experimento fíxose entre o 20 de abril e o 5 de xuño de 2021 no laboratorio da empresa *Neurologyca* en Santiago de Compostela.

Os estímulos presentados foron 3 vídeos de publicidade incrustados entres os contidos de 3 coñecidas plataformas: *Atresmedia*, *Facebook* e *YouTube*, e mostráronse nos tres tipos de dispositivos: móbil, PC e TV.

As conclusións desta Tese Doutoral divídense en dous grupos:

Conclusións e contribucións: Grupo de hipóteses 1

Os resultados correspondentes ás dimensións cognitiva e afectiva do "*engagement*" do consumidor, medidos cos diferente algoritmos (Facet e Kopérnica) de consumer neuroscience, non teñen correlación.

En canto á dimensión cognitiva, a correlación de interese (Kopérnica) coa carga cognitiva (*iMotions*) é negativa e non significativa. Isto tamén ocorre na correlación de interese (Kopérnica) co estado cognitivo (*iMotions*). Como pode observarse, esta correlación é negativa, pero non significativa. Este resultado indica que a dimensión cognitiva que miden estes algoritmos é diferente e, dado que a atención e o interese deberían teoricamente estar relacionados positivamente, expón interrogantes sobre o que mide cada algoritmo.

En canto á dimensión afectiva, ningunha das dúas correlacións métricas de valencia cos algoritmos considerados é significativa. En estas correlacións chama a atención que, por exemplo, a valencia + correspondente ao algoritmo de Kopérnica ten correlación negativa co mesmo constructo medido polo algoritmo *iMotions*. Neste caso, dado que o constructo é o mesmo, xorde a pregunta de cal dos dous algoritmos mide adecuadamente o constructo.

Os nosos resultados mostran que as correlacións entre as métricas de Kopérnica e as métricas de *iMotions* non son significativas. Os resultados sobre valencia de Facet e Kopérnica, utilizando o mesmo estímulo e participantes no mesmo lugar e ao mesmo tempo, é un exemplo. Hai dúas explicacións principais para estes resultados. Primeiro, que os provedores de software probablemente sexan diferentes o que explicaría a diferencia nos resultados; ademais, os provedores non explican a composición dos algoritmos, polo que non é posible identificar de onde proveñen esas diferenzas. En segundo lugar, con respecto á valencia, medida a través de FEA, os provedores de software usan diferentes bases de datos para comparar expresións faciais con expresións faciais nos experimentos co fin de obter emocións, polo que os resultados tamén son diferentes.

Dado que todas as correlacións examinadas mostran que os resultados obtidos por diferentes algoritmos de neurociencia do consumidor non son significativas, concluímos que a primeira hipótese está soportada. Polo tanto, non hai relación entre os resultados obtidos cos distintos algoritmos de neurociencia do consumidor considerados. Estes resultados obtidos están en liña con investigadores anteriores (Alcañiz et al., 2017; Varan et al., 2015) sobre o principal problema de neurociencia do consumidor, a falta de métricas estandarizadas. Deste resultado, xorde a pregunta sobre cal é o mellor algoritmo aplicable en orde á medir a efectividade dos anuncios de vídeo.

Os resultados correspondentes ás dimensións cognitivas e afectivas do "*engagement*" do consumidor, proporcionadas pola enquisa, e os diversos algoritmos de tecnoloxías de neurociencia do consumidor mostran unha correlación significativa, polo que a hipótese H1b está parcialmente apoiada.

Cando a enquisa se emprega para obter datos de *engagement* do consumidor e os datos sobre este constructo tamén se obteñen mediante técnicas de neurociencia, espérase unha relación positiva entre ámbolos dous resultados. Unha asociación positiva entre os resultados dos datos da enquisa e os datos das tecnoloxías de neurociencia indicaría que ámbalas dúas metodoloxías son converxentes na medición do *engagement*, fortalecendo os resultados da investigación. Pola contra, da non correlación entre os resultados xorden varias preguntas. Primeiro, as diversas metodoloxías ¿ miden realmente o *engagement*? En segundo lugar, se deste xeito, ¿cal proporciona os mellores resultados? En terceiro lugar, ¿deberían utilizarse as diversas metodoloxías de forma complementaria para ter unha visión máis completa da eficacia dos anuncios?

As correlacións entre atención e absorción (enquisa) coa carga cognitiva e o estado cognitivo EEG-*engagement* (*iMotions* Facet) non foron significativas, aínda que é interesante sinalar que ámbalas dúas parecen coherentes, xa que unha maior carga cognitiva pode levar a unha menor atención pero, ao mesmo tempo, leva a unha maior absorción, como comentamos en análises anteriores. Ademais, as correlacións entre o entusiasmo e o goce (enquisa de "*engagement*" afectivo) fronte a intensidade ou a excitación, valence + e valence - (Kopérnica de "*engagement*" afectivo) non foron significativas, aínda que é interesante resaltar que valencia+ e valencia– e a súa correlación con entusiasmo e goce parecen coherentes, xa que unha maior valencia+ conduce a un maior entusiasmo e goce, mentres que unha maior valencia- conduce a un menor entusiasmo e goce. Menos consistentes son as correlacións coa intensidade emocional, nas que se esperaba unha relación positiva.

A única correlación significativa atopouse cunha das métricas de *iMotions*. As correlacións entre entusiasmo e goce (enquisa de *engagement* afectivo) fronte a intensidade ou excitación, valencia+ e valencia- (Facet, *engagement* afectivo) non foron significativas, agás unha correlación negativa significativa entre goce (*engagement* afectivo, enquisa) e valencia- (Facet, *engagement* afectivo).

Este resultado é consistente, xa que indica que a valencia- está inversamente relacionada co goce. Aínda que xa se sinalou a non significación do resto de correlacións, con respecto aos signos, sorprende a relación negativa entre entusiasmo e goce con valencia+, xa que o gusto polo anuncio debe incrementar o entusiasmo e o goce.

Aínda que hai unha correlación significativa e a hipótese h1b está parcialmente apoiada, non podemos suxerir ningunha implicación para os profesionais, xa que as outras correlacións non son significativas.

Conclusións e achegas: Conxunto 2 da hipótese.

Ámbalas dúas hipóteses, H2a1 e H2a2 apóianse debido á existencia dunha diferenza de medias significativa, a carga cognitiva no móbil é menor que en PC e TV. A pesares do uso de anuncios de vídeo en pantalla completa, a carga cognitiva na televisión é menor que en PC ou dispositivos móbiles. Como podemos ver, as diferenzas entre os tres dispositivos non son moi elevadas, o máximo é 0,11. En liña con isto, os resultados suxiren que un televisor cun tamaño de pantalla máis grande reduce a carga cognitiva, pero quizais sexa interesante subliñar que o valor mínimo na carga cognitiva non é un televisor cunha pantalla de maior tamaño (Min = 0,34) senón unha PC (Min = 0,27). Tamén o valor mínimo en móbil e TV é o mesmo (0,34) en liña coa nosa idea de valores máis próximos nos tres dispositivos por mor das pantallas de maior tamaño no móbil e maior consumo no móbil de vídeos a pantalla completa.

As hipóteses H2b1 e H2b2 non están confirmadas. Hai diferenzas de medias significativas, pero esas diferenzas de medias son máis altas en PC e TV que en dispositivos móbiles. Non temos unha explicación clara de por que o PC obtén o maior interese en comparación con outros dous dispositivos. Este maior interese no PC que na TV está en liña con Brasel and Gips (2011) en termos de maior duración da mirada no PC que na TV.

Os nosos resultados suxiren que só o formato de vídeo de pantalla completa para dispositivos móbiles non é suficiente para captar a atención dos consumidores, aínda que probablemente se reduza a diferenza de atención cos outros dispositivos, PC e TV.

Non podemos concluír que a atención no móbil sexa superior a outros dispositivos como o PC, como propoñemos na nosa hipótese e sinala MMA (2020). Os resultados mostran que a atención é maior en PC e TV que no dispositivo móbil, pero non podemos concluír que canto maior sexa o tamaño da pantalla, maior sería a atención, xa que vemos que PC ten mellor atención que TV. Isto non significa pola contra, que a atención aumente cun tamaño de pantalla máis baixo. Os resultados de que a atención é maior en PC que en TV están en liña con Babiloni (2019).

As hipóteses H2c1 e H2c2 non están confirmadas, porque tanto no recordo espontáneo, como no recordo suxerido, non existen diferenzas significativas entre o dispositivo móbil e os dispositivos de PC ou TV e, polo tanto, o recordo da marca dos anuncios de vídeo móbiles non é menor que a obtida en PC ou na TV. A maioría dos participantes lembran bastante ben as marcas utilizadas no estímulo. Este resultado é diferente ao de Muñoz-Leiva et al. (2019), que suxiren que os participantes, en xeral, non lembran a maioría dos anuncios. A nosa explicación é que, dado que os participantes tiñan que responder as preguntas de recordo espontáneo e suxerido na enquisa inmediatamente despois de rematar o experimento de neurociencia do consumidor, puideron lembrar as marcas con máis facilidade que se completasen a enquisa máis tarde. Así pois, non podemos concluír que unha pantalla de maior tamaño signifique un maior recordo, como postula Kim (2011), ou que a televisión teña un maior recordo que os dispositivos móbiles.

As hipóteses H2d1 e H2d2 non están confirmadas. Os resultados sinalan que non hai unha diferenza significativa nas medias na intensidade emocional no móbil fronte á TV, aínda que a media é menor no móbil, que no PC. A nosa explicación destes resultados no móbil é que o aumento de tamaño dos novos dispositivos móbiles e o uso de anuncios de vídeo en pantalla completa reducen o efecto do tamaño da pantalla na intensidade emocional. De acordo con Wesel e Moser (2017) non hai diferenza na dita intensidade.

As hipóteses de valencia H2e1 e H2e2 non están confirmadas, porque os resultados da diferenza de medias non son importantes para dispositivos móbiles fronte a PC ou TV, tanto para a valencia+ como para a valencia-, nos algoritmos de Kopérnica e *iMotions*. A valencia nos anuncios de vídeo para móbiles non é máis negativa que no PC ou na TV. A pesares de que as medias non son significativas, é interesante subliñar, en base aos nosos resultados, que a media de valencia negativa en dispositivos móbiles ten unha diferenza de 1,96 con PC e 1,02 con TV. Isto está en liña cos postulados de Werlen e Moser (2017), de que a valencia é máis negativa na pantalla pequena que na pantalla grande. Concluímos que pode ser que os anuncios de vídeo para dispositivos móbiles en pantalla completa reduzan a diferenza de valencia- cos anuncios de TV ou PC, pero non dispoñemos de datos anteriores para facer unha comparativa.

Finalmente, en relación as hipóteses H2f1 e H2f2, os resultados indican que os anuncios de vídeo para dispositivos móbiles non son máis intrusivos que os anuncios en PC ou TV. Aínda que a media da intrusión nos dispositivos móbiles é máis alta que en PC, sorprendentemente a intrusión da televisión é superior que ao dos móbiles. Este resultado non está en liña coa conclusión de Truong e Simmons (2010) de que o tamaño máis pequeno da pantalla fai que os participantes sexan máis sensibles á intrusión da publicidade nos seus teléfonos móbiles en comparación coas pantallas de maior tamaño. A nosa explicación é que aos participantes que viron o estímulo na televisión non lles gustaba o contido do anuncio, polo que a percepción de intrusión foi maior. Tamén a idade dos participantes pode explicar a maior intrusión na televisión que no PC, xa que a maioría deles eran novos e non ven televisión. Probablemente a diferenza de intrusión nos dispositivos móbiles fronte a outros dispositivos sexa debido ao tipo de estímulo, aos anuncios de vídeo en pantalla completa.

Implicacións para os xerentes de Marketing

A partires dos dous conxuntos de hipóteses, propóñense diferentes implicacións:

Con respecto ao primeiro conxunto de hipótese, subliñamos as seguintes implicacións, baseadas nos resultados da investigación:

• Con respecto ao uso de provedores de *software* (ferramentas para estudos con neurociencia do consumidor), concluímos que é mellor usar un provedor de software para todos os experimentos co fin de ter o mesmo algoritmo para todas as análises, mesmo se non hai consenso sobre cal é o mellor.

• Tamén do noso estudo resulta que pode ser necesario implantar unha base de datos común para toda a analítica FEA.

• En base a todo o analizado, parece necesario establecer definicións estándar de cada métrica de neurociencia do consumidor e unha forma de medición.

• Finalmente, do análise feito xurde a necesidade de establecer pautas para informar os resultados de cada tecnoloxía de neurociencia do consumidor que axuden a estandarizar a medición. Nesta liña, a guía de seguimento ocular de Fiedler et al. (2020), é un bo exemplo.

Con respecto ao segundo conxunto de hipótese, dos nosos descubrimentos despréndese as seguintes implicacións:

En primeiro lugar, co mesmo estímulo de vídeo (dado que a carga cognitiva é maior no móbil que no PC ou na TV), os profesionais deben deseñar os anuncios de publicidade de xeito que non contribúan a aumentar esa carga cognitiva. Os anuncios en dispositivos móbiles deben minimizar o texto, utilizar unha fonte de gran tamaño que sexa fácil de ler e poucas imaxes que comuniquen a mensaxe principal. Nesta liña, o estudo suxire a utilización mais do vídeo que o texto no deseño publicitario en dispositivos móbiles para non aumentar a carga cognitiva.

Tamén dos descubrimentos feitos nesta Tese Doutoral xurde a necesidade de deseñar publicidade especificamente para dispositivos móbiles que aproveiten a pantalla completa do dispositivo. Como a posición vertical é a que mais se usa nos móbiles, é recomendable usar un formato de vídeo que aproveite mellor a pantalla completa, como é o formato "*interstitial*".

Segundo o noso análise, compre suxerir aos anunciantes que, no momento de deseñar anuncios para dispositivos dixitais, fagan diferentes anuncios para móbil que para PC ou TV, co fin de evitar a pouca atención prestada aos anuncios nos dispositivos móbiles.

<u>Limitacións</u>

Atopáronse varias limitacións, durante e despois da investigación, que poden afectar aos resultados deste estudo:

- O uso dun laboratorio para facer o experimento probablemente tivo consecuencias xa que os participantes estaban condicionados por todos os sesgos do laboratorio. Entrar nun laboratorio de neurociencia de consumo pode xerar tensión cando os participantes ven todos os dispositivos tecnolóxicos que teñen que usar, como sensores EEG no coiro cabeludo ou GSR no dedo, e probablemente esta tensión poida afectar aos resultados.

- Ademais, facer o experimento no laboratorio con todos os equipos de neurociencia de consumo e sen ter idea de cal é o obxectivo do experimento, fai que probablemente os participantes estean máis concentrados do que están na vida normal, polo que lembran as marcas moito mellor.

- Aínda que ningunha información sobre o obxectivo da investigación foi entregada aos participantes no experimento antes de entrar ao laboratorio, sempre existe unha predisposición a intentar coñecer o propósito da investigación, que pode afectar aos resultados. Este matiz non ocorre cando os participantes están fóra do laboratorio usando os seus teléfonos móbiles, PC ou interactuando cun televisor intelixente.

- Asemade, as explicacións do coordinador do laboratorio, mentres prepara ao participante para o experimento, afectan ao estado emocional e, a consecuencia disto, poden afectar aos resultados.

- Os estudos de neurociencia do consumidor utilizan tamaños de mostra de entre 30 e 100 participantes, como indicouse no capítulo 4. Meng-Hsien et al. (2018) sinalan que aínda que se pode percibir que estes tamaños de mostra son pequenos e, como resultado, dan un baixo poder estatístico, esta limitación percibida a miúdo débese a unha percepción errónea con respecto aos datos de neurociencia. Con todo, as nosas análises suxiren que o tamaño da mostra tamén pode ser outra limitación, xa que nalgúns dos datos de saída de equipos tecnolóxicos, como EEG ou FEA, non obtivemos valores dalgúns participantes, por mor de diferentes problemas, tales coma movementos do participante, mala detección de rostros ou erros do equipo. Destes problemas compre suxerir, que aínda que se utilizaron mostras de neurociencia do consumidor, é mellor contar con entre 50 e 100 participantes como mínimo.

- Outra das limitacións foi que os participantes non manexaban o móbil nas súas mans, ao estar o móbil nunha posición fixa no "Soporte Tobii", e esa non é a forma natural en que os consumidores manexan e navegan co dispositivo móbil, polo que isto pode afectar aos resultados.

- Nesta mesma liña tamén pode haber a limitación de que o teléfono móbil sempre estivo en posición vertical, que é a posición principal que na realidade usan os consumidores, polo que os vídeos víronse sempre nesta posición, pero na realidade, segundo o contido e, concretamente para ver vídeos, os consumidores usan a posición horizontal ao igual que, por exemplo, para ver series.

- E por último, pero non por elo menos importante, os participantes non podían usar os seus teléfonos móbiles, polo que probablemente algunhas medidas poderían verse afectadas.

- Polo que respecta ao estímulo, usamos o contido das plataformas de dous famosos programas de televisión "*El Hormiguero*" e " *Got talent*" ademais dunha receita de tarta de queixo de *YouTube*, pero puxemos unha limitación no contido, polo cal podían navegar e isto pode afectar emocionalmente á experiencia, cando os participantes viron os anuncios de vídeo incrustados.

- Finalmente, houbo unha limitación respecto da persoalizacion de estímulos. Non foi posible empregar datos de consumidores anteriores desde dispositivos móbiles para persoalizar anuncios ou escoller outras plataformas en función deses datos. Esta falta de persoalización probablemente afecte algunhas métricas.

Futuras liñas de investigación

Sobre a base das limitacións anteriores, propóñense futuras liñas de investigación co fin de reducir o impacto das mesmas:

- Unha delas sería non realizar o experimento no laboratorio, senón na vida normal, na que os participantes usaran os seus móbiles e interactuaran coa televisión ou un PC nas súas plataformas favoritas. O uso de FEA e seguimento ocular, coa cámara dos usuarios no fogar podería ser levado a cabo por novos provedores de software como *Neurologyca* e *iMotions*.

- Outra posibilidade é a busca de definicións para cada unha das métricas, coa participación de diferentes provedores de software e académicos, co fin de propoñer e definir estándares para cada unha.

- Tamén podería ser interesante comparar anuncios de vídeos móbiles en posición horizontal e vertical para ver se a carga cognitiva é maior en horizontal e ten resultados similares a outros dispositivos como PC ou TV.

- Outra liña de investigación futura puidera ser empregar dous conxuntos de anuncios (persoalizar anuncios baseados en datos do consumidor e anuncios que non son persoalizados) e facer unha comparativa a atención prestada nos diferentes dispositivos -móbiles, PC e TV- co obxecto de ver que porcentaxe de atención se debe ao tamaño da pantalla e que porcentaxe se debe á personalización.

- Ademais sería interesante no futuro analizar se a idade afecta á atención prestada polos participantes no estudo, xa que os mozos non ven televisión e iso podería explicar a maior atención no PC que na televisión.

- Como liña de investigación futura tamén sería útil usar máis dun anuncio por dispositivo, en orde á análise do recordo ou memoria axudada ou non axudada en función do contido dos diferentes anuncios e estudar cal dos dous factores -o contido ou o tamaño da pantalla- explica un mellor recordo do anuncio. Nesta liña, tamén pode ser interesante probar grupos de diferentes anuncios como adoitan aparecer nas plataformas de internet e analizar o recordo en función da posición dos anuncios en diferentes dispositivos para comprender cal é o impacto das distintas posicións.

- En canto á intensidade emocional poden resultar interesantes dúas novas liñas de investigación. A primeira sería a inclusión de dous factores: persoalizar o contido e o formato de vídeo a pantalla completa e comprobar se a persoalización da contribución do contido é maior que o formato de vídeo, para que os profesionais poidan utilizar outros formatos para dispositivos móbiles. En segundo lugar, pode ser interesante analizar a intensidade emocional en dispositivos móbiles de diferentes formatos como *banner* (o máis utilizado) e nativo fronte a outros dispositivos como PC ou TV.

- E, para rematar, compre propoñer respecto da intrusión, dúas opcións en orde ao seu estudo. A primeira delas podería ser unha comparativa entre o estímulo persoalizado co estímulo non persoalizado, para ver se esta contribúe a minimizar as percepcións de intrusión dos consumidores respecto dos anuncios de vídeo en pantalla completa. A segunda liña de investigación sería a análise de en que medida afecta a idade respecto da intrusión, xa que como se sinalou con anterioridade, a xuventude hoxe en día non é proclive ao uso da televisión, o que podería explicar a maior atención prestada no PC que na TV.

Palabras clave: Móbil, *engagement*, neurociencia do consumidor, *neuromarketing*, publicidade dixital, eficacia, publicidade móbil.

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ABBREVIATIONS

ACC. Anterior cingulate cortex
AI. *Artificial Intelligence*, *Anterior insula*
AMYG. Amygdala
ANN. *Artificial Neural Network*
ANS. *Autonomic Nervous System, Autonomic Nervous System*
AOI. *Area of interest*
API. Application Programming Interfaces
AUs. *Action Units*
BOPIS. *Buy Online Pick-Up In Store*
CNS. *central nervous system*, central nervous system
CPM. *Cost per mille*
dlPFC. *dorsolateral prefrontal cortex*
DLPFC. *Dorsolateral prefrontal cortex*
EDA. *Electro dermal activation*
EEG. *Electroencephalography*
ET. *Eye Tracking*
FACS. *Facial Action Coding System*
FB. *Number of fixations before getting to the AOI.*
FD. *Fixation duration*
FDG. *fluorodeoxyglucose*
FEA. *Facial expressions analysis*
fMRI. *Functional magnetic resonance imaging*
fNIRS. *functional near-infrared spectroscopy*
GSR. Galvanic skin conductance
HPC. *Hippocampus*
HR. *Heart Rate*
HRV. Heart rate variability, Heart rate variability

HYP. Hypothalamus
IAB. *Interactive Advertising Bureau*
IAPS. *International affective picture system*
ICA. *independent component analysis*
INS. Insula
LDA. *Linear Discriminant Analysis*
MEG. *Magnetoencephalography*
MMA. Mobile Marketing Association
MPFC. medial prefrontal cortex
MSI. *Marketing Science Institute*
MVPA. Multivariate pattern analysis
NAcc. accumbens
OFC. orbitofrontal cortex
OTT. *Over the Top*, *Over the top*
PNS. *peripheral nervous system*, peripheral nervous system
PPC. *Posterior parietal cortex*
PPG. Photoplethysmography
PRC. *Precuneus*
ROI. *Return of investment*, *Region of interest*
SCR. *Skin conductance*
SERP. *Search engine result page*
SMS. *Short Message Service*
STT. *Steady State Topography*
SVM. *Support Vector Machine*
TFD. *Total fixation duration*
TFF. *Time to first fixation*
TMS. *Transcranial Magnetic Stimulation*
vmPFC. *ventral medial prefrontal cortex*
VTA. *ventral tegmental area*
WOM. Word of mouth

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INTRODUCTION

During the last 20 years, advertising has been moving from traditional to digital media. The latter was based in the interactive nature of online advertising, which was a factor of attraction and indeed, constantly evolving based on market requirements and technological progress.

This swift has been confirmed by the growth of the digital advertising expenditure during the past 20 years, and even during the recent Covid situation, it grew 12,7% in 2020, exceeding $378 billion worldwide (eMarketer, 2021). This represented a 58,2% of the total ad spending and the forecast for 2024 is estimated to be 68,7%. This data confirms that the size and range of online advertisement is increasing dramatically (Deshwal, 2016), and online advertising is clearly becoming the main source of advertising. While online advertising is evolving, so it does academic research (Liu-Thompkins, 2018).

There are several reasons behind this swift towards online advertising, not just low cost of targeting (Goldfarb, 2014), but also wider geographical reach, no rigorous payment, easy result measurement, more targeted audiences, speed, informative, better return of investment, easy audience engagement or better branding (Deshwal, 2016).

This online advertising trend has brought to light one important research topic, the online advertising effectiveness. Previous research, (e.g., Liu-Thompkins, 2018), points out the superiority of online advertising over the traditional printed media and also that the online advertising produces positive returns. However, the magnitude varies significantly with the product category, customer segment, and ad format. It shows more complexities as well, possibly due to the more diverse online and offline advertising formats.

Regarding devices, online advertising started in 1996 with the first banner in PC, and during the next 15 years it was main device used by practitioners for online advertising. However, during the last 10 years, as consumers spend more time on their mobile devices, the expenditure on online advertising in mobile has increase substantially; but nowadays it is the turn for the TV new platforms and its new advertising strategies, to reach consumers.

Last year 66% of the population worldwide were mobile phone users, which are increasingly attached to their smartphones as confirmed by 2020 data; 52,8% of the daily time spent using the internet (6h:54min) was on mobile, in particular using apps.

During the first half of 2020, in the USA users spend more than the 88% of the online time with apps, which is consistent with the download rate of apps from the iOS App Store and Android's Google Play which together topped 64 billion downloads, a 10% increase from 2019 figures (Koetsier, 2020).

Out of the time spent in mobiles, 63% of the traffic is video (Appannie, 2020; Ericsson, 2020; Kemp, 2021) and the main driver for this traffic is the rapid diffusion of video content such as video embedded in web browsing, social media, as well as increased video streaming and sharing services. For the latter, a 30% increase has been forecasted for each coming year.

As video mobile consumption is increasing, so it does mobile advertising. One of the reasons for theses increase is that advertisers are looking for new media, such as mobile devices, to attract customer attention by avoiding actual clutter in media with lots of competitors and platforms. Mobile ad spending was 68% of the total digital ad spending reaching $247 billion which is an increase of 31% during 2020.

As the mobile advertising expenditure has increased during the last 10 years so it has the mobile advertising research. As a consequence, several issues have arisen. It's clear that mobile advertising need to be different to increase effectiveness. A simple transfer of traditional broadcast advertising content into mobile has been found ineffective. This strategy doesn't account for the contextual environment that mobile creates; nor for the differences in the attention and engagement of the mobile audience, and finally does not account either, for repetition, an essential feature of traditional advertising, that doesn't make sense on mobiles, as users get irritated and frustrated.

Another important research topic is effectiveness of mobile advertising against PC or TV to determine which one is higher. In this line, Fulgoni and Lipsman (2017) point out that mobile advertisements performed better than PC at reaching their target audience and were significantly less affected by invalid traffic. However, practitioners suggest that advertising in mobile is less effective than in TV.

It is also an important research topic the interactive aspect of mobile communication. Traditional advertising is a one-way communication, but within the mobile environment users can interact with the brands, and indeed they do so, in a two-way communication channel.

Traditional advertising as a mass media communication channel, does not deliver personalize advertising which is what mobile requires. In this line, in 2017 a Bain and Company (2017) survey found, that people interact with their devices an average of 200 times per day for communication, information, entertainment, socializing and shopping Therefore, there is the idea that, if companies want to reach consumers, mobile is the easiest way compared to TV, print media or PC (Beaudin et al., 2016).

Personalization based on data has become another important mobile research subject. Practitioners and researchers point out that consumers, demand more personalized communication with them (MMA, 2020; Rivero and Mendez, 2020). As consumers may perceive these personalize services more attractive (Shareef et al., 2017) many brands exploit user data through advanced internet and computing technologies, in order to implement online personalized advertising on their platforms (Kim and Kim, 2017). In this line, location-based marketing is the most popular practice to find location data when marketers seek to reach mobile consumers. A new strategy to find mobile based consumer data which is also becoming popular, is synced advertising, technique that shows simultaneously a message relevant to TV content on a second device, aiming to persuade the consumer (Segijn, 2016).

Mobile advertising research is also arising important problems that need to be faced in the coming years. One of them is the consumers concern about the use of personal data. Online personalized advertising may cause consumers' unfavorable beliefs, as they may perceive that the personal data collected may limit their capacities and ability to choose and buy (Aguirre et al., 2015).

Another important problem found is strategies that consumer applies to avoid advertising in their mobiles, like banner blindness, ad-blocking or fraud. Banner blindness usually refers to the finding of internet users avoid looking at or paying attention to ad banners inserted on web pages Hervet et al. (2011) and Lapa (2007) also points out that banner blindness increases, and to do it reduce ad effectiveness.

The number of people using ad-blocking technology on mobile browsers has have an a 64% increase over the last three years (Shankland, 2020), mainly because of saturation, irrelevant or annoying ads and intrusive perception (Kemp, 2021).

Last, but not least, is fraud. *Juniper Research* (2017) estimated that advertising fraud cost online advertisers US$19 billion worldwide in 2018, equivalent to $51 million per day and it is expected a 132% increase, reaching $44 billion by 2022. This is becoming an important problem for online advertising.

The last group of issues related to mobile advertising is about measurement. According to the MMA (2020) study, the biggest barrier to growth in mobile advertising is the derivative of the measure of its effectiveness and the metrics to be used. Online advertising, in particular mobile advertising, generates a lot of data that may be used to measure advertising effectiveness. Actually, there is no consensus on which metrics should be used and how to measure them. Practitioners and academics use different technologies, propose different metrics and scales, and differ in the interpretation of the results. Organizations like IAB and MMA are working with academics to clarify and establish clear solutions to face this important problem.

Research objective

The digital transformation that the advertising industry is carrying out, has arisen some important problems that have to be resolve. One of them, is the digital advertising measurement to compare its effectiveness against traditional advertising. Practitioners and academics work in this field and the general objective of this Doctoral Thesis is to show the importance of mobile advertising today, as well as the methodologies for measuring mobile advertising effectiveness.

This general objective of the Doctoral Thesis may be break down in several objectives that may contribute to achieve the general one.

First objective is to develop a general view of mobile advertising ecosystem, explaining why is so important, which are the trends in consumer time spend with this devices and mobile advertising expenditure worldwide. In this line, this Doctoral Thesis analyze and discuss some important topics in mobile advertising: most used mobile platforms, main formats, strategies apply in mobile advertising and specially incentivized advertising and problems that mobile advertising is facing with.

Second objective is to analyze engagement as a measure of advertising effectiveness in mobile. A lot of research has been developed about engagement and this thesis analyze literature and actual situation proposing a model of engagement to measure advertising effectiveness in mobile.

Third objective is to propose consumer neuroscience as a complement traditional research to measure advertising effectiveness in mobile. Consumer neuroscience has been study by academics and practitioners for a long time and actually used in many research. This Doctoral Thesis objective is to compare traditional research survey with consumer neuroscience technologies and see if they complement each other.

Fourth objective of this Doctoral Thesis is to compare if measurement metrics from different Software Vendors have similar results or not and why. In line with this objective, this research introduces and analyze results from a new algorithm, Kopernica from Neurologyca.

Finally, this Doctoral Thesis objective is to validate engagement in mobile compare with other commonly used devices like PC and TV using consumer neuroscience.

Thesis structure

This Doctoral Thesis is organized in five chapters, and begins with an introduction that offers the reader a clear and concise description of increasing importance of digital advertising worldwide.

Chapter 1 provides an actual analysis and situation of mobile advertising industry. First analyze different definitions for mobile advertising. Explains in detail the growth in time spent by consumers in mobile, as one of the main reasons for the growth trend that mobile advertising expenditure had during last years. Next parts of the chapter concentrate in different aspects of mobile advertising. Mobile advertising platforms, formats and strategies are analyzed, specially incentivize mobile advertising that is concentrating industry interest. Finally, chapter ends with the analysis of the main mobile advertising problems that mobile the industry must face with and analyzing consumer attitudes in mobile advertising.

Chapter 2 analyzes the literature about measuring advertising effectiveness through engagement and specifically mobile advertising effectiveness. Chapter starts analyzing several measurement methodologies and dedicates a specific part of the chapter to analyze in detail consumer neuroscience as a methodology to measure mobile advertising effectiveness and complement traditional methodologies. Once consumer neuroscience is defined, a detail research was done about main technologies used in consumer neuroscience and chapter finish analyzing previous research done in consumer neuroscience.

Chapter 3, define the main hypothesis of this Doctoral Thesis. Two sets of hypotheses are propose dividing the chapter in two parts: Hypothesis about video ads effectiveness measured through traditional and neuroscience techniques and Hypothesis about video ads effectiveness in mobile, PC and TV. First set of hypotheses covers in detail consumer engagement concept as a great variable to measure advertising effectiveness in mobile. Second set of hypotheses analyze in detail consumer neuroscience metrics that will be used in the experiment.

Chapter 4 defines research methodology used in the consumer neuroscience experiment data analysis and results of the experiment. The chapters start defining the sample and covers a detail analysis of samples size used in different studies. Methodology is explained in detail presenting technologies and algorithms used, devices, stimulus and platforms, laboratory used end all the procedures used to make the experiment. Results are presented and explain in detail based in the statistical methodologies used and finally hypothesis are validated or not based on the results.

Chapter 5 is dedicated to the contributions, implications, limitations, and future research. Chapter starts explaining conclusions and as a consequence contribution of the two sets of hypotheses. Based on those contributions the next part of the chapter explains which are de implications for the marketing managers and advertising industry. This chapter finish with the explanation of some limitations that may affect the results of the experiment and propose some interesting future research lines.

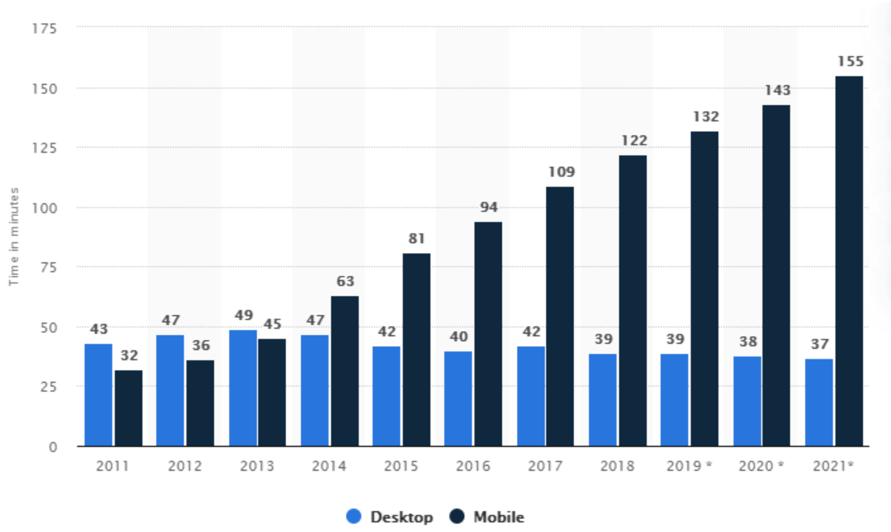
Last part of this Doctoral Thesis presents an important set of references that were used in the above chapters and two appendixes with information about scales of consumer engagement and the questionnaire used in the experiment.

CHAPTER 1. MOBILE ADVERTISING

Last year 66% of the population worldwide (5,2 billion people) were mobile phone users and increasingly attached to their smartphones. According to the latest reports, in 2020, 52,8% of the daily time that users spent on the internet (6h:54min) was on mobile. Covid-19 increased the mobile usage, and mobile users now spend more time on their phones than they do watching TV, clearly positioning the smartphone as today's "first screen" (Kemp, 2021).

Data confirm these trend since 2011, as we can see in graphic 1. *Statista* forecasts 155 min. per day and user in 2021 based on its data of internet time spent in mobile worldwide and a decrease trend in relation to PC (Statista, 2019).

Graphic 1: Daily time spent in internet per capita worldwide by device.



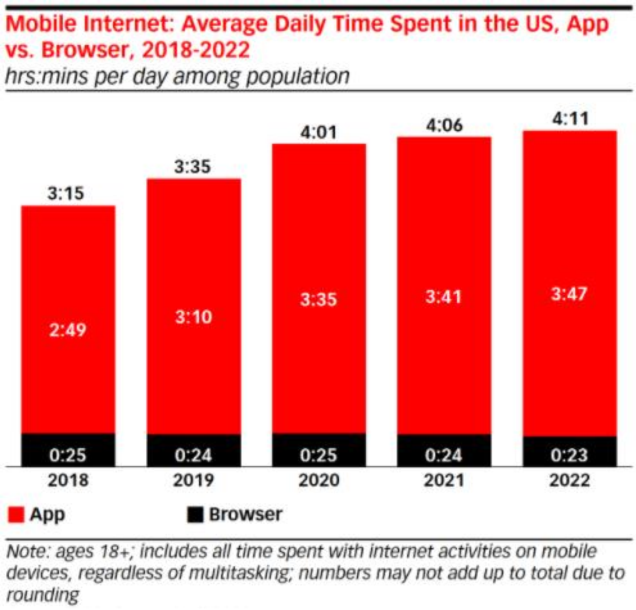
Source: Statista (2019)[1]

Researchers and practitioners agree that Covid-19 is accelerating this trend, and the first data gathered of time spent on mobile in the US does confirm it, showing an 11,4% increase from April 2019 to April 2020 (Chaffey, 2020; eMarketer, 2020a; Wurmser, 2020). Also, a report from *Ditrendia* shows that the mobile time spent on the internet is 3h:22 min per day (Rivero and Mendez, 2020). *We Are Social* points out that average daily time spent on internet using mobile devices is 3h:39 min (Kemp, 2021), and *App Annie* reports 4h:10 min which

[1] https://www.statista.com/statistics/319732/daily-time-spent-online-device/

represents an increase of 20% when compared with last year (Appannie, 2020). People spend more time on their mobile and specifically using apps (graphic 2).

Graphic 2: US smartphones daily time spent per capita.



Source: eMarketer (2020)[2]

A recent report from *App Annie* points out that 92% of the time spent on mobile is using apps and only 8% in using browsers (Appannie, 2020). *We Are Social* indicates that 44% of that app time spent is on social communication apps, 26% on video and entertainment apps, 9% on games and 21% using other kind of apps (Kemp, 2021). However, the vast majority of downloads and time spent on apps come from only the top few apps (Mindsea, 2020; Sensortower, 2018).

According to Appannie (2020), most downloaded apps, and most used, are from Facebook.

Table 1: Most downloaded and used mobile apps in 2020.

Most downloaded

Top Apps

1	Facebook Messenger	Facebook
2	Facebook	Facebook
3	WhatsApp Messenger	Facebook
4	TikTok	ByteDance
5	Instagram	Facebook
6	SHAREit	SHAREit
7	Likee	YY Inc
8	Snapchat	Snap
9	Netflix	Netflix
10	Spotify	Spotify

Most used

Top Apps

1	WhatsApp Messenger	Facebook
2	Facebook	Facebook
3	Facebook Messenger	Facebook
4	WeChat	Tencent
5	Instagram	Facebook
6	TikTok	ByteDance
7	Alipay	Ant Financial Services Group
8	QQ	Tencent
9	Taobao	Alibaba Group
10	Baidu	Baidu

[2] https://www.emarketer.com/content/the-majority-of-americans-mobile-time-spent-takes-place-in-apps

Source: App Annie (2020)[3]

Also, mobile eCommerce is increasing and *eMarketer* estimates that 72,9% of the total eCommerce will be done through mobiles in 2021 (Statista, 2020). In this line, Vibes reports that BOPIS (*Buy Online Pick-Up in Store*) usage increased by four times from 2019 to 2020. However, researchers suggests that the new ecommerce habits that people have adopted during lockdown will last well beyond the pandemic (Kemp, 2021). Out of the time spent in mobile, 63% of the traffic is video (Appannie, 2020; Ericsson, 2020; Kemp, 2021) and the main driver for this is the rapid diffusion of video content, such as embedded video in web browsing, social media, video streaming and sharing services. The increase forecasted for the next comings year is 30%. According to *Cisco's Visual Networking Index*, 79% of the world's mobile data traffic will be video by 2022 (Cisco, 2018).

The growth in mobile video is part of a bigger trend toward digital video and OTT (*Over the Top*[4]) platforms (MMA, 2020). The pandemic has also increased the mobile time spent on video and gaming. *eMarketer* (2020b) points out that the average US adult will watch more than 2 hours a day of digital video in 2020, 19 minutes more than 2019. In line with this, a recent study done by *Qustodio* on the most relevant categories of mobile apps (online video, social media, video games and education), points out that kids spent an average of 85 min per day watching YouTube videos compared with 80 minutes in TikTok, this means twice as many videos per day as they did four years ago (Perez, 2020).

1.1 **¿What is Mobile advertising?**

According to Reyck and Degraeve (2003), mobile advertising is defined as targeting well-identified potential customers with text messages, thereby increasing the response-to-advertisement. In addition, Leppäniemi and Karjaluoto (2005) defined mobile advertising as the business of encouraging people to buy products and services using the mobile channel as a medium to deliver the advertising message.

Although there is a general definition of the concept due to the *Mobile Marketing Association* as "a form of advertising that transmits advertisement messages to users via mobile phones or other wireless communication devices" (Chen and Hsieh, 2012, p. 3), there's a lot of controversy based on the indistinct use of two different terms: Mobile marketing and Mobile advertising (Tähtinen, 2005).

Practitioners point out that while mobile advertising is synonymous to mobile marketing, they are different in terms of applications. Mobile marketing is an umbrella term that includes mobile advertising. Mobile marketing makes use of multiple services and data information like location-based services, buyer persona and their habits, user preferences, and so on. Therefore, certain mobile ads will appear only when a user enters a certain geo marked boundary (Mobileads, 2020).

[3] https://www.appannie.com/en/go/state-of-mobile-2020/

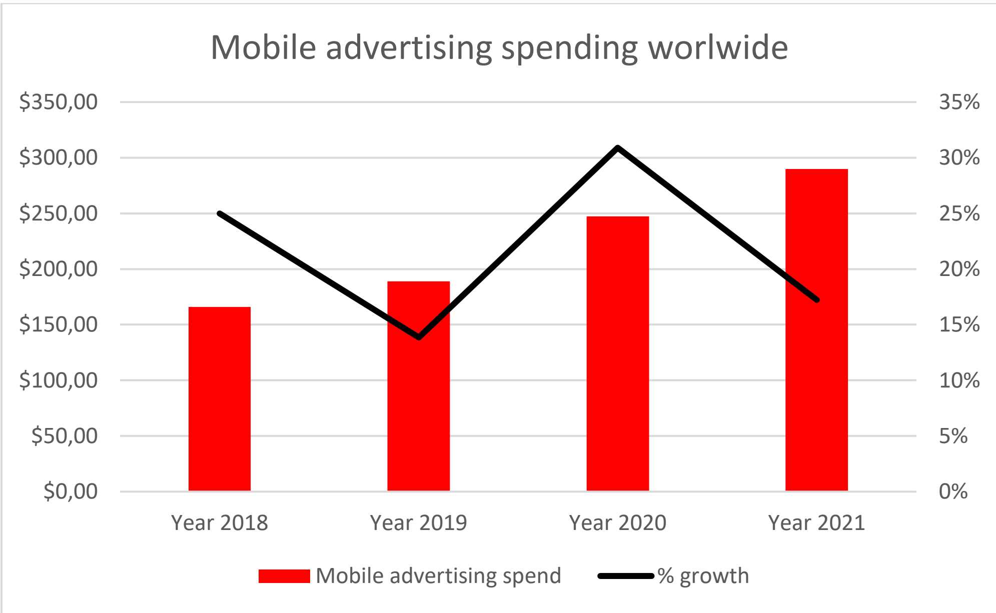
[4] Over the Top: Refers to any streaming service that delivers content over the internet.

Based on these issues, “Mobile marketing communication or m-adcom”, as proposed by Tähtinen (2005), will resume better MMA definition, integrating all the elements of the mobile environment.

1.2 **Mobile marketing communication spend**

According to *Statista Digital*, advertising market worldwide was $355,6 billion in 2020 which represents a 6,5% increase in relation to 2019. Out of total digital ad spending, mobile ad spending accounted for a 68%, reaching $247 billion, a 31% increase in relation to the previous year. However, other researchers, like *eMarketer* or IAB (Interactive Advertising Bureau), suggest that this growth will be negatively affected by the already the advertising spend reduction that Covid- 19 has cause worldwide during the first half 2020.

Graphic 3: Mobile advertising spending worldwide



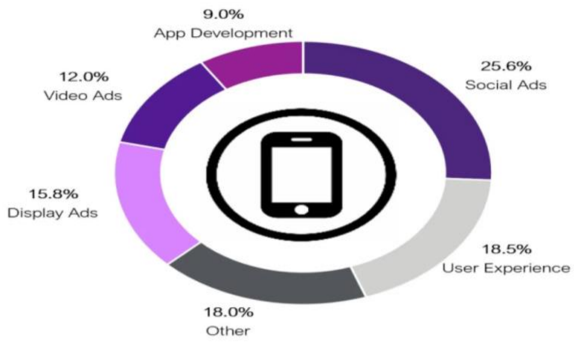
Source: Statista (2020) and Appannie (2020)[6]

The forecast for 2019, predicted to reach $240 billion by 2022, but covid-19 has clearly brought forward this prediction and the new forecast is already $290 billion for 2021, a 17% increase. According to *AppAnnie* mobile, ad placements increased 70% in the first half of 2020 (Appannie, 2020). In line with this trend, practitioners point out that consumers will continue shopping, eating, and enjoying entertainment from home, as we have seen during this pandemic year, and to keep up with the increase of at-home mobile browsing, brands will invest more in mobile ad spending (Deloitte, 2021; Mgage, 2021).

[6] https://www.appannie.com/en/go/state-of-mobile-2020/

A *Deloitte* survey done in 2020 point out that there is a balanced mix of mobile type of ads and stands out the 25,6% expenditure of social ads. (Deloitte, 2021). These data agree with the general trend where social media is still the most dominant platform in digital advertising.

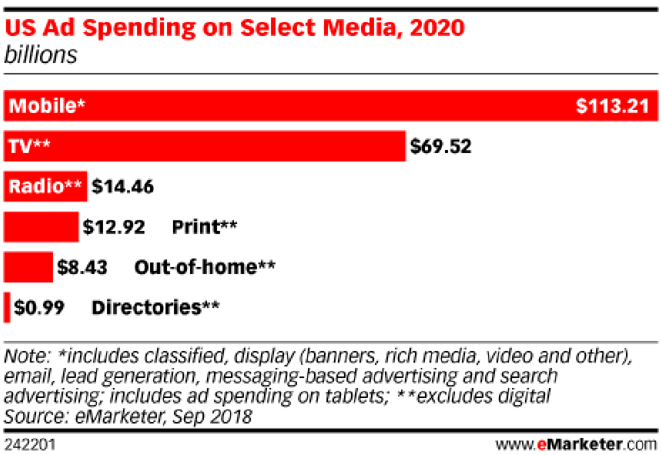
Graphic 4: Mobile types of ads spend in 2020



Source: Deloitte (2021)[7]

As North America is the world´s largest market region for mobile advertising, is interesting to analyze its data and to see trends that can be applied to the rest of the world. According to a study by *eMarketer*, mobile claimed about 70% of the total US digital ads space in 2018 (Gogel, 2018) and the prediction for 2020 was that mobile ad spend, would almost double TV ad spend in the US.

Graphic 5: US ad spending by media

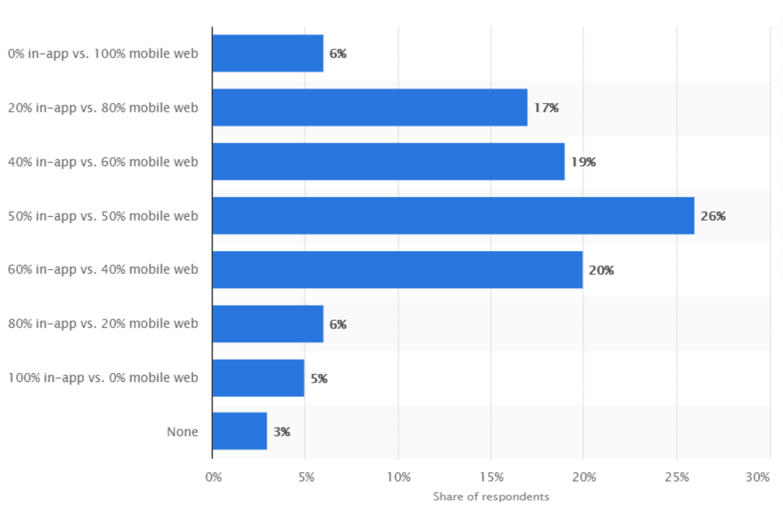


Source: eMarketer (2020)[8]

[7] https://www.ama.org/marketing-news/now-more-than-ever-is-the-time-for-mobile-marketing/
[8] https://www.emarketer.com/chart/223275/us-ad-spending-on-select-media-2020-billions

Grewal et al. (2016) point out that people surf the web on their mobile devices and use various mobile applications (apps), many of which facilitate the delivery of advertising content. In this line, a *Statista* survey in US and UK points out that, although consumers spend more time in mobile apps[9] than in mobile webs [10], advertising expenditure is well balance in the US (Statista, 2019).

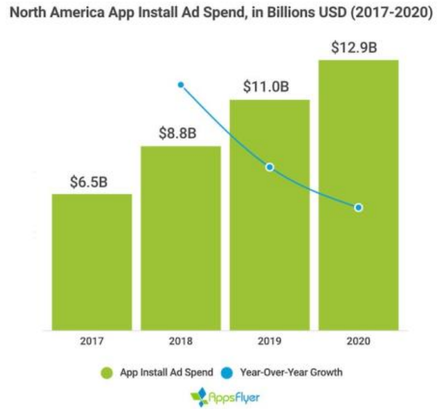
Graphic 6: Share of budgets devoted to in-app vs. mobile web advertising in US in 2019.



Source: Statista (2019)[13]

Nevertheless, *Appsflyer* points out that the spending on ads within apps installed in the US will grow 17% in 2020.

Graphic 7: US app install ad spend

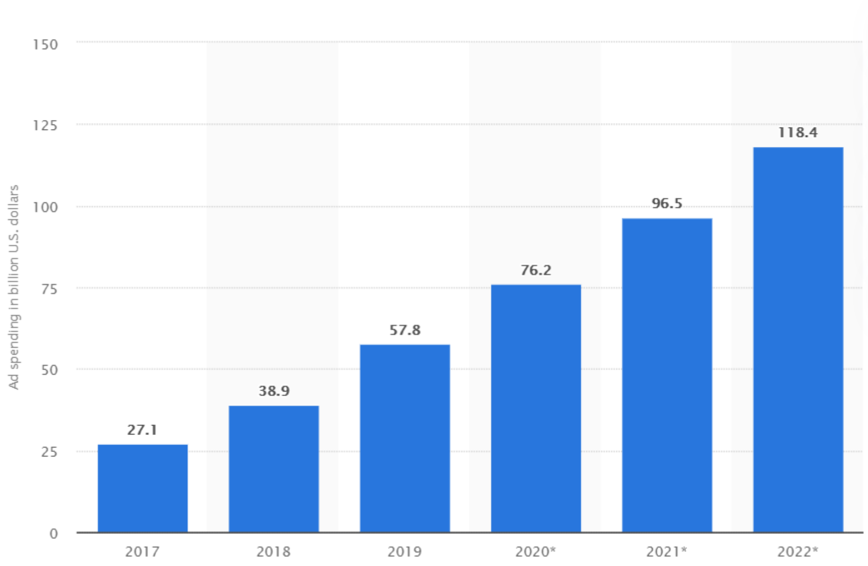


Source: AppsFlyer (2021)[14]

[9] Apps: Software applications developed for mobile and tablets.
[10] Mobile Webs: Pages that are arranged to fit the mobile screen sizes (both smartphones and tablets).
[13] https://www.statista.com/statistics/1108552/share-of-in-app-vs-mobile-web-advertising-budgets
[14] https://www.adweek.com/performance-marketing/appsflyer-sees-global-app-install-spend-reaching-64-billion-in-2020/

In line with this, *Statista* worldwide confirms this trend, and forecasts a 30% worldwide growth for 2020.

Graphic 8: Mobile app install advertising expenditures worldwide from 2017 to 2022



Source: Statista (2019)[15]

These figures suggest that mobile advertising expenditure is on mobile apps and is the communication strategy that practitioners used to promote their products. Apps are easy to download and use and are highly preferred by today´s mobile users. In-App advertisements are those that are visible within these apps, they are specifically designed to target user behavior and preferences, and to give them the best browsing experience (Appannie, 2020; eMarketer, 2020a).

1.3 **Mobile advertising platforms**

Mobile Ad Platform [16] acts as a broker between publishers and advertisers who want to place ads on mobile apps. Wang et al. (2016) point out that scholars began to recognize the emerging power of mobile platforms as a new and interactive way to communicate with and attract consumers. Mobile platforms provide them with an interactive brand experience, which enhances the firm's persuasive effectiveness and increases consumers' positive attitudes and purchase intentions.

Since last decade, when the first platforms were developed, hundreds of mobile advertising platforms deliver mobile ads, and some companies, like *Appsflyer*, publish performance indexes to provide a ranking of mobile advertising platforms (AppsFlyer, 2021).

[15] https://www.statista.com/statistics/986536/mobile-app-install-advertising-spending-global/

[16] Also known as mobile ad network. For example: Facebook audience network

Those indexes reflect the fact that the most used apps are from *Google* and *Facebook*, which is also reflected by the demand for advertising platforms (Topcu and Eren, 2018).

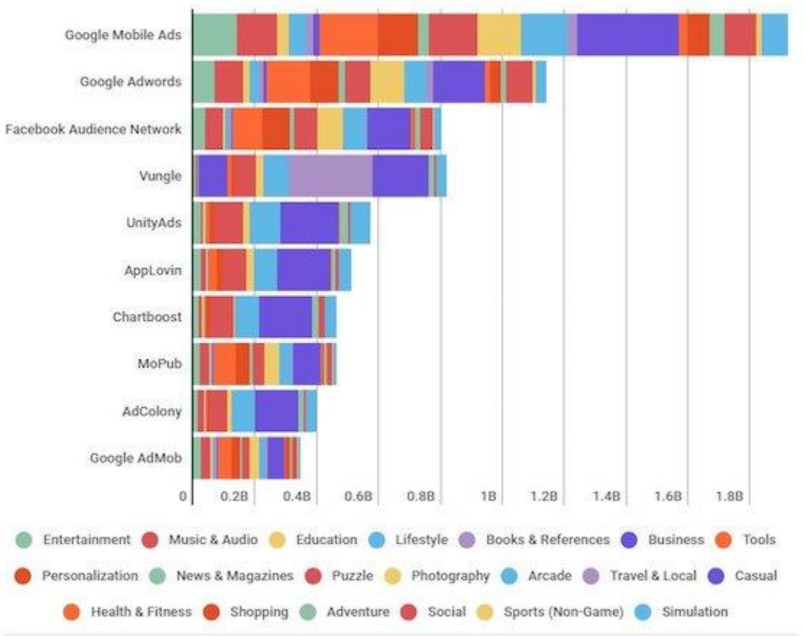
Based on actual data from *Appsflyer*, the main mobile advertising platforms used by practitioners are:

- Google ads
- Facebook ads
- Instagram ads
- In-app ads of a specific mobile app

These confirms *Statista* and *ComScore* data that show that users spent 96% of their time in their top 10 apps, and just on their top 3 apps, they spent a 77%.

Some practitioners, like *Instapage* or *Businessforapps*, provide a list of these main platforms sorted by an index and industry sectors (Instapage, 2018).

Graphic 9: *Instapage* mobile ad platforms and industry sectors



Source: Instapage (2018)[18]

These platforms work in two ways: Allowing publishers to sell ads (and earn advertising revenue) and advertisers deliver ads to potential customers and communicate their brand.

[18] https://instapage.com/blog/mobile-ad-platforms

Planning campaigns with these mobile platforms is based, as programmatic advertising, on segments and their profile (Buyer persona[19]).

All these apps have in common a large inventory of possible ad placements, advanced analytics and targeting, access to a global market and mobile support on all the main operating systems. Therefore, the differences between them are based on the type of ads each one supports.

Mobile apps have become the major inventory for ads to be displayed in, (it's called in-app advertising) replacing traditional mobile web due to the fact consumers spend most of the time with mobile devices, using apps, not browsing web sites, as we mention above.

Fulgoni and Lipsman (2017) point out that Facebook, YouTube, Instagram, and the fast-emerging Snapchat are among the largest and highest-engagement brand advertising platforms in digital media today, and their ability to deliver massive daily audience reach depends significantly on mobile usage. In March 2016, 75% of Facebook time and 69% of You-Tube video-viewing time occurred on mobile. Regarding social media platform, with the absence of a "side bar" and limited screen space on mobile devices compared to their webpage counterparts, the most prominent methods of mobile advertising in social media is "sponsored" content or posts.

The mobile advertising ecosystem is changing very quickly, even if one mobile ad platform gets popularity on the market, it could close up next year, or one brand-new mobile ad platform would gain success immediately just a couple of months after its establishment (Topcu and Eren, 2018).

Wang et al. (2016) suggest that one of the issues of mobile platforms is that requires consumers to opt-in (i.e., consumer consent is needed for an ad or app to show up on their devices), and it is also unconstrained by neither time nor location.

1.4 **Mobile advertising formats**

Based on mobile platforms defined above, mobile advertising is usually classified into three channel types: SMS (Short Message Service) ads, web ads, and in-app ads. Since the first mobile SMS ads were published, mobile ad formats have become richer and more varied, giving practitioners more formats to work with, and more opportunities to make an impact. Topcu and Eren (2018) posit that, as mobile advertising platforms use ad-units in order to simplify and deliver ads from different networks, there are four types of ad-units to display four different formats of advertisements such as banner, interstitial, rewarded video and native.

In this line, *Statista* (2019) maintains the three channel types, dividing between SMS, web ads and in-app ads and subdividing web ads in search and display. It separates video mobile ad spending based on the increasing trend on video consumption that we have previously analyze.

[19] Buyer persona: A buyer persona is a fictional representation of your ideal client or target audience.

Table 2: Statista mobile ad classification.

Timeframe
Display
– Banners and other
– Rich media
— Video
Search
SMS/MMS/P2P messaging
Other (classifieds/email/lead gen)

Source: Statista (2019)[20]

SMS was the earliest form of mobile advertising and has followed the mobile trends, as it is a built-in feature in most smartphones, which is why it's easier to use than the other two advertising channels. Practitioners, like *Salesforce* and *Smsglobal*, indicate that SMS has an open rate of 98%, and a response rate close to 45%, much better than the 20% open rates of email (McMahon, 2021).

In-app ads continue to growth because, as we saw previously, time spend on mobile apps has been gradually increasing year by year, and consumers spend around 90% of their time on smartphones accessing apps, and only 10% on mobile websites. But time spent on mobile apps is not only the reason for the mentioned growth, but also the advanced targeting options we have in apps due to user's location data that advertisers can access.

Although users spent only 10% of their time mobile web apps, they have some benefits when compare with in-apps. They do cost less, which is an important point for companies, but also have less maintenance and compatibility problems than in-apps ads and may reach larger audience.

With the exception of SMS, that remains as the simplest messaging text in most cases, web and in-app ads are using mobile ads formats as suggested by Topcu and Eren (2018) and new ones are coming out like playable ads.

Image 1: Mobile ads formats.

Source: Author

[20] https://www.statista.com/statistics/742690/most-anticipated-mobile-ad-types/

Banner ads are “horizontal rectangular-shaped ads located at the top of a webpage” (Li et al., 2016, p. 2). Actually, those ads could appear along the top or the bottom of the screen. They can popup, refresh ads at different intervals, or be static, and can be hyperlinked and interacted with the user.

Interstitials ads are “usually full-screen ads appearing unexpectedly during gameplay, and users have to wait until the entire ad has run as there is generally no “exit” option to stop or delete an interstitial” (Wang et al., 2019, p. 1). They appear in a large format taking up most of the mobile screen during a period, so that they do not seem intrusive and usually are interactive. Practitioners point out that interstitial ads are the most used mobile ads and also have the higher CPM (Cost per mille[21]) pricing (Setupad, 2021). Regarding formats, *AppAnnie* report that interstitial ads grew by 205% during the first half of 2020, representing 54% of all ad formats placed on that network in June 2020, reaching 30% market share in January 2020 (Appannie, 2020).

Native advertising is “a type of advertising that matches the form and function of the platform on which it appears” (Aribarg and Schwartz, 2018, p. 3). They are designed to seem a part of the content and non-disruptive. Main format here are In-feed ads[22], and usually, are place between the content of a feed, or where a feed begins or ends. As visitors scroll down content, they encounter In-feed ads, and as they fit seamlessly inside a feed, they're not intrusive and they don't break the user's flow. In-feed ads only use creativity of have high quality ad elements that are more visually appealing, but they may have a lower CPM in the short term.

Video ads are advertisements shown in video format. Practitioners point out that video ads is the main trend in mobile ads, especially in social media like *Facebook*, *Instagram* and *YouTube*. In this line, *eMarketer* (2020b) posits that video advertising will also become less skippable and more interactive. MMA (2019) proposes mobile advertising with a short-form of mobile video storytelling, as brands have less time than they thought they have to attract consumers based on a recent study, concluding that the cognitive process is faster than we thought, and that the human brain needs less than half-a-second to engage with mobile advertising and trigger a reaction, positive or negative. According to *IAB*, 61% consumers prefer pre-roll[23] video but with skip button (IAB, 2018a). Regarding watching mobile ads most mobile users prefer vertical than portrait orientation, especially in full-screen and live video (eMarketer, 2020b). In fact *Scientiamobile* (2019) points out that 82,5% of mobile users select portrait orientation to watch videos, basically due to Instagram Reels format, *Tiktok* and *YouTube* shorts format.

1.5 **Mobile advertising strategies**

In 2017 a *Bain and Company* (2017) survey found that people interact with their devices an average of 200 times per day for communication, information, entertainment, socializing or to

[21] Cost per mille or cost per thousand: It is the cost an advertiser pays for one thousand views or impressions of an advertisement.

[22] In-feed ads: Format place inside a feed to help monetize a site and provide a better user experience to users.

[23] Pre-roll: Video starts before information is served to consumers. Mid-roll: Video starts while consumers see information. Post-roll: Video starts after consumer sees information.

make a purchase. Therefore there is an extended idea that if companies want to reach consumers, mobile is the easiest way compare to TV, print media or PC (Beaudin et al., 2016).

Researchers point out, that most mobile advertisers are not taking advantage yet of the interactive aspect mobile platforms provide and they try to apply traditional advertising strategies that doesn't work in mobile. As mobile market is saturated, brands and developers advertising strategies are becoming more sophisticated, and many mobile advertisements are currently delivered during the content-consumption experience based on location.

1.5.1 Location based marketing

Location based marketing is defined as "mobile advertising that utilizes and is tailored to the geographic location of the consumer" (Limpf and Voorveld, 2015, p. 5). Location based marketing is the most popular use for location data, as marketers usually seek to reach mobile consumers when they are in the high street. Researchers and practitioners call this "micro moments" used by marketers to capture the consumers attention through their mobiles (Beaudin, 2017).

According to *Bia advisory* (2019), location-based marketing in US was $22,1 billion in 2018 and forecasted a 61% increase for 2021. Their survey highlights that the largest area of mobile growth is location-targeted ads, finding that 35.5% of businesses are using mobile location-aware, and almost 24% of them are using mobile search. In this line, *Lawless Research* (2018) found that 87% of marketers were using location data and targeting, in their marketing campaigns, expecting to increase to 94% in 2020, out of which, a 67% will be based on targeting. Most practitioners indicate that using location-based marketing results in higher sales (*Lawless research*, 2019).

1.5.2 Personalization

Practitioners and researchers are finding that consumers demand more personalize communication (MMA, 2020; Rivero and Mendez, 2020). As consumers may perceive these personalize services more attractive (Shareef et al., 2017), many brands use advanced internet and computing technologies to exploit user data in order to implement this online personalized advertising on their platforms (Kim and Kim, 2017). In this line, Xu (2006) posits that the personalization of content is the most effective way to prevent mobile advertising from being perceived as intrusive and irritating.

However, online personalized advertising may cause consumers' unfavorable beliefs as they may perceive privacy concerns in relation to their personal data collected tacitly that may limit their ability to make their own purchasing decisions (Aguirre et al, 2015). Although consumers demand personalize advertising, Baek and Morimoto (2012) posit that this advertising could intrude consumer´s privacy, making them to perceive information as a threat. They found a strong correlation between perceived ad irritation and ad avoidance, the higher they perceived ad irritation, the greater the consumer avoidance of personalized advertising. However, they posit that increased perceived personalization leads directly to decreased ad avoidance.

To personalize ads, Vesanen (2007) posit that the use of mobile technologies to gather consumer information, such as demographics, locations, and lifestyles, provide a huge stock of consumer data. This data can be used to personalize advertising and obtain a better ROI (Return of investment). As Chrome (39% market share in mobile) will stop supporting third-party cookies, first party data will become the main data source that brands will use to personalize their communication.

Mobile generates a vast amount of data, like consumer information (name, phone, email, country, carrier, and device type), shopping preferences, or the time of the day of more consumer engagement. Marketers need to capitalize the data they collect to be successful. Collecting consumer data enables retailers to build consumer profiles and provide more automated and personalized services to satisfy their demands. Nowadays to analyze those mobile data, AI (Artificial intelligence) it's been used to identify key characteristics of consumers to provide them a much more personalized experience (Llanas, 2019).

1.5.3 Voice and audio

According to MMA (2020), while a user can type 40 words per minute in a mobile, they can speak 150 words during the same time. Therefore, as speaking makes it easier to interact with a mobile phone, brands have begun to leverage audio technology to reach out their audience. Voice assistants are "a type of voice-enabled artificial intelligence" (Poushneh, 2021, p. 1) that save consumer´s time spent on apps and websites, provide them with more enjoyable simplified experiences, and increase efficiency.

Voice assistants, and specially chatbots[25], had an important growth in last two years, especially in Asia. Consumers not only use them to search for information or interact with other devices, but also for e-commerce. In this line, voice mobile e-commerce has been used by 35% of users worldwide during last year (Rivero and Mendez, 2020).

eMarketer (2020b) points out that consumers are also looking for ways to reduce screen time, which may increase opportunities in audio advertising. In relation to this, MMA (2020), indicates that 38% of consumers who engaged with voice ads, find it less interfering as compared to other forms of advertising.

1.5.4 Synced advertising

Synced advertising is "showing a message on a second screen device simultaneously with relevant TV content (or other medium) with the aim to persuade the consumer" (Segijn, 2016, p. 12). Advertising on user´s mobile device is then personalized based on other media content that user is consuming at the same time.

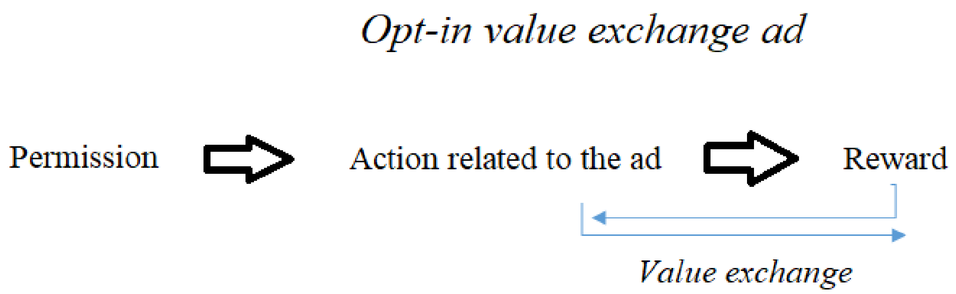
The above is achieved by using tracking hashtags on Twitter of popular shows alone or combined with programmatic ads, advanced segmentation techniques, commercial watermarking, or installing 'free' mobile applications (apps) where people give consent for data collection (Segijn, 2019).

[25] Chatbot: A chatbot is a software application used to conduct an on-line chat conversation via text or text-to-speech.

1.5.5 Incentivized mobile advertising

A general definition of incentivized mobile advertising establishes that "incentivized advertising takes the form of rewarding a user for completing an action related to the ad" (Chiong et al., 2017, p. 3). As rewarding is part of the definition, incentivized advertising is also commonly known as "reward advertising". A more detailed definition includes permission and suggests that, instead of pushing ads to consumers, let consumers opt-in[26] for ads in exchange for rewards. These definitions also use the term "value exchange" when referring to "rewarded advertising" or "incentivized advertising". On the same topic, IAB (2018b) establishes a new definition of incentivized advertising "opt-in value exchange ads as premium ads that offer consumers something of value in exchange for providing their time and attention" (p. 5). Being video today´s the main reward advertising media, *Tapjoy* webpage uses rewarded video as an ad format that allows the audience to decide whether or not they want to watch a video, in exchange for rewards such as in-app currency, bonuses, or other premium content (Tapjoy, 2019b).

Based on all these definitions there are three components that must be present, permission, action related to the ad, and reward. The flow is represented in this image:



Incentivized advertising on mobiles started with advertising in gaming apps as a new monetization mechanism. In the social gaming environment, these ads appear at a critical time for the player in the game and are well designed in the content/game flow. Regarding gaming apps, Chiong et al. (2017) posit that, incentivized ads allow for a more seamless transition between gameplay and ads, which improves the playability of the game and reduces the annoyance due to interruptions. This reduction of annoyance is one of the key reasons for its popularity in mobile advertising. This new monetization mechanism has gain popularity, not only among app developers, but also among publishers of the digital advertising industry.

Freedom and value exchange are two key issues to increase the incentivized advertising popularity. Mansuri (2019) states that instead of fighting consumers, is preferable to respect them, give them the autonomy and freedom (permission) to decide by themselves whether to view an ad, and also give them something in return of their time.

The value exchange concept is not a new concept. Television ads, radio ads, and even pre-roll units are all incentivized (we go through them to the content). The only difference with digital value exchange is that people choose when and where to participate, and that's key.

[26] Opt-in means that the consumer has a choice to engage or not with the offer that is provided by the publisher. (IAB, 2018b)

When someone decides on her own to engage with an advertiser it’s a deeper and richer experience that yields better results for all parties involved.

Value exchange advertising puts people in control of their ad experiences, and IAB (2018b) indicates that with value exchange, audiences actively engage with advertisers to unlock entertainment, reward points, Wi-Fi[28], or other digital content. Additionally, value exchange ads are always viewable, resistant to fraud, and immune to ad blocking because people actively choose to open them.

Value-exchange provides a huge amount of information that help brands to talk to audiences. This value-exchange in case of monetary value could be done by transferring some of the revenue that goes to media houses, to the consumer´s pocket´s.

<u>Incentivized mobile advertising formats and rewards.</u>

Incentivized ads first appeared among mobile gaming apps. Examples include ad placements where publishers reward users with in-game virtual items, additional game levels and lives, for viewing an ad, typically in a full-screen video format (Chiong et al., 2017). Nowadays, most popular platforms like Google and Facebook are developing incentive mobile advertising models and research.

The format can be deployed within apps using a variety of methods — such as offerwalls or native integrations —given users the opportunity to opt-in to the viewing experience. Offerwalls “are in-app advertising units that monetize apps through incentivized engagements” (Tapjoy, 2019a, p. 1).

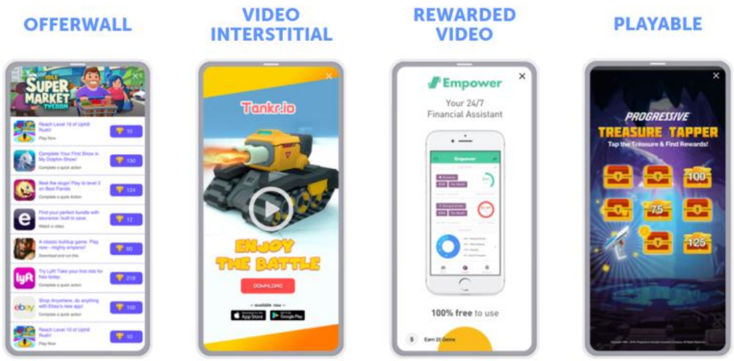
Offerwalls reward users for taking specific actions by pushing them to enter a mini ‘store’ with special offers linked to the in-app rewards. This unique style of value-exchange advertising makes rewarded videos an ideal method for monetizing apps that benefit players, developers, and advertisers alike, while ensuring the best possible user experience.

The main formats for incentivized mobile advertising that brands start to use were first the SMS (starting in 2010), which waw followed by banners at a later state.

IAB (2018b) established which are the most common formats use in incentivized mobile advertising:

[28] Wi-Fi: Is the wireless technology used to connect computers, tablets, smartphones and other devices to the internet.

Image 2: Incentivized mobile advertising formats.



Source: IAB (2018b)[29]

Video Interstitials engage users with rich, customizable, and appealing ads that pop up during the natural pauses of the app's flow, which ensures minimum disruption of the user experience, while achieving monetization goals.

Rewarded Video grant users access to premium content or in-app currency in exchange for watching a full screen high-quality video in less than 45 seconds. Once users watch a full video, the reward is unlocked, however, they can exit the video any time. New formats are coming out, but the most currently used is Rewarded Video as *Mopub*, a division from Twitter Inc. (Boiteux et al., 2018).

Playable ad "is a single ad unit that combines interactivity - all the core mobile gestures like touch, swipe, flip and tap - with gamification to enable full-funnel marketing brand communication" (IAB, 2019, p. 4). In this interactive video ad format, a short demo is usually played to show the consumer how to play, after which they play the game by themselves, and a call-to-action pops up at the end.

Reward ads are found in a broad range of apps including games, news, utilities, and social networking apps, with the type of rewards ranging from virtual items, discounts, coupons, lotteries, credits, and gifts, and non-monetary, digital content, and unlocking certain app features. Researchers point out that regarding rewards, some of the most common types of reward-based mobile advertising are trailers for other apps, games, and products (Mansuri, 2019). Incentives or reward types depend on the user's interest in getting those rewards, bonuses, additional features, extra life, or access to premium content for free.

The IAB (2018b) points out that there are two different types of value exchange. One relates to the media experience, which is directly related to the user experience when accessing the selected media. The other is not media experience related, which means a different value exchange must be offered.

29 https://www.iab.com/opt-in-value-exchange/

Literature review

In 2012, Varnali et al. point out that the two most critical determinants of consumer responses in mobile advertising were incentives provided to and permissions granted by the target audience. Incorporating incentives in mobile advertising campaigns could lead to improved return rates.

Regarding non-monetary incentives, when an incentive is provided not only there are more favorable evaluations of the campaign in terms of both perceived intrusiveness and overall campaign attitude, but also that consumers who received the message with an explicit incentive appear significantly more responsive than those who did not (Varnali et al., 2012). These researchers also suggest that existence of an incentive within the message may reduce response delay and increase the recipients' willingness to make WOM (Worth of Mouth) referrals about the campaign.

Heine's (2013) research about the banner format in mobile, confirmed Varnali et al. statement and showed that consumers react positively twice as often to mobile ads when they get something valuable, relevant and/or engaging in exchange for their time. Smartphone users will click mobile banners if there is a gift card, coupon, events tickets or loyalty points—in that order—on the other side.

About the rewarded video format in mobile, Cohen-Aslatei (2016) points out that value exchange ads consistently deliver engagement rates that are more than 2x that of industry benchmarks, especially on mobile with 99% video completion rates and reducing ad-blocking. In this line, Mansuri (2019) also comments that when users are blocking intrusive ads, reward-based advertising might be the way ahead to restore the lost sheen of consumer engagement. Cohen-Aslatei (2016) suggests that, benefits like consumers feel compensated, app developers get ad revenue, and brands benefit from a more engaged audience, may arise when consumers choose to view rewards ads.

Also, Chiong et al. (2017) point out that rewarding users to watch an ad could affect the mood of the users, contribute to an overall positive perception towards the ads and has an overall positive effect on the ad conversion rate. However, two issues may reduce the effectiveness of incentivized ads, delayed rewards as users prefer to collect their rewards immediately after watching the incentivized ads and adverse selection, where reward-seeking users select into incentivized ad placements to obtain rewards.

Clark et al. (2018), using consumer neuroscience technics, support previous findings and conclude that incentivized ads drive high effectiveness. They found that attention and engagement with pre-roll advertisements would vary as a function of incentivation and incited more opt-ins of advertisements, greater overall attention to the advertisement content, higher brand recognition following the test paradigm, and greater positive emotional affect during advertisement viewing.

As a resume in next table, we resume main conclusions from the literature abut incentivized advertising.

Table 3: Incentivized advertising conclusions

Research	Theme	Conclusions
(Michael and Salter, 2006)	SMS format	✓ Incentives in mobile advertising campaigns lead to improved return rates.
Varnali et al., 2012	determinants of consumer responses in mobile advertising	✓ Two most critical determinants of consumer responses in mobile advertising, were incentives provided to and permissions granted by the target audience. ✓ When an incentive is provided there are more favorable evaluations of the campaign in terms of both perceived intrusiveness and overall campaign attitude. ✓ Consumers who received the message with an explicit incentive also appear significantly more responsive than those who did not. ✓ When the effects of individual differences (i.e. content involvement, prior experience, and medium-fit perceptions) are controlled for, the impact of incentive on actual response behavior becomes non-significant. ✓ Incentive within the message may hasten response behavior (reduce response delay) and increase the recipients' willingness to make WOM. ✓ Effect of non-monetary incentives on behavioral response intention does not differ significantly from that of monetary incentives.
(Heine, 2013)	banners format in mobile	✓ Consumers react positively twice as often to mobile ads when they get something valuable, relevant and/or engaging in exchange for their time. ✓ Smartphone users will click mobile banners if there's a gift card, coupon, events tickets or loyalty points—in that order—on the other side
(Cohen-Aslatei, 2016)	value exchange ads	✓ Value exchange ads consistently deliver the best results in the industry, especially on mobile. ✓ Users of value exchange products have experienced video completion rates of up to 99%, with engagement rates that are more than 2x that of industry benchmarks. ✓ Value exchange solves the ad-blocking quandary.
(Chiong et al., 2017; IAB, 2018)	Reward ads	✓ Rewarding users to watch an ad could affect the mood of the users and contribute to an overall positive perception towards the ads. ✓ Rewarding users to watch an ad has an overall positive effect on the ad conversion rate.
(Clark et al., 2018)	Incentivation and ads format	✓ Incentivized advertisements drive high effectiveness. ✓ Attention and engagement with pre-roll advertisements would vary as a function of incentivation. ✓ Pre-roll incentivized advertisement placement yielded greater star ratings for editorial content than did in-stream conditions.

		✓ Incentives incited more opt-ins of advertisements, greater overall attention to the advertisement content, higher brand recognition following the test paradigm, and greater positive emotional affect during advertisement viewing. ✓ Users likely will not click opt-in advertisement units unless there is an explicit incentive to do so in return for their time.
Guo et al., 2019	Rate of reward	✓ Often optimal to offer reward ads jointly with direct selling of premium content. ✓ A high reward rate could decrease the number of reward ads viewed because of accelerated satiation for premium content.

Source: Author

Mansuri (2019) points out that incentivized video ads are growing more that 100% in terms of inventory and space and developers and publishers are implementing them based on their main benefits, increase in engagement and session time, increased ad revenue, higher conversion and better retention. In this line, IAB (2018b) identified some factors that contribute to this growth, for the brands: consumer annoyance with intrusive ads, especially on mobile devices, brand desire to connect with consumers in more native and organic ways, brand desire for better performing ads that are engaging, viewable and brand safe, and for the publisher: publisher desire for ads that engage and keep viewers on-site, especially on mobile devices, publisher desire for new ad revenue streams that provide a “win-win” for all, technology that enables scalability of value exchange formats and increasing subscription-based publisher world where publishers can offer value in exchange for advertising views.

1.6 **Mobile advertising problems**

Mobile advertising suffers basically same problems that traditional online advertising in PC, TV, or tablet.

One of them is privacy concerns consumers have about use of personal data. Online personalized advertising may cause consumers’ unfavorable beliefs as they may perceive privacy concerns in terms of personal data that is collected tacitly and limited capacities to choose and buy (Aguirre et al., 2015).

Another important issue are consumer strategies to avoid advertising in their mobiles, like banner blindness, ad-blocking, or fraud. Banner blindness usually refers to the finding that internet users avoid looking at or paying attention to ad banners inserted on web pages. Hervet et al. (2011) and Lapa (2007) point out that this banner blindness increases, and reduce ads effectiveness. Number of people using ad-blocking technology on mobile browsers has increase a 64% over the last three years (Shankland, 2020) mainly because of saturation, irrelevant or annoying ads and intrusive perception (Kemp, 2021). Last, but not less important, is fraud. *Juniper Research* (2017) estimated that advertising frauds cost online advertisers US$19 billion worldwide in 2018, equivalent to $51 million per day and forecast a 132% growth reaching $44 billion by 2022 becoming an important problem for online advertising.

1.6.1 Banner blindness

Banner blindness usually refers to the finding that Internet users avoid looking at or paying attention to ad banners inserted on web pages (Hervet et al., 2011). Dreze and Zufryden (1997) found that consumers were avoiding online banner advertising defining this behavior as banner blindness and Balkenious and Lundagfird (2000) point out that this avoid behavior was mainly to useless ads. Banner blindness has been studied during last 20 years.

Burke et al. (2005) conclude that users rarely look directly at banners, but Hervet et al. (2011), analyzing banner blindness, conclude that users fixate the ads at least once during their website visit, and even though the congruency between the ad and the editorial content had no effect on fixation duration on the ad, congruent ads were better memorized than incongruent ads.

Banner blindness has become so powerful that users tend to ignore all content resembling a banner ad, or a text-based ad, even if it is not, as studies have found in mobile where consumers try to avoid mobile ads (Button & AppAnnie, 2017).

Forcing users to watch these ads seems to be not a great approach and practitioners and researchers propose personalization, deliver fewer but more relevant and targeted messages, and carefully design banners and usability as a solution (Haring, 2016).

1.6.2 Ad-blocking software

Ad blockers "refer to various software tools (most typically browser plug-ins) that monitor browsers' requests for editorial and advertising content and prevent the display of any advertising content that matches an entry in the blacklists maintained by ad-blocking companies/user communities" (Redondo, 2018, p. 4). Adblockers known also as content blockers are usually web add-ons[30] allow web pages to load faster offering a better overall browser experience, although strong adblocker might break some websites and disrupt the browsing experience.

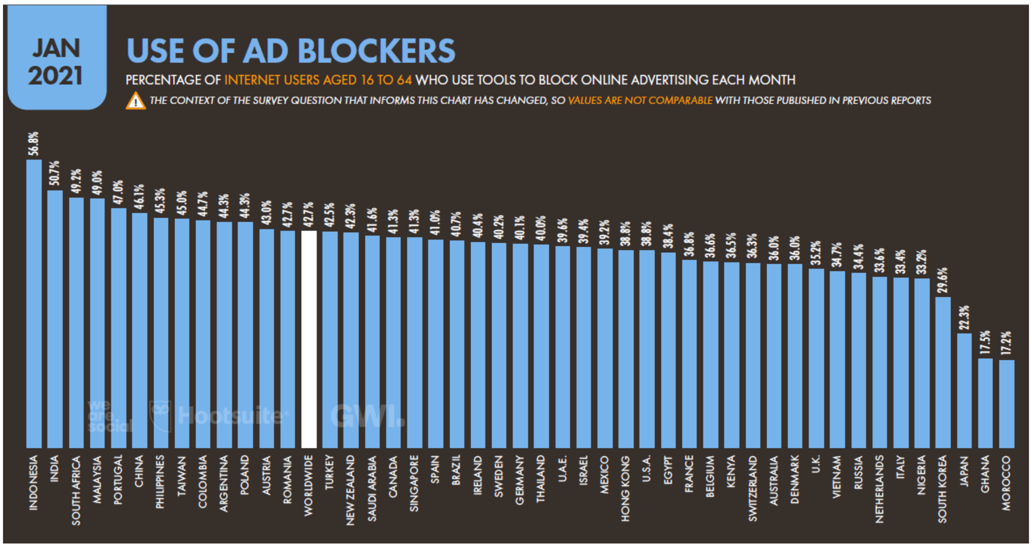
Adblock technology relies on filter lists (maintain by third party community that is not affiliated with the developers of adblockers or ad companies) and a set of rules that determine what to block on the pages users visit.

The dominant ad blocking software (60% market share), *Adblock Plus* was created in Germany by Wladimir Palant in 2006 for PC and there is also an android version. Later Apple in 2015 included content blocker in IOS 9 and allowed developers to build ad blocking extensions for Safari. Ad-blocking software has become an important problem in webs (social networks don't allow you to access their websites with an Adblock turned on) and in mobile web apps and the adoption of ad-blocking software worldwide, actually 42,7%, continues to grow (Kemp, 2021).

Regarding mobile, the number of people using ad-blocking technology on mobile browsers has surged to 527 million, an increase of 64% over the last three years (Shankland, 2020).

[30] Add-on: A software add-on or extension is any third-party software program or script that is added to a program to give it additional features and abilities.

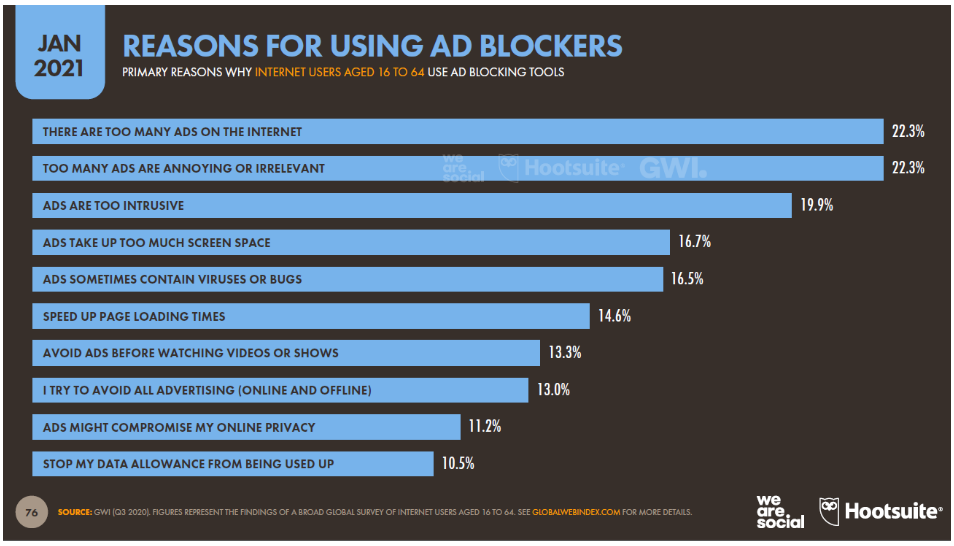
Graphic 10: Use of ad blockers worldwide



Source: We are Social (2021)[32]

Last digital report from We are social, conclude that main reasons for ad-blocking are saturation, irrelevant or annoying ads and intrusive perception (Kemp, 2021). In this line, Clark et al. (2018) conclude that disruptive ads elicited a strong negative emotional response and increase consumers' perceived financial utility for ad-blocking.

Graphic 11: Reasons for using ad blockers



Source: We are Social (2021)[33]

[32] https://datareportal.com/reports/digital-2021-global-overview-report
[33] https://datareportal.com/reports/digital-2021-global-overview-report

Although there is growing industry-led support for advertisement-blocking software to attenuate eventual widespread adoption of advertisement blocking (Clark et al., 2018), brands need to respect the consumers and come up with non-disruptive and non-intrusive ways when accessing our information, without invading one's privacy. In this line several agreements around the creation, format and placement of ads have been placed based in two committees[34].

Shiller at al. (2018) posit that sites with more users who block ads experience reductions in traffic, "which we presume arise from the sites loss of revenue. Our interpretation of the result is that revenue reductions undermine investment which, in turn, compromises site quality, making consumers less interested in visiting in the first place" (p. 17). They conclude that ad blocking appears to have a large and meaningful impact on the quality of content created.

1.6.3 Ad fraud

Ad fraud is any attempt to defraud digital advertising networks for financial gain. Specially in mobile free apps, where the only way to support them is with ads paid by the advertisers, ad fraud is through "unreal" clicks or impressions, using a miscreant code that automatically counts these clicks or impressions as real. Most used are click bots, programmed to imitate real users, that produce fake clicks on digital ads that appear on properties the scammers own, generating revenue for them.

Juniper Research (2017) estimated that advertising frauds cost online advertisers US$19 billion worldwide in 2018, equivalent to $51 million per day and forecast a 132% growth reaching $44 billion by 2022 becoming an important problem for online advertising.

Researchers have study different fraud types and propose different software solutions. Crussell et al. (2014) propose a software solution identify two fraudulent ad behaviors in apps: First, requesting ads while the app is in the background, and second clicking on ads without user interaction. Liu et al. (2014) recommend a solution for another type of ad fraud based on ad placements. Software automatically discovers various placement frauds scanning through a large number of visual elements within a limited time. Dong et al. (2018) point out a novel hybrid approach software solution to detect ad frauds in mobile Android apps that analyses apps dynamically to build user interface state transition graphs and collects their associated runtime network traffics, which are then leveraged to check against a set of heuristic-based rules for identifying ad fraudulent behaviors.

Practitioners demand an independent third-party method that measures accurate online advertising delivery and *Blockchain*[36] seems to be a good solution (Kshetri and Voas, 2019). Recently IAB formed a blockchain working group to address this problem.

Ad fraud was detected fist in web but is present in mobile specially in mobile apps.

[34] Two committees: The Acceptable Ads Standards Committee (AAC) and the Coalition of Better Ads (CBA).
[36] A blockchain is a digital record of transactions. The name comes from its structure, in which individual records, called blocks, are linked together in single list, called a chain.

1.6.4 Screen size

Mobile screen size compared to other online devices like tablet, PC or TV it’s an important problem for mobile advertising effectiveness. This problem leads to typical screen navigation issues in mobile, like sidebar absence that PC and TV have or click errors due to little space for click button as we comment before.

Also problems managing information or advertisements, where consumers need to make extra effort to read them while in PC or TV this doesn’t usually happen. In this line, researchers (Clark er al., 2018; Gupta and Mateen, 2014; Hancok et al., 2015) point out that mobile viewing behaviors for advertisements are fundamentally different from viewing on a traditional television or computer screen. In this line, Babiloni (2019) posits that screen size on different devices leads to different advertising effectiveness.

Differences in screen size affect consumers:

- Arousal. Lombard et al. (2000) conclude that small screens, like mobile, elicit lower arousal than bigger screens like PC.

- Recall. Okazaki et al. (2007) found that a mobile campaign's recall largely depends on perceptions of both the medium and the advertised content.

- Enjoyment. Kim et al. (2011) showed that smaller screen-size elicited greater perceived mobility while larger screen-size was key to greater enjoyment.

- Attention. Researchers (Troscianko et al., 2012; Segijn and Eisend, 2019) comment about attention that small screen gets lower attention than bigger screen and conclude that attention varies with screen size.

- Perceived usability and efficacy. Ciceri et al. (2019) posit that users are more efficient in seeking information if they interact with screens larger than 4.3 inches like PC or TV screens.

Technology has been trying to solve this problem in several ways developing bigger screens in mobile phones and new formats as Kim et al. (2011) point out screen-size are becoming larger and larger, and watching videos on mobile device is no longer as uncomfortable as it was before on smaller screens, so video modality has now become a standard in mobile devices. Moreover, Nipan et al. (2008) posit that video-based material displayed on a mobile device gets higher effectiveness than text.

Actually, also in order to avoid this problem usually mobile ads are video full-screen advertisements and many based on interstitial format.

1.7 **Consumer attitude toward mobile advertising**

Millennials have shown to have strong negative feelings towards mobile marketing communications (Grant and O’Donohoe, 2007). However, Lafferty (2016) suggests that they are more attentive when consuming media on mobile devices and feel more positively toward the information presented on a smartphone. Thus, there is a need to increase the understanding of millennials online search behavior and attitudes towards sponsored search results on mobile devices (Gupta and Mateen, 2014; Murillo, 2017).

Another finding from previous research states that consumers interact more with ads in apps than in web. What makes this so intriguing is that, briefly, it appears as though users are interacting with ads in their mobile apps more than on the Web, especially in gaming apps. Some initial theories suggest that this may be a psychological response or perhaps only attributed to the mobile nature of having the device on one's person for a significantly longer time than what is spent on a PC or television. In this line, Alnawas and Aburub (2016) point out that there are four interaction-based benefits in the context of mobile apps: learning benefits, social integrative benefits, personal integrative benefits and hedonic benefits. Except from social integrative benefits, the other three benefits are found to influence consumer satisfaction to varying degrees and the study confirms the relationship between consumer satisfaction and purchase intentions in a mobile context.

An attitude towards advertising is defined as a ‘‘predisposition to respond in a favorable or an unfavorable manner to a particular advertising stimulus during a particular exposure occasion’’ (MacKenzie and Lutz, 1989, p. 49).

To have a comprehensive view of attitudes, the ABC Model of Attitudes was developed Ostrom (1969). This model divides attitudes into three components: Affect, Behavior and Cognition, which are referred as the verbs "feel, do and think". Okazaki et al. (2007) found that attitude has a positive impact on user's intention and that the effects of mobile advertising trust on attitude toward mobile advertising were stronger than those of other relationships.

Researchers on mobile advertising (Kim and Han, 2014; Martins et al., 2017; Murillo, 2017) have considered to apply the model constructed by Ducoffe (1996) in order to create an understanding of individuals' attitudes. The model is used to understand the variables affecting attitudes towards advertisement in online advertising by analyzing factors which affect the advertising value of a consumer. Variables included in the model were: informativeness, irritation, and entertainment that have impact and influence individuals.

Informativeness refers to the ability to effectively provide relevant information. Murillo (2017) points out that informativeness in mobile search ads had a significant positive effect on perceived advertising value as well as consumers' attitude towards mobile search ads.

Irritation is defined, in the context of advertising, as "when advertising employs tactics that annoy, offend, insult, or are overly manipulative consumers are likely to perceive it as unwanted and irritating influence" (Ducoffe, 1996, p. 3). However, irritation (the basis of intrusiveness) is usually considered more negative than dislike. Perceived intrusiveness of a SMS message and overall attitude toward the campaign are deemed as the two most important attitudinal reactions triggered by a mobile advertising campaign. The very personal nature of mobile devices is the main reason that mobile advertising is perceived as more intrusive than other media (Wehmeyer, 2007).

Brackett & Jr (2001) concluded that although Ducoffe's sample did not find web advertising to be irritating, annoying, or insulting to peoples' intelligence, their student sample did.

Entertainment refers to happiness valence perceived by users in the process of using a product/service. Saadeghvarizi et al. (2013) suggest that the entertainment of mobile advertising led consumers to develop positive attitudes toward mobile advertising.

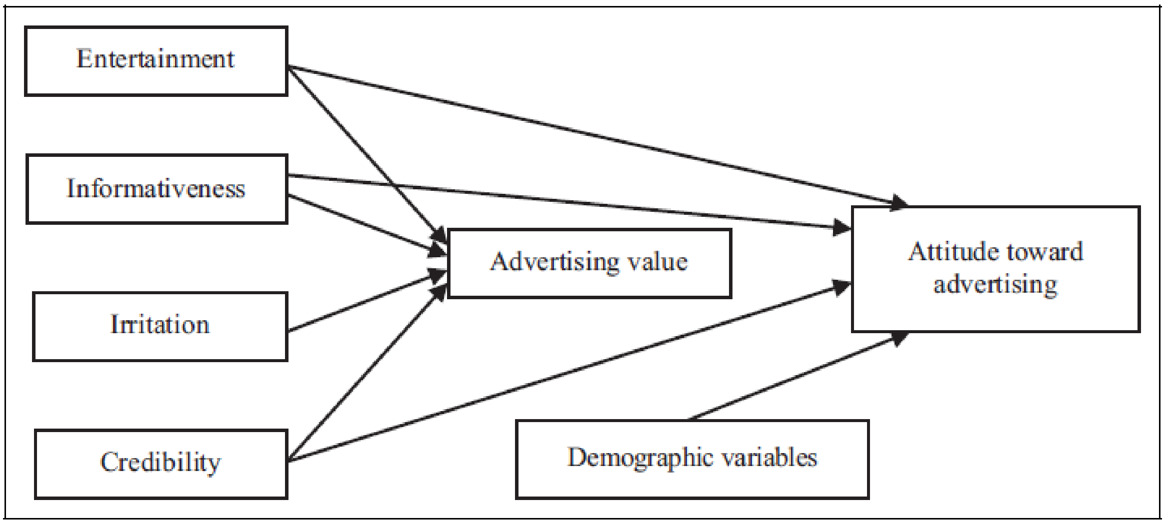
A mobile advertisement that is perceived as annoying and unwanted will reflect in negative feelings of the consumer towards the brand presenting the advertisement, asserting that irritating messages affects consumers' attitude towards receiving mobile advertising. In this line, Altuna and Konuk (2009) indicated that irritation comprised the only negative dimension of consumer attitudes towards mobile advertising and Huq et al. (2015) showed that irritation had a direct negative and significant influence on consumer attitude towards mobile advertising.

Other studies that analyze the attitude toward advertising in the mobile environment have identified new variables. These variables are credibility, permission, incentives, flow experience, perceived usefulness, and ease of use.

Credibility indicates a person's perception towards the truthfulness and believability of advertising. Brackett and Jr (2001) complemented Ducoffe model including credibility, suggesting that credibility is a vital factor.

Merisavo et al. (2007) point out that credibility positively influenced the adoption of mobile advertising in Finland. Le and Nguyen (2014) suggest that although many users do not have positive feelings toward advertising, if mobile advertisers can present credibility and entertainment in their advertisements, consumers are willing to view the ads and be influenced to buy products and services.

Image 3: Brackett et al. model



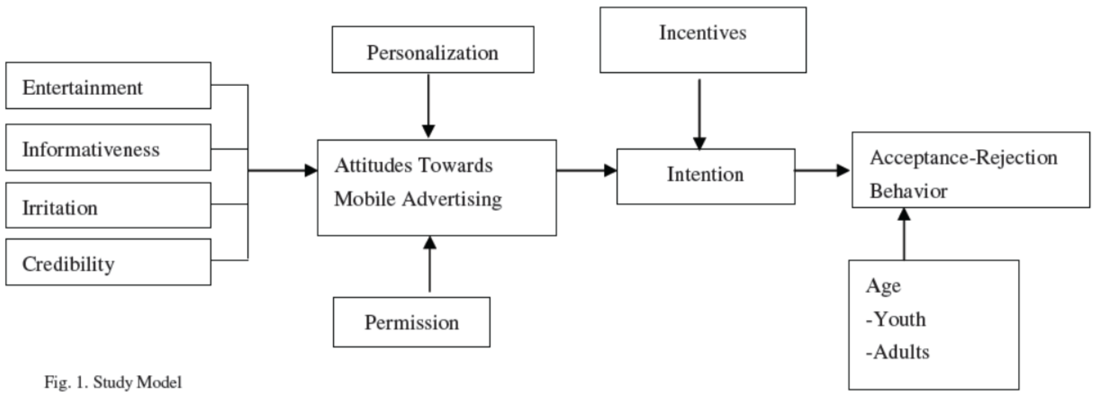
Source : (Brackett and Jr, 2001)[38]

In permission-based advertising, consumers give the permission to marketers to receive information and advertising messages only about relevant products and services they have chosen before. Permission is considered critical in the mobile advertising context because messages are delivered to the personal handsets of individuals. Tsang et al. (2004) found that with permission consumers experience generated less irritation and Ünal et al. (2011) point out

38 https://www.researchgate.net/publication/279704496_Cyberspace_Advertising_vs_Other_Media_Consumer_vs_Mature_Student_Attitudes

that when consumers participate in marketing activities voluntarily, 30% higher response rate can be observed.

Image 4: Ünal et al. model

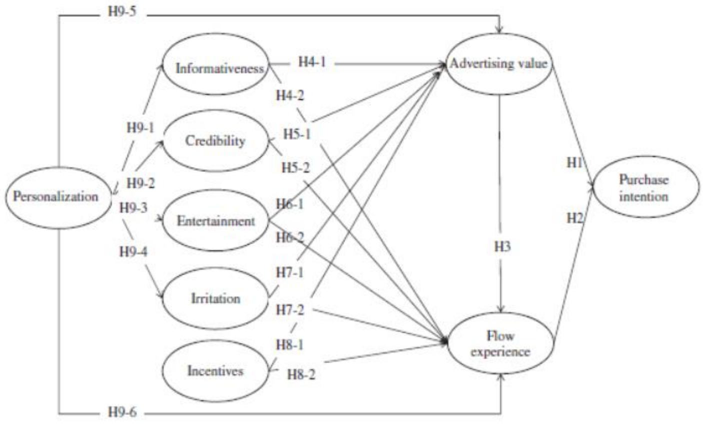


Source: (Ünal et al., 2011)[39]

Personalization is one of the main strategies of mobile advertising and an important component that improves a consumer's attitude toward mobile advertising. Personalization refers to the ability to proactively tailor products and product purchasing experiences to the tastes of individual consumers based upon their personal and preference information. Researchers (e.g., Ünal et al., 2011) point out that mobile users prefer advertisements which are customized to their interests and relevant to them and personalized messages make people think that they are being respected.

Kim and Han (2014) proposed that personalization has a positive association with informativeness, credibility, and entertainment of the advertising message while having a negative association with irritation.

Image 5: Kim and Han model

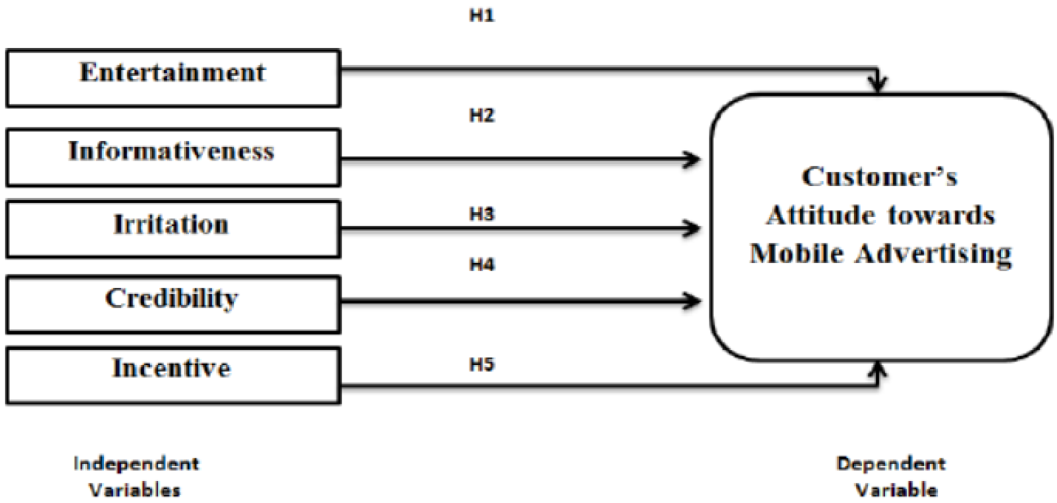


Source: (Kim and Han, 2014)[40]

[39] https://www.sciencedirect.com/science/article/pii/S1877042811015953
[40] https://www.sciencedirect.com/science/article/abs/pii/S074756321400020X

Incentivized advertising takes the form of rewarding a user for completing an action related to the ad usually in mobile. Huq et al. (2015) point out that 69.8% of customer's attitude towards the mobile advertising was explained by the independent variables and entertainment, informativeness, credibility and incentive have positive influence and irritation has negative influence on consumer attitude.

Image 6: Huq et al. model



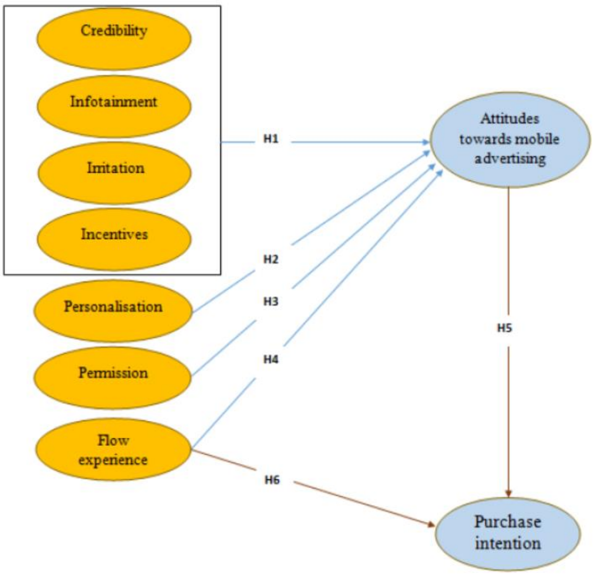
Source: (Huq et al., 2015)[41]

The concept of flow experience relates to a lack of disruption and historically is defined as "someone's flowing from one moment to the next, in which he is in control of his actions, and in which there is a little distinction between self and environment, between stimulus and response, between past, present, and future" (Csikzentmihalyi, 2000, p. 34). Audience receptivity to content relates to low incidence of disruption during consumption.

Abeywickrama and Vasickova (2014) used a model with seven variables including flow experience to analyze attitude toward mobile advertising. They concluded that permission, personalization, infotainment, and incentives are related to attitudes towards mobile advertising and flow experience and attitude towards mobile advertising explained purchase intention.

41 https://www.researchgate.net/publication/315117546_Customer's_Attitude_Towards_Mobile_Advertising_in_Bangladesh

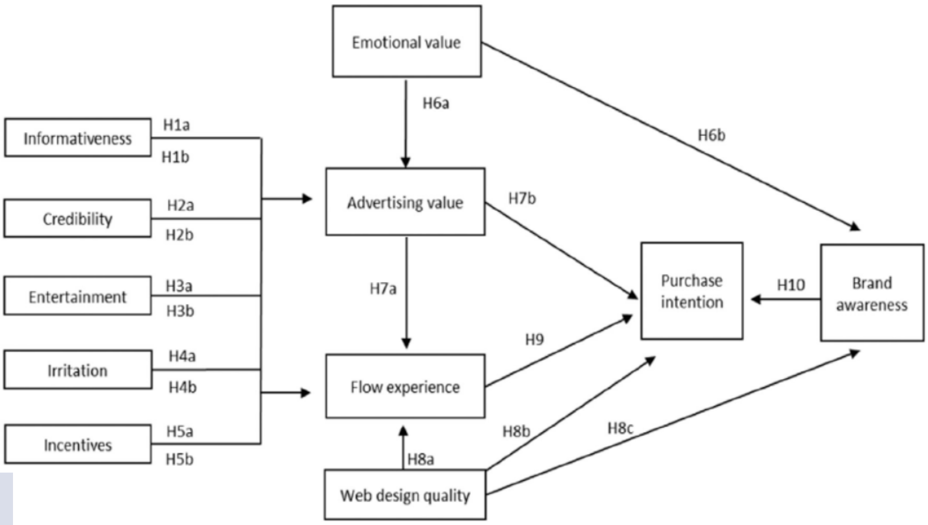
Image 7: Abeywickrama and Vasickova model



Source: (Abeywickrama and Vasickova, 2014)[42]

Martins et al. (2017) proposed a conceptual model that combines Ducoffe's advertising model and flow experience theory and their results showed that advertising value, flow experience, web design quality, and brand awareness explain purchase intention.

Image 8: Martins et al. model

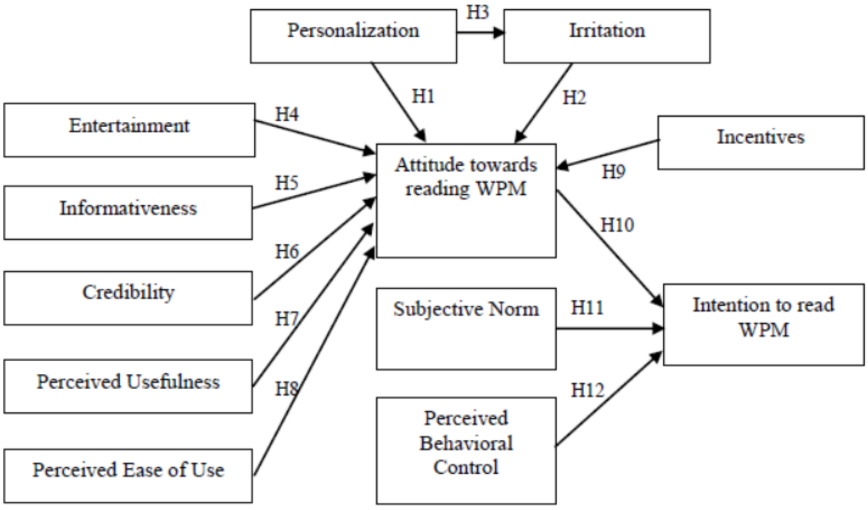


Fuente: (Martins et al., 2017)[43]

[42] http://www.diva-portal.org/smash/record.jsf?pid=diva2%3A731522&dswid=3428
[43] https://www.sciencedirect.com/science/article/abs/pii/S0148296317305507

Perceived usefulness and ease of use were used by Sam and Chatwin (2019), with entertainment, informativeness, credibility, personalization, and irritation, in a model to explain attitude toward mobile advertising. The results indicate that personalization, entertainment, incentives, and perceived usefulness positively influence users' attitudes towards reading WPM (web promotional materials) in mobile.

Image 9: Sam and Chatwin model



Fuente: (Sam and Chatwin, 2019)[44]

44 https://www.researchgate.net/publication/332100414_UNDERSTANDING_WECHAT_USERS'_MOTIVATIONS_ATTITUDES_AND_INTENTION_OF_READING_PROMOTIONAL_MATERIAL_KIN_MENG_SAM_CORRESPONDING_AUTHOR_UNIVERSITY_OF_MACAU_tonysamumacmo

CHAPTER 2. MEASURING MOBILE ADVERTISING EFFECTIVENESS

Companies often view mobile advertising through the prism of digital media, applying the same expectations, practices, and measurements with their mobile advertising spend as they do with other forms of online advertising, but the mobile has its own characteristics (Beaudin, 2017).

It seems also that advertising researchers do not understand fully the impact different advertisement placement and delivery vehicle have on the mobile user's experience. Marketers face a hard problem in mobile advertising: the lack of standardized metrics in the advertising industry (Clark et al., 2018; Grewal et al., 2016). This lack of standardized metrics makes it difficult to measure any outcome other than direct behavioral response and usually requires the additional design and implementation of a post-campaign survey instrument.

2.1 **Methodologies to measure impact of mobile advertising**

Traditional methodologies to measure mobile advertising effectiveness are surveys and self-reports. Practitioners and academics indicate the limitations of these measurement methodologies.

Academics posit that there are not ideal methods, if we use them alone, because what we say is not necessarily what we feel and what we feel is not necessarily what we think and what we think is not necessarily what we say. Also, there are a lot of biases that affect results (context, cultural influences, location, attitudes, and so on) (Álvarez del Blanco, 2018; Clark et al., 2018; Eijlers et al., 2020; Hsu, 2017; Ohme et al., 2011).

Clark et al. (2018) point out several problems with surveys. One key issue relates to the nature of post hoc evaluations of advertisements, in that self-report occurs after the user's actual experience consuming an advertisement. Such evaluations are biased by time and decontextualized from the programmatic content in which the advertisement is placed. Measurements that occur in the context in which the advertisement is placed often are highly disruptive to the user experience of the surrounding content.

Alvarez del Blanco (2018) suggests that surveys have significant errors specially when people should answer questions about what they think or feel. At that moment we should take care about their emotional situation that indeed could change. Not only this but also language or emotional situation of the interviewer made influence user responses. Moreover, as IAB (2013, p. 9) points out on brand engagement, "However, the lower cost and ease of deploying surveys online have made it the industry's preferred method of measuring brand engagement".

In line with previous academics, Casado (2018) posits that self-report tools are subjective, likely social desirability bias, conscious processing, delayed measurement, not recommended for sensitive topics, dependent on language and require recall. Also, Marques dos Santos et al. (2020) indicate that what users manifest as intentions in surveys or focus group is different from what they really do and one cause could be that these methodologies assume the consumer as a full rational decision-maker[46], although most consumption acts arise in the non-conscious plan, where intuition and emotions play the most important roles. In this line Eijlers et al. (2020) point out that people are limited in their ability to reflect accurately on their internal mental processes and also that their ability to report on mental states requires cognitive processing, which may interfere with or even change the originally evoked feelings.

To avoid these limitations, especially cognitive biases, another methodology is proposed to measure mobile advertising effectiveness, neuroscience methodology, that study unconscious physical reactions. In this line, Hsu (2017) suggests that in addition to validating insights from traditional methods, brain-based or neurophysiological methods can be used to generate novel insights by providing new or improved measures for marketers in abstract constructs.

There is growing interest in consumer neuroscience approach that may enable managers to directly probe customers' underlying thoughts, feelings, and intentions (Hsu, 2017). Biosensors can extend traditional methods with new techniques that help to understand behavior, recording psychological reactions (most of them unconscious) during exposure to stimuli.

Marketers agree that measurement technologies in consumer neuroscience are complementary to traditional research methods. Implicit and explicit measurement approaches are complementary (Chan, 2020; Deitz et al., 2016; Karmarkar and Plassmann, 2019; Micu and Plummer, 2010; Segijn et al., 2017). In this line, Venkatraman et al. (2015) point out that neurophysiological methods can explain significantly greater variance in advertising elasticities than traditional advertising methods alone. Also, Aliagas and Torres (2018) posit that the analysis of neurophysiologic responses may be a validation of traditional responses and Clark et al. (2018) indicate that researchers can measure relevant psychophysiological responses related to cognitive effort and motivation during consumption to measure the audience's flow like experience during consumption.

Other marketers (Cerci and Koyluoglu, 2020; Mostafa, 2014) propose that while neuromarketing is aware of the fact that traditional methods have some limitations in achieving objective and accurate results, it supports traditional research methods by providing them with neuroscientific bases, in other words, by providing means to act together, not by opposing traditional methods. In this line several marketers (Baldo et al., 2015; Berns and Moore, 2010; Bigné, 2015; Falk at al., 2010; Poels and Dewitte, 2006) posit that neural responses could be more accurate predictors of consumer behavior than self-reported responses. Alvarez del Blanco (2018) suggests that consumer neuroscience provides important information in order to optimize products, campaigns or offers because it understands consumer emotions.

According to Harrell (2019), brain data can predict the future success of products more accurately than traditional market research tools such as surveys and focus groups can do: "For example, respondents aren't always forthcoming about their memories, feelings, and preferences. People have flawed recall; they lie when they're trying to please or are embarrassed; their perceptions can be influenced by how a question is asked. What comes out

[46] This idea comes from cognitive psychology assuming that consumption acts are performed grounded on consciousness and deliberation.

of our mouths is not always a perfect rendition of what's going on in our brains." (p. 5) In this line, Malygina and Perepelkina (2020) consider that nonverbal and physiological responses are more informative than self-reports in terms of time resolution and are less affected by social desirability.

Consumer neuroscience studies identified neural correlates of marketing relevant behavior (Karmarkar and Plassmann, 2019). Moreover, consumer neuroscience also suffers from severe handicaps and limitations, for example, in terms of credibility "neuromarketing is a business opportunity for people with wide creativity in business, people who know make money through business brain unconventional measurements, or people interested in making money with the ignorance of the subject by people" (Valencia, 2017, p. 2), but when the neuromarketing is discussed from a scientific point of view and not from a commercial point of view, loss of credibility on the subject has poorly unfounded.

It's not only credibility but also trustworthiness of the information (Raj, 2018). Over the past, like in many new disciplines, there has been a normal opposition from scientific community to the studies that didn't have a scientific rigor. Lindstrom (2011) study about ring tones iPhones New York Times 2011 contributed to this opposition. In this line also, is famous a research about the dead salmon study that circulated prominently in the social media, or the hundreds of books with titles like "Neuromania" warned of how neuro-results are being fetishized (Murray and Antonakis, 2019).

Researchers also point out that placing irrelevant neuroscience information sways readers into thinking the information therein is more credible; this "allure of neuroscience" bias has been, for instance, besides the issue regarding statistical control for type 1 error rates following multiple testing, one of the biggest challenges that faces neuroscience findings concerns what has been dubbed as problem of "reverse inference".

Other type of limitations has to do with the difficulty to reproduce complex scenery like point of sales or the needed of metrics ad hoc (Alcañiz at al., 2017).

Despite the methodological, analytical, and interpretational limitations; however, the potential gains from using neuroscience techniques are far more considerable (Murray and Antonakis, 2019). In this line, Bigné (2015) identifies benefits using consumer neuroscience techniques in marketing such as: able to reveal unconscious reactions, objective psychophysiology information, get study results immediately, capacity to measure consumer interactivity indifferent situations, results integration from different techniques and portability. Consumer neuroscience and its range of neuroscientific techniques may help in understanding the intrinsic state and the dynamics of consumers' emotional states and other brain-based processes (Marques dos Santos et al., 2020) and the data obtained by neuromarketing methods allow enterprises to move to a more effective decision-making stage and to achieve competitive advantage (Cerci and Koyluoglu, 2020).

High analytical accuracy from the engineering part of neuromarketing has substantiated its acceptance over the world. Hence, reviewing the building blocks of neuromarketing is essential to evaluate its scopes and capacities to contribute new perspective in this field (Rawnaque et al., 2020).

Many industries are using neuromarketing: media, consumer goods, financial services, technology and telco, automotive, travel, and services. Most of them for research in market and consumer insights, communication, product design, customer experience, usability, and so on. Most famous market research companies, like *Millward Brown*, *Nielsen* and *Ipsos*, have developed consumer neuroscience departments and begun doing a lot of neuromarketing research for some companies (Raj, 2018). Also, many books have used neuromarketing as a fashionable term that help to attract consumers who want to know about this discipline.

Neuroscience methods being used by practitioners today are incredibly diverse, so conclusions drawn from various methods are different. Then, it becomes important to determine what is optimal from the standpoint of validity (Daugherty at al., 2018). In last meeting "Neuromarketing World Forum", held in Rome 2019, Moses and Tullman (2019) suggests, for the next future, the following goals of this discipline: develop valid neuroscientific techniques, methodologies, and standard metrics.

2.2 **Consumer neuroscience methodology**

Persons are not only rational but also emotional creatures. They use their brain to analyze and understand any situation. Brain is relevant in any situation but specially in business because brain drives behavior. There are a lot of factors that affect behavior: cognitive workload, emotions, stress, motivation, perception, context, information processing, risk aversion, social dynamics, and so on.

Nobel laureate Francis Crick (1994) called it the astonishing hypothesis: the idea that all human feelings, thoughts, and actions, even consciousness itself, are just the products of neural activity in the brain. For marketers the promise of this idea is that neurobiology can reduce the uncertainty and conjecture that traditionally hamper efforts to understand consumer behavior.

In this line Damasio (1996) posits the somatic marker hypothesis as a way of explaining how the brain and body work in concert with one another to lead individuals towards the decisions they make. The somatic marker hypothesis suggests that decision making is a learning process. When we decide, or a choice, and we experience the outcome, we have some low-level emotional response to that outcome manifested as some series of bodily reactions – an increase in skin sweat, a decrease in heart rate variability, an expression of emotion on our face – and information about that response is stored as a "somatic marker" (soma meaning "body") in the brain. When people later find themselves in a similar situation, or making a similar choice, the relevant somatic markers are retrieved and provide information to help guide the decision process.

According to Zaltman (2003), 95% of our decisions related to purchasing are made on a subconscious level, so there are a huge amount of data that are not used because there is simply no way of gathering, analyzing and measuring it. Consumer neuroscience allows capturing and analyze consumers' unspoken cognitive and emotional response to various marketing stimuli and may forecast consumers' behavior. For marketers the promise is that neurobiology can reduce the uncertainty and conjecture that traditionally hamper efforts to understand consumer behavior.

2.2.1 Consumer neuroscience definition

Once neuroscience was applied to the economic field a new term came out neuroeconomics and, logically, new subfields begun to be used combining neuroscience and economics, one of them was consumer neuroscience.

Regarding practitioner's, consumer neuroscience is also known as "Neuromarketing". Professor Dr. Ale Smidts, used the concept of neuromarketing for the first time in 2002 (Cerci and Koyluoglu, 2020; Cherubino et al., 2019). Most practitioners and marketeers use both terms, consumer neuroscience and neuromarketing. However, Hubert (2008) posits a distinct definition of both terms, consumer neuroscience as the scientific proceeding, and neuromarketing as the application of these findings within the scope of managerial practice. Some marketeers suggest that neuromarketing seeks to apply the principles, methodologies and findings of neuroscience to further understand the impact of marketing on human behavior (Daugherty et al., 2018; Lee et al., 2007). Cherubino et al. (2019) make a distinction between consumer neuroscience that, refers to academic research at the intersection of neuroscience and consumer psychology and "neuromarketing," which refers to the application of consumer neuroscience in the marketplace using neurophysiological tools, such as eye tracking, electroencephalography, and functional magnetic resonance imaging, to conduct specific market research.

Some marketers (Daugherty et al., 2018; García and Saad, 2008) suggest that neuromarketing lies at the intersection of multiple disciplines (i.e., psychology, marketing, neuroscience, economics, …).

Most famous market research companies, like *Millward Brown*, *Nielsen* and *Ipsos*, have developed consumer neuroscience departments and begun doing a lot of neuromarketing research for some companies (Raj, 2018). Also, many books have used neuromarketing as a fashionable term that help to attract consumers who want to know about this discipline.

Table 4 collect definitions based on the way marketeers and practitioners name the concept.

Table 4: Consumer neuroscience definitions

Concept	Definition	Author
Neuromarketing	"the application of neuroscientific methods to analyze and understand human behavior in relation to markets and marketing exchanges"	(Lee et al., 2007, p. 200)
Consumer neuroscience	"a sub-area of neuroeconomics that addresses marketing relevant problems with methods and insights from brain research"	(Hubert and Kenning, 2008, p. 1)
Consumer neuroscience	"explores the relationship between the consumer's nervous system and decision making with an interdisciplinary perspective as a combination of both disciplines"	(Hubert and Kenning, 2008, p. 1)

Consumer neuroscience	“the study of the neural conditions and processes that underlie consumption, their psychological meaning, and their behavioral consequences”	(Reimann at al., 2011, p. 610)
Consumer neuroscience	“is the branch of neuroscience research that aims to better understand the consumer through his unconscious processes and has application in marketing, explaining consumer's preferences, motivations and expectations, predicting his behavior and explaining successes or failures of advertising messages...”	(Bercea, 2012, p. 2)
Neuromarketing	“a discipline that studies cerebral process that explain behavior and decisions making in traditional marketing areas: business intelligence, product design, communication, pricing, branding, positioning, targeting, channels and sales.”	(Braidot, 2013, p. 18)
Neuromarketing	“the discipline that investigates and examines brain processes that explain the behavior and decisions of individuals in the fields of action of traditional marketing: market intelligence, product design and service, communications, prices, brand positioning and sales channels”	(Valencia, E., 2017, p. 5)
Consumer neuroscience	“an interdisciplinary area that benefits from neuroscientific methods and findings to gain understanding of the (neuro)- physiological fundamentals of consumer behavior”	(Casado, 2018, p. 26)
Neuromarketing	“represents the encounter end dialogue between scientific knowledge – neurology, behavior psychology, psychiatry -, technologies FMRI, EEG, ME, TMS, TCDS- and economy and marketing in order to study brain reactions to certain stimuli”	(Álvarez del Blanco, 2018, p. 20)
Neuromarketing	“the measurement of physiological and neural signals to gain insight into customers’ motivations, preferences, and decisions, which can help inform creative advertising, product	(Harrell, 2019, p. 64)

	development, pricing, and other marketing areas”	
Consumer neuroscience	“the use neurophysiological signals to gain deeper insight into a consumer brain”	(Alsakaa et al., 2020, p. 1)

Source: Author

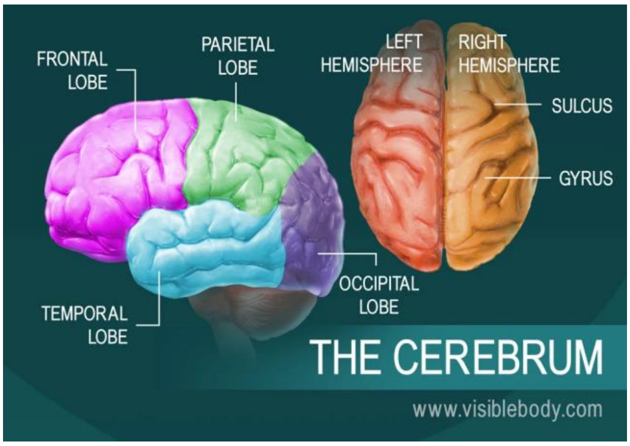
2.2.2 Brain responses

Brain is one of the most complicated and detailed organs in the human body. It is based in a network of nerves and cells that controls every decision that people make daily.

The knowledge of brain anatomy and the physiological functions of brain areas as well as the physiological response due to external stimuli make possible to model brain activity and predict hidden response. So, it is important to recall the interconnection between brain functions with human behavior and actions triggered by the external stimuli.

Brain is a three-pound organ that controls all functions of the body. It controls intelligence, creativity, emotion, and memory. Brain receives information through five senses namely sight, smell, touch, taste, and hearing. It accepts and processes the information and stores it for future use in our memory. The cerebrum is the largest part of the brain. The cerebrum has two distinct hemispheres. Each hemisphere has frontal, temporal, parietal, and occipital lobe. Frontal lobe plays a role in behavior, emotions, Judgment, planning, and problem solving. Parietal lobe Interprets signals from vision, hearing, motor, sensory and memory. Temporal lobe enables understanding of language Wernicke’s area and memory (Raj, 2018). The occipital lobe is responsible for visual perception, including color, form, and motion.

Image 10: Cerebrum parts



Source: www.visiblebody.com[47]

[47] https://www.visiblebody.com/es/learn/nervous/brain

During human cognition cerebrum activates sets of neural circuits underlying for example, perception, attention, or memory. These circuits as abstractions of biological processes. Each circuit is a collection of cerebrum regions which coordinate activity led to these processes.

In his well-known book, “The buying brain”, Pradeep and Patel (2010) explain that brain operates through electrical activity. As different clusters of neurons fire in unison, they create measurable electrical brainwaves at consistent frequencies that are the mechanism of communication between different regions of the brain. Electrical activity begins at frequencies that excites other neurons and the brain starts with different patterns of oscillating electrical rhythms in different regions defining a set of neural circuits.

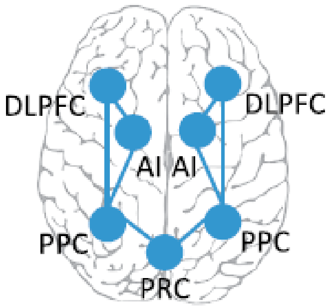
Regarding marketing there are some basic neural circuits that are of relevance for consumer cognition and behavior: attention, emotion, memory and valuation (Álvarez del Blanco, 2018; Hsu, 2017).

Attention circuit

Without a correct attention it’s not possible to get brand or product memory and it’s a fundamental step in advertising. The technique used to understand what captures our gaze is eye tracking (Alcañiz et al., 2017).

Attention circuit enables concentration capacity in one aspect of the stimuli, while others that are also perceived are ignored. Cerebrum circuits activated are AI (anterior insula), DLPFC (dorsolateral prefrontal cortex), PPC (posterior parietal cortex) and PRC (precuneus).

Image 11: Attention circuit.



Source: Hsu (2017)[48]

Emotional circuit

Emotions are one of the most powerful forces driving behavior. Not surprisingly, marketers have long sought to maximize positive emotional associations consumers have with a firm’s product offerings while minimizing negative associations. We still lack scientific

48 https://www.researchgate.net/publication/318979135_Neuromarketing_Inside_the_Mind_of_the_Consumer

consensus on how to define and measure emotions, as well as how they affect choice (Hsu, 2017).

Emotion circuit enables subjective feelings of emotional states such as fear, anger, joy, and sadness. Cerebrum circuits activated are the HYP (hypothalamus), AMYG (amygdala), as well as INS (insula) and ACC (anterior cingulate cortex).

Image 12: Emotional circuit.

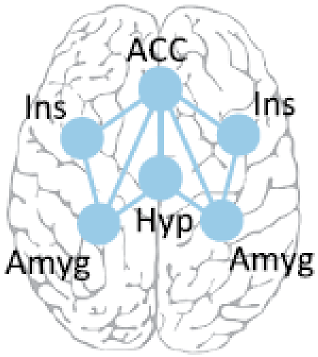


Image 13: Positive affect

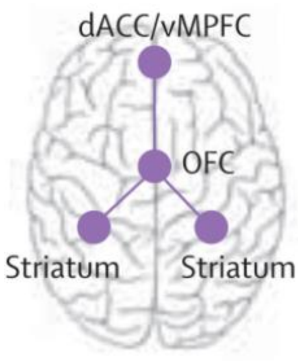
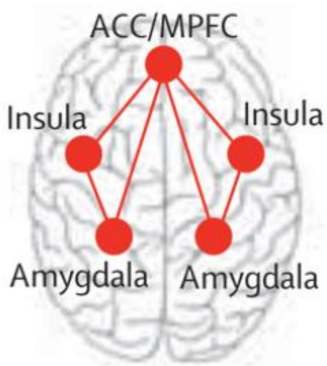


Image 14: Negative affect



Source: Hsu (2017)[49]

Among the consumer emotion recognition-based experiments is observed a trend of analyzing frontal and prefrontal alpha band signals, which corresponds to frontal alpha asymmetry theory (Rawnaque et al., 2020).

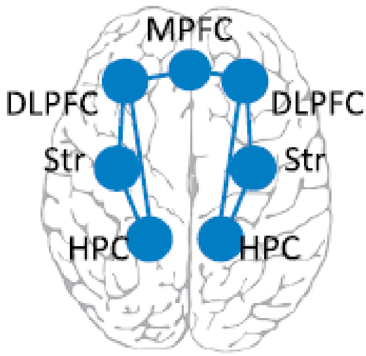
49 https://www.researchgate.net/publication/318979135_Neuromarketing_Inside_the_Mind_of_the_Consumer

Memory circuit

Marketers invest substantially in shaping consumer memories of a firm's brand and product offerings across touch points. An immense amount is known about different forms of memory, the distinct ways in which they form and degrade over time, as well as how they interact and compete.

Memory circuit enables retention and retrieval of facts and events, including one's autobiographical history and knowledge of the world (declarative memory) and execution of integrated procedures such as riding a bike (procedural memory). Formation of declarative memory traces depends on integrity of the HPC (hippocampus), whereas procedural memory depends on striatum. Upon consolidation, long-term memory is thought to be widely distributed across the cerebral cortex, and retrieved by prefrontal cortices, including DLPFC and MPFC (medial prefrontal cortex).

Image 15. Memory circuits.



Source: Hsu (2017)[50]

Valuation circuit.

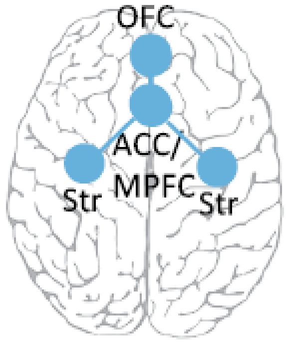
Valuation circuit enables the ability to make cost-benefit tradeoffs and decisions. Hsu (2017) suggests that there are two directions in the valuation circuit that can further benefit marketers. First, examining the structure of neural computations in the context of choice behavior can improve existing models, for example by providing a mechanistic explanation for "irrationalities," such as choice overload, the role of default options, and so on. Second, a better understanding how different circuits interact would allow marketers to map whether and how

50 https://www.researchgate.net/publication/318979135_Neuromarketing_Inside_the_Mind_of_the_Consumer

channels and actions take differential routes to influencing consumer choice, and to optimize the marketing mix as a result.

Valuation circuit is the critical link between upstream processes such as attention to actual choice. Depends critically on the neurotransmitter molecule dopamine, which is released from the VTA (ventral tegmental area) and transmitted to the broader reward circuit including STR (striatum), anterior cingulate, MPFC and OFC (orbitofrontal cortex).

Image 16: Valuation circuit.



Source: Hsu (2017)[51]

There has been skepticism from the beginning about our ability to directly extract hidden information from neural data that are of interest to marketers. However, numerous studies with participants evaluating consumer products and brands during fMRI scanning have found that nucleus NAcc (accumbens), vmPFC (ventral medial prefrontal cortex) and dlPFC (dorsolateral prefrontal cortex) contain information about the consumer's expected utility (Chan, 2020).

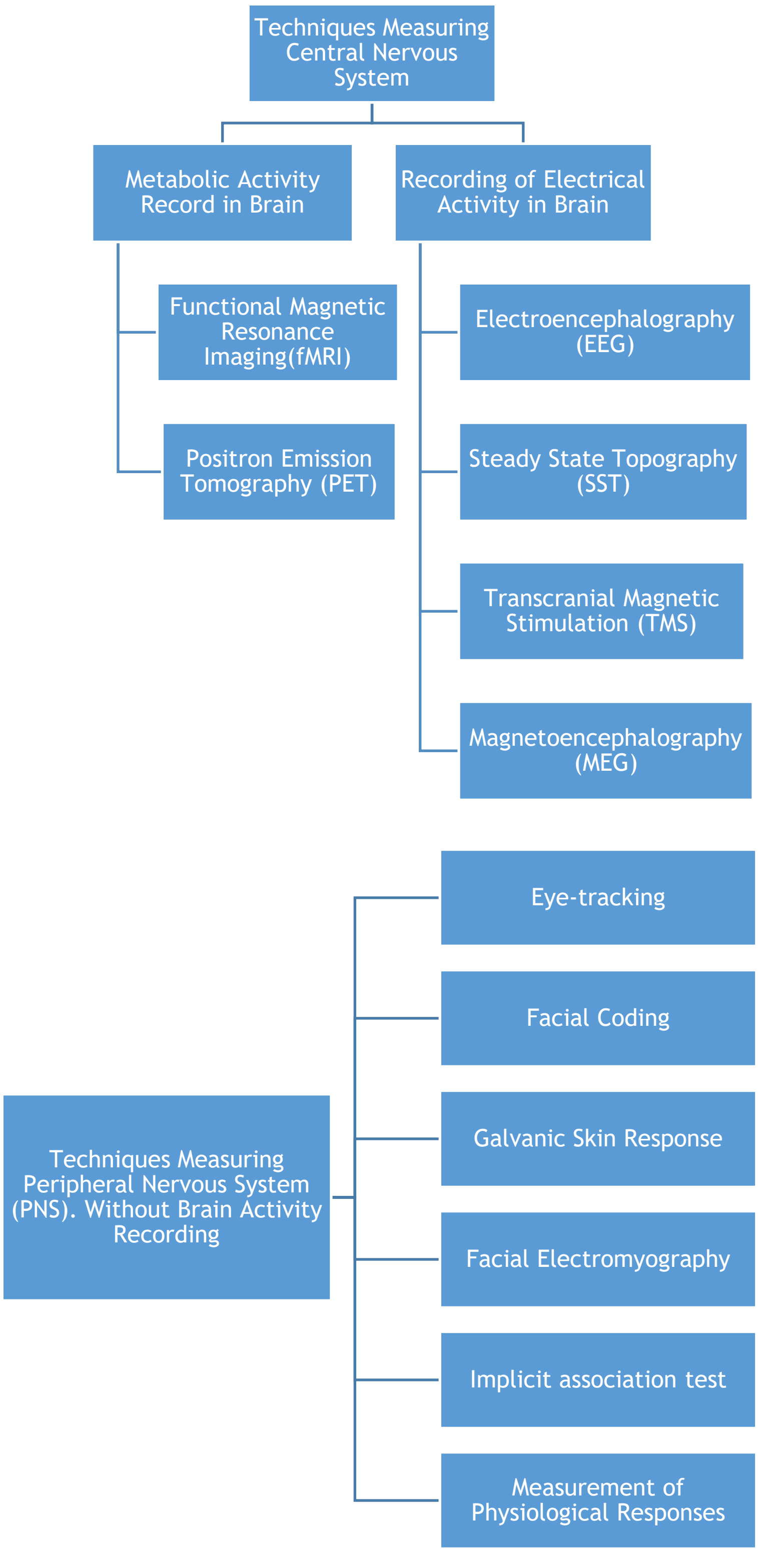
2.2.3 Measurement technologies in consumer neuroscience

Only techniques that measure changes in electrical or metabolic neural activity, namely fMRI, EEG and MEG, are strictly neuroscience techniques. Other tools, such as biometrics or eye-tracking are, of course, useful to advancing in the domain of consumer automatic responses, but they only measure physiological (and not neurological) changes in response to marketing stimuli.

Some marketers (Calvert and Thesen, 2004; Cherubino et al., 2019; Kenning and Plassmann, 2005; Zurawicki, 2010) proposed a division of the research techniques used in consumer neuroscience in two parts: (1) techniques measuring CNS (central nervous system) and (2) techniques measuring PNS (peripheral nervous system). In addition to these techniques, it is necessary to consider the technique HRV (Heart Rate Variability), used in assessments of the Autonomic Nervous System (ANS).

51 https://www.researchgate.net/publication/318979135_Neuromarketing_Inside_the_Mind_of_the_Consumer

Table 5: Consumer neuroscience techniques



Source: Author

2.2.3.1 Techniques measuring CNS (central nervous system)

fMRI (Functional magnetic resonance imaging) is one of the techniques that record metabolic activity in the brain measuring an increase in the oxygen level in the blood flow of the brain (Casado, 2018; Cerci and Koyluoglu, 2020) and using MVPA (Multivariate pattern analysis) moves beyond single voxel activation and focuses on finding activation patterns in a subset of voxels (Chan, 2020).

Karmarkar and Plassmann (2019) suggest that fMRI is by far the most commonly used neurophysiological technique in academic consumer neuroscience research, however, the range of methods available offers researchers the ability to target their experiments to the specific question of interest.

In order to go beyond fMRI limitations other marketers propose using fNIRS (functional near-infrared spectroscopy), which employs headgear similar to EEGs that can track what part of the brain is active (Ahn and Jun, 2017; Çakir et al., 2018; Krampe et al., 2018; Quaresima and Ferrari, 2019; Strait and Scheutz, 2014).

Other researchers suggest PET, as it is one of the most advanced nuclear medicine imaging methods. PET requires, (to show brain blood flow, blood volume, glucose, and oxygen consumption in cells), the injection of radio-active elements to subjects so as to perform imaging and is a rather costly method used mostly in clinical studies. One of the substances commonly used in PET is FDG (fluorodeoxyglucose) that emits positrons and is absorbed by cells with higher activity as they need more energy to compensate for their consumption and PET detects the regions that have activity in the brain by following this molecule. Is less frequently used in neuromarketing research due to its cost and as it can be a disturbing experience for subjects (Bercea, 2012; Cerci and Koyluoglu, 2020; Hsu et al., 2018).

Electroencephalogram (EEG)

EEG is a noninvasive technique (electrodes are place on the head of a person) that measures the electrical activity of the brain, amplifying electric signal, when a group of neurons signal at an external stimulus, however, unlike fMRI, EEG does not grant access to deep parts of the brain. The higher number of electrodes the better monitor of the activity. The activity of neurons creates potential electrical differences within the skull, and this can be measured using an electrode connected to the device that usually records data from 1 to 3 milliseconds.

Although scholars propose that using fMRI is better than using EEG to identify the specific brain location at a high special resolution recording neural activity (Casado, 2018), many researchers (Eijlers et al., 2020; Rawnaque et al., 2020; Yadava et al., 2017) point out that the EEG signals offer a high temporal resolution, is cheaper than fMRI, easy handling, wireless connectivity, it allows for movement of the subject and has lower maintenance cost. Therefore, the downfalls of fMRI are its price, equipment is very expensive to operate, and inconvenience because subjects must lie completely still in a large machine (Harrel, 2019).

Image 17: EEG iMotions device

Source: iMotions (2020)[52]

The use of electroencephalogram (EEG) is found favorable by over functional magnetic resonance imaging (fMRI) in video advertisement-based neuromarketing experiments (Yadava et al., 2017). Thus, in commercial applications, EEG is currently the most popular method and fMRI, which is widely used and more popular in scientific and clinical use, is less often used in marketing and other business-related applications (Hsu, 2017).

STT (Steady State Topography) records and measures electrical signals at the scalp to build a second-by-second picture of activity in the brain (Silberstein et al., 1990). SST allows a researcher to get a consumer response to a stimulus the first time while takes multiple readings over a period.

TMS (Transcranial Magnetic Stimulation) is a technique for noninvasive stimulation of the human brain. Stimulation is produced by generating a brief, high-intensity magnetic field by passing a brief electric current through a magnetic coil. The field can excite or inhibit a small area of brain below the coil. All parts of the brain just beneath the skull can be influenced, but most studies have been of the motor cortex where a focal muscle twitch can be produced, called the motor-evoked potential (Hallet, 2007).

MEG (Magnetoencephalography) tracks the magnetic fields generated by the electrical activity of synchronized neurons. This technique provides information about brain activity using a magnetic field. Unlike functional measurements, such as fMRI, MEG allows direct measurement of brain activity. It has a high temporal and spatial resolution. In contrast to EEG, MEG can display deeper brain structures, but this method is much less used due to its high cost, although it gives more data than EEG (Cerci & Koyluoglu, 2020).

[52] https://imotions.com/

Based on that the use of EEG is found favorable by many researchers over fMRI in video advertisement-based neuromarketing experiments (Eijlers et al., 2020; Rawnaque et al., 2020; Yadava et al., 2017), we analyze more in detail the characteristics of EEG, that records electrical activity.

EEG relates to three analyses measurement-based different aspects of the electric signal: (1) frequency brain waves analysis; (2) hemisphere asymmetric analysis, and (3) even-related potential analysis.

Frequency brain waves analysis

Brain emits in different frequencies, measure in Hz, depending on different mental states, time or different brain parts. Most common frequency is 10hz. Delta is less than 4hz usually sleeping, Theta is between 4-8 hz usually internal process memory activation or conscious concentration, Alpha is between 8-12 hz usually relax or paying attention, Betha is between 13-30hz usually alert and Gamma usually more than 30hz processing information, learning or emotional process.

EEG uses two metrics to measure frequencies:

- Power: Amount of activity in a frequency in a period of time. High power means great activity in a brain region with a frequency.
- Coherence: Consistency or frequency correlation in different parts of the brain. High coherence between regions means that those regions are connected in a process.

Hemisphere asymmetric analysis

Frontal asymmetry theory Davidson et al. (1979) proposed that there is a hemispheric asymmetry regarding the alpha oscillations among the frontal channels, suggesting that the left frontal cortex is more activated during the processing of positive affects whereas the left prefrontal cortex is responsible for the negative affect experienced. Touchette and Lee (2016) have validated this theory.

Regarding hemisphere asymmetry analysis, EEG measures proximity or avoidance of the stimuli. Two frequency bands, theta and alpha, are closely related to frontal asymmetry. When consumers have positive emotions to a stimulus these waves are detected more in front left hemisphere than in the right one and the opposite when consumers avoid stimuli.

Even-related potential analysis

Comparing components, brain response sequencies to a stimulus, we can conclude about different responses conscious or unconscious, personal relevance, attention, expectative or emotions. EEG measures even related potential using components based on:

- Polarity: negative or positive. For example, P300 means is positive and after 300 ms. N400 means is negative and after 400 ms.
- Latency: How long after exposition component happens.

For what refers to the measurement of the constructs and the metrics in EEG, these can be summarized as follows:

- Construct's measure: Attention, cognitive states, mental workload, emotional arousal, motivation, drowsiness, and fatigue.
- Metrics: Frequency band; power: delta, theta, alpha, beta, gamma bands; frontal laterization and asymmetry; even-related potential index; and wavelets.

Rawnaque et al. (2020) point out that alongside traditional filtering methods, ICA (independent component analysis) was found most commonly in artifact removal from neural signal. In consumer response prediction and classification, ANN (Artificial Neural Network), SVM (Support Vector Machine) and LDA (Linear Discriminant Analysis) have performed with the highest average accuracy among other machine learning algorithms used in these literatures. In next table we collect advantages and disadvantages about EEG proposed.

Table 6: EEG advantages and disadvantages

Advantages	Disadvantages
Silent technology	False positives
Noninvasive technique	Artifacts
Harmless device	Difficulty to interpret metric
Excellent temporal resolution	Does not grant access to deep parts of the brain
Unique to register brain activity at speed cognition.	Reverse inference problem
Low cost versus fMRI	Low spatial resolution
Portability	Non scalable

Source: Author

To examine advertising, Krugman (1971) was among the first to use EEG (electroencephalography) (Daugherty et al., 2018). Basar et al. (1999) have shown that oscillations in the EEG signal in certain frequency ranges can be associated with specific psychological processes in the brain. Next table resumes main research marketing results using EEG:

Table 7: EEG marketing research

Study	Results
(Ambler et al., 2004)	Found improvement in predicting the product brand choice based on strong correlations between the brain activation in right parietal cortex with the subject's familiarity with the brand.
(Berka et al., 2007; Chanel et al., 2006)	EEG has been shown to accurately reflect subtle shifts in alertness, attention and workload that can be identified and quantified on a second-by-second time-frame.
(Briesemeister et al., 2013; Ohme et al., 2009)	Frontal alpha asymmetry (FAA) can be used as a potential indicator for identification of the valence of emotions.
(Khushaba et al., 2012)	A significant change in the spectral activity with theta bands were recorded in the frontal, parietal and occipital areas while the participants were indicating their preference by computing mutual information between the user's preference and different EEG bands.
(Kawasaki and Yamaguchi, 2012)	Found an increment in the theta amplitudes when the preferred color was presented or selected by a user.
(Uusberg et al., 2013)	Processing of emotional arousing stimuli is related to alpha suppression.
(Boksem and Smidts, 2014)	High frequencies beta and gamma were significant correlated to individual preferences and population preferences.
(Telpaz et al., 2015)	An increase in N200 component in the mid-frontal electrode and a correlation between the theta band power and the preferred products.
(Baldo et al., 2015)	Classification of products using EEG signals was better than the rating-based classification and proposed a pre-market forecasting system for products
(Venkatraman et al., 2015)	This technique only offers the chance to reveal the neural mechanisms triggered by two main consumer behavior constructs, attention and affect.
(Aliagas and Torres, 2018; Ohme et al., 2011)	A correlation between neural activity, behavior, cognition, and emotion.
(Yadava et al., 2017)	Proposed a predictive modeling framework to understand consumer choice towards E-commerce products in terms of "likes" and "dislikes"
(Palmiero and Piccardi, 2017)	Results were found to be contradictory. Gender and age are critical variables that should be better addressed in future studies; bodily states and hormonal responses might mediate the relationship between frontal EEG asymmetries and mood.
(Barnett and Cerf, 2017)	propose a new methodology measuring neural data to assess the degree of similarity between multiple brains experiencing the same advertisements, and demonstrate that this similarity can predict important marketing outcome

(Karmarkar and Plassmann, 2019)	EEG can be used to measure arousal and engagement responses to information that changes quickly over time
(Eijlers et al., 2020)	Neural measure of arousal is positively associated with notability of ads in the population at large but may be negatively associated with attitude toward these ads.
(Alsakaa et al., 2020)	Results have shown the differences in commercial reception especially memorization and approach-withdrawal. When the commercial is broadcasted when the product is needed, the response of the viewers is better.

Source: Author

2.2.3.2 Techniques measuring PNS (peripheral nervous system)

Many academics prefer brain scanning to physiological proxies for their research (Harrell, 2019), however, practitioners use to apply physiological measuring techniques, because they have been around longer, are less expensive, require less technical expertise to administer, and can easily be paired with more-traditional marketing research tools, such as surveys, focus groups, and implicit association measures.

Techniques measuring PNS used in consumer analysis are Eye-tracking, facial coding, galvanic skin response, facial Electromyography, Implicit association test, and Measurement of Physiological Response.

<u>**Eye-tracking technologies**</u>

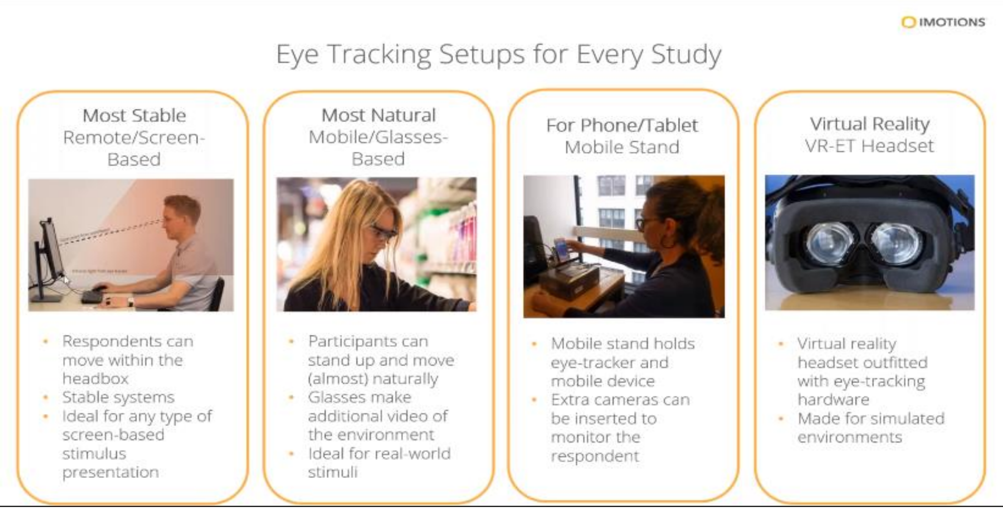
Eye trackers can give indication about human interest by providing information about his/her attention through recording gaze locations and extracting fixations and saccades (Al-Azawi, 2019).

First studies with eye-tracking techniques begun in 1950 (Blascheck et al., 2017) but it’s in the last 20 years that there has been a huge number of studies with eye-tracking technologies (Fiedler et al., 2020; King et al., 2019).

Marketers point out that eye-tracking is important for evaluating user visual behavior and offers one of the best measures of visual attention (Al-Azawi, 2019; Alcañiz et al., 2017; Blascheck et al., 2017; Karmarkar and Plassmann, 2019; King et al., 2019; Lee et al., 2015; Mealha et al., 2011; Muñoz-Leiva et al., 2019; Tangmanee, 2016; Wedel and Pieters, 2013). In this line, King et al. (2019) point out that eye-tracking provide researchers the ability to monitor visual behavior (refers generally to visual perception, visual processing, visual attention, and a variety of other concepts and terms that refer to how sighted people use their vision) via the position and movement of one’s eyes related to events or stimuli displayed on various electronic display screens (e.g., advertisements, video content, online information) or in real-world environments (e.g., objects within a living room setting, particular products on shelves in retail spaces, and so on).

Eye-tracking devices commonly used are screen-based, glasses or virtual reality. Most academics use screen-based because is more suitable for controlled environments, advertisement, user experience, while glasses are more suitable for in store testing, real life situations or package design. Virtual reality is better for simulations or user experience.

Image 18: Eye tracking devices



Source: IMotions (2020)[53]

All these devices follow the eye movement of a user and record gaze point's coordinates (x and y) as large volumes of raw data. The number of gaze points depends on the recording rate of the eye tracking device. The recording rate specifies how many gaze points are recorded per second, ranging from 25 Hz (collects 25 gaze points every second) to 2,000 Hz (collects 2,000 gaze points every second). A good device allows rates between 60 and 500 Hz or more.

Researchers in communication science do not examine raw gaze data, instead, these gaze points can be aggregated into fixations and saccades, the two major categories of eye movement, and record span time, scan paths pupil size and eye blinking developing several concepts, definitions and metrics. Although in relation to definitions of basic eye-tracking terms researchers do not always agree on them, in general most researchers accept the following (Hessels et al., 2018):

- Gaze points: Are the points where the eyes are looking. Depending on device rate data are collected.

- Fixation: Is the aggregation of the gaze points, from which one can inform the observer's interest. Gaze points are aggregated based on a specified area (where they are very closed) and time span, usually between 200 and 300 ms using algorithms. Metrics for fixations are the fixation count (number of fixations), the fixation duration (in milliseconds) and the fixation distribution given as x, y, z coordinates. Fixations are excellent measures of visual attention.

[53] https://imotions.com/

- Saccade: Is the fast movement of the eye from one fixation to another. Saccades typically last about 30–80 ms. Common metrics are saccadic amplitude (distance of a saccade), saccadic duration (in milliseconds) and saccadic velocity (in degrees per second).

- Scan path: Is a sequence of alternating fixations and saccades and gives information about the search behavior of the user. An ideal scan path would be a straight line to a specified target. Deviance from this ideal scan path can be interpreted as poor search. Scan path metrics include the convex hull (which area a scan path covers), scan path length (in pixels) and scan path duration (in milliseconds).

- AOI or ROI: Area of interest or region of interest.

- TFF (Time to first fixation): indicates the amount of time that it takes a respondent (or all respondents on average) to look at a specific AOI from stimulus onset. Provide information about how certain aspects of a visual scene are prioritized.

- FB: Number of fixations before getting to the AOI.

- FD: Fixation duration.

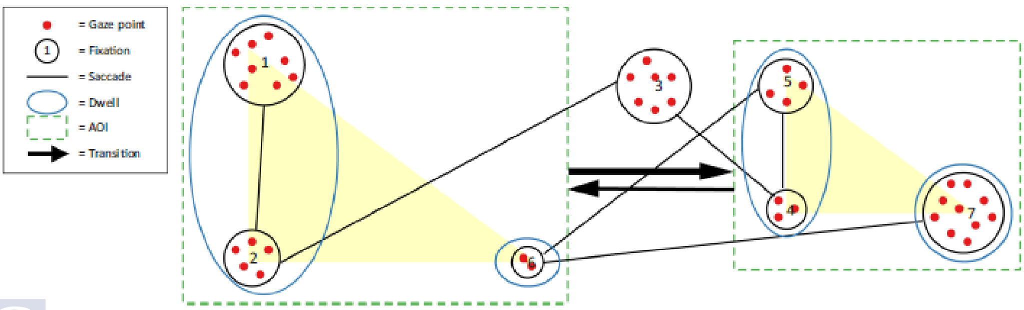
- TFD: Total fixation duration.

- Ratio: Is defined as how many respondents guided their gaze towards a specific AOI. Shows which areas of an image draw the most or least attention, and those areas that weren't attended to at all.

- Revisits: How many times a participant returned their gaze to a particular spot, defined by an AOI.

- Relative time spent quantifies the amount of time spent, expressed as a percentage, actively attending to a particular area or object relative to how long it is shown on the screen.

Image 19: Eye tracking terminology



Source: Blascheck et al. (2017)[54]

54 https://www.researchgate.net/publication/313544252_Visualization_of_Eye_Tracking_Data_A_Taxonomy_and_Survey_Visualization_of_Eye_Tracking_Data

Another important issue for researchers is how these concepts and data are presented in a visual manner, in terms of visualizations. Blascheck et al. (2017) identified two main categories: point-based and areas of interest-based methods.

- Gaze plot. Is a map which shows fixations and saccades.

Image 20: Gaze plot

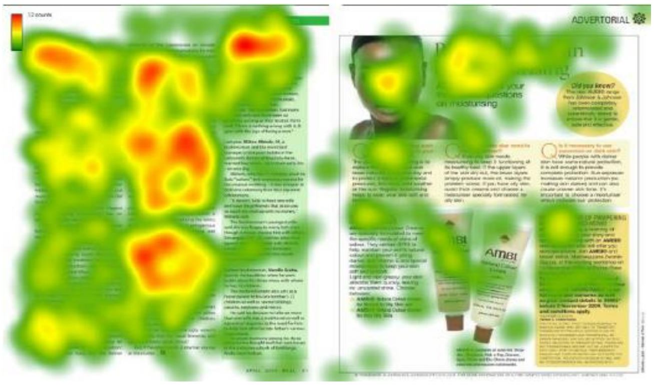
Source: iMotions (2020)[55]

- Gaze replay: Dynamically represents the viewing behavior. It replays the viewing pattern (and possibly the audio as well) on top of the submitted content or the test product. A gaze replay is a playback of an individual test session. Showing gaze data as it looked at any point in time, it allows for deep insight

- Heat map: Are visualizations which show the general distribution of gaze points. Usually based on cursor movement. The assumption is where the cursor goes, so does a visitor's eye. They are displayed as a color gradient overlay on the presented image or stimulus. The red, yellow, and green colors represent in descending order the amount of gaze points that were directed towards parts of the image.

Image 21: Heatmap

[55] https://imotions.com/



Source: researchgate.net (2021)[56]

- Bee swarm. The bee swarm representation shows individual eye gaze fixation events with transition lines between successive fixations. Information is aggregated from each person and visually represented by points that correspond to fixations of each one (red for women and blue for men). If there are a significant number of points in a region it's surrounded by a line.

Image 22: Bee swarm

Source: iMotions (2020)[57]

- Cluster. Visual cluster map representation divides the image in clusters representing the different areas. In the image represents percentage of the participants that see

[56] https://www.researchgate.net/figure/Heat-map-advertisement-in-the-magazine_fig4_273946421
[57] https://imotions.com/

marked areas and it's clustered in two areas 100% first area in green and 56% the upper left of the image.

Image 23: Visual cluster map.

Source: Cerci et al. (2020)[58]

- AOI or ROI (Area of interest or Region of interest): Is the area or region which contains the fixation points. It's not a metric. Transition is the eye movement from one AOI to another and dwell time or time spent is a temporal aggregation of fixations within an AOI. Common metrics for AOIs are the transition count (number of transitions between AOIs), the dwell time within an AOI (in milliseconds) and the AOI hit, which defines whether a fixation is within an AOI or not. It is possible to have more than one AOI.

Image 24: Area of interest

Source: iMotions (2020)[59]

[58] www.igi-global.com/chapter/understanding-consumer-behavior-through-eye-tracking/258414
[59] https://imotions.com/

Data quality and completeness are influenced by many factor including participants, operators, recording environments, eye-tracker unit set-up, and the tasks required of participants. (Holmqvist et al., 2011; Orquin and Holmqvist, 2017). In this line Rayner (2009) posits that eye movement also varies depending on factors such as tasks or goals.

Other problem is that there are many ways that raw eye-tracking data can be aggregated related to position, movement, and other considerations, so it´s necessary to fix standards in eye-tracking methodology (Fiedler et al., 2020; Holmqvist et al., 2011; King et al., 2019). Also missing data management (eye closures/blinks, sneezes, gazes away from stimuli, equipment malfunction) needs to be considered for studies using eye tracking (King et al., 2019).

Researchers should be transparent and complete in their reporting particularly in relation to providing information about data collection procedures, missing data management, and research practice explanations. Fiedler et al. (2020) have recently published a guideline for Reporting Standards of Eye-tracking research in decision sciences.

Blascheck et al. (2017) suggest, that researchers should be trained in how to use visualizations, since although statistical analysis provides quantitative results, visualization techniques allow researchers to consider other aspects of recorded eye-tracking data in an exploratory and qualitative way. Visualization techniques help understand spatiotemporal aspects of eye tracking data and complex relationships within the data.

In Table 8 we have resumed advantages and disadvantages of eye-tracking based on marketer's research.

Table 8: Eye tracking advantages and disadvantages.

Advantages	**Disadvantages**
Accessible	Different aggregation methodologies
Easy to understand	Different software proprietary methodologies
Easy handling	Low flexibility since it does not work efficiently with glasses and contact lenses.
Not intrusive	Researchers should be trained in how to use visualizations.
Applicable to any visual stimuli	Does not measure emotions

Relatively inexpensive	Don't tell about perception, only what subjects see
Portability	Records the center of the visual gaze not the periphery

Source: Author

In advertising research, two important issues that practitioners and researchers are working on are viewability and percentage seen of an ad.

Viewability is a measure of how visible ads are to a user. The IAB (2016) defines a viewable impression as one that's at least 50% visible for at least one second. A practitioner research done by Batkin (2021) found that when an ad has been viewed for 20 seconds or longer, brand awareness increases by 334 per cent when compared to an ad that is 50 per cent in-view for just one second.

The MMA (2019) refers percentage seen as the percentage of people that have a minimum of three gaze points (60ms) on an ad in a given ad duration. Clark et al. (2018) suggested that the percentage of the advertisement viewed is determined by the amount of time visual attention was fixated on the advertisement.

Regarding advertising research with eye-tracking, Simola et al. (2013) point out a discrepancy between attention and memory results, suggesting that incongruence increased attention to ads, whereas congruency improved recognition of ads. In addition, ads presented on the right attracted more attention and were recognized better than ads on the left.

Tangmanee (2016) showed that: (1) nearly all subjects fixated at least once on an ad banner in a clip, but less than 10% were able to correctly recall the ad content viewed, although half of viewers were able to correctly recall clip details, (2) fixation duration on the banner and fixation counts on the clip are negatively correlated, and (3) relationship between fixation duration and counts on the banner was insignificant. Visual attention measures based on eye-tracking data differs from measures of self-reported recall and visual attention to an ad banner is paid at a low level of awareness, which explains why the associations with the ad did not activate its subsequent recall. (Muñoz-Leiva et al., 2019)

Investigating snippet length in mobile with eye-tracking, Sachse (2019) indicates a strong influence of page fold on scrolling behavior and attention distribution across search results. Regardless of query type, short snippets seem to provide too little information about the result, so that search performance and subjective measures are negatively affected. Long snippets of five lines lead to better performance than medium snippets for navigational queries, but to worse performance for informational queries.

Wang et al. (2019) using the motion of the eyes as a descriptor of the image, investigate if images can be discriminated based on the gaze patterns recorded while users merely recall an image. Their results indicate that image retrieval is possible with an accuracy significantly above chance.

Based on previous communication research, we can make a resume of which metrics and constructs research used in eye-tracking:

- Construct's measure: Visual attention, emotional arousal, engagement, drowsiness, and fatigue.
- Metrics: Eye movements: gaze, fixations, saccades; blinks, and pupil dilatation.

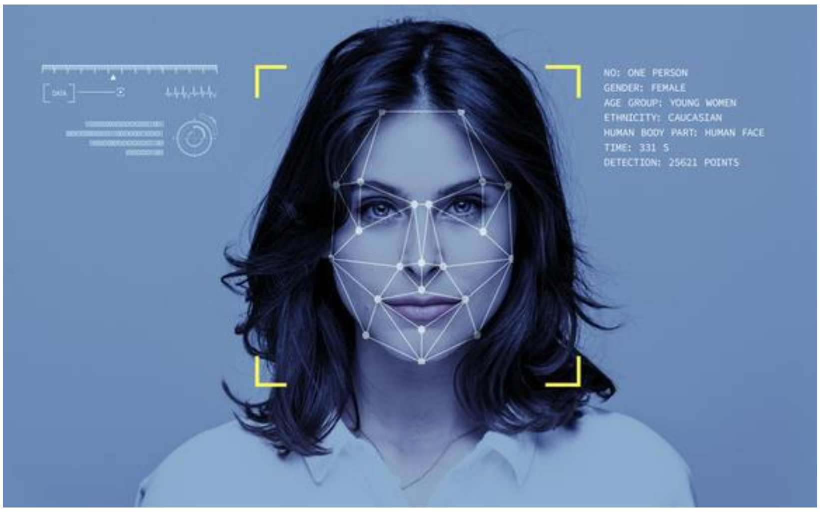
Facial coding

The measurement, collection, and systematic analysis of facial expressions are commonly known as Facial coding, FEA (Facial expressions analysis) or FACS (Facial Action Coding System[60]) and has been used to reveal emotional responses (Ekman et al., 1987).

Facial expressions are movements of the numerous muscles supplied by the facial nerve that are attached to and move the facial skin. Facial nerve connects most of the muscles in the face with the brain, specifically with the amygdala that also modulates the emission of cortisol and other stress hormones into the bloodstream that control heart rate, skin conductance and respiration as well as observable behaviors. Amygdala has been found to be responsible for autonomic functions associated with emotional arousal.

FEA software systems usually first detect landmark points in a face via facial alignment, and then map the temporal changes of landmark points to emotions via the FACS as we can see in this image.

Image 25: Facial alignment



Source: Neurologyca (2020)[61]

[60] The Facial Action Coding System is a catalog of 44 unique action units (AUs) that correspond to each of the face's 27 muscles.
[61] https://neurologyca.com/

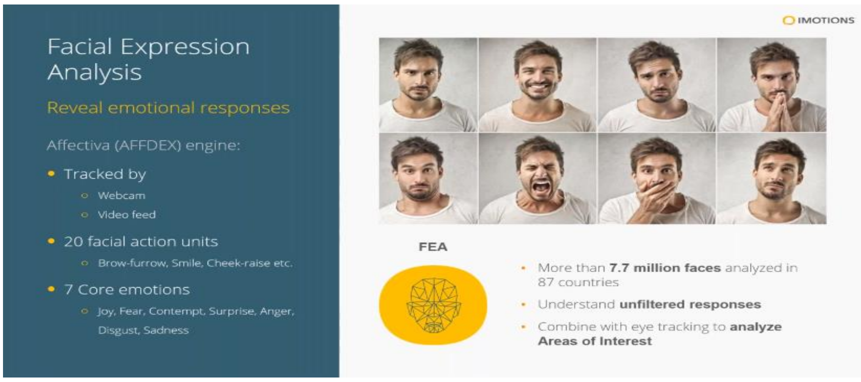
FACS allows a modular construction of emotions based on the combination of AUs (Action Units). Each AU correspond to an individual face muscle identified by a number AU1, AU2, and so on, so all facial expressions can be split in AUs and use the three facial expressions categories: (1) macro expressions that typically last 0,5-4 seconds in daily interactions; (2) micro expressions last 0,5 second when trying to consciously or unconsciously conceal current emotional state; and (3) subtle expressions associated with the intensity and depth of the underlining emotion. All software does the same analysis procedure based on face detection, facial landmark detection and registration and facial expression and emotion classification.

Three software and algorithms have been used to assess emotions using the Facial Action Coding System and differ basically in the number of metrics that they automatically coded using different databases:

- Face Reader-FEBE system (Lewinski et al., 2014).
- GfK-EMO Scan software (Harmeling et al., 2017)
- AFFDEX and FACET. These two algorithms are used by iMotions to classify emotions from facial expressions. According to Stöckli et al. (2018) iMotions can achieve acceptable accuracy for standardized pictures of prototypical (vs. natural) facial expressions but performs worse for more natural facial expressions. Also, Taggart et al. (2016) point out that iMotions software is not designed for remote use and it's not intended to provide higher analytical capabilities.

Software use a webcam to record facial expressions and compare them (using statistics) with a database of facial expressions. The classification is based on a probabilistic result reflecting the likelihood that the facial expression coincides with the right one.

Image 26: Emotions Facial Expression Analysis

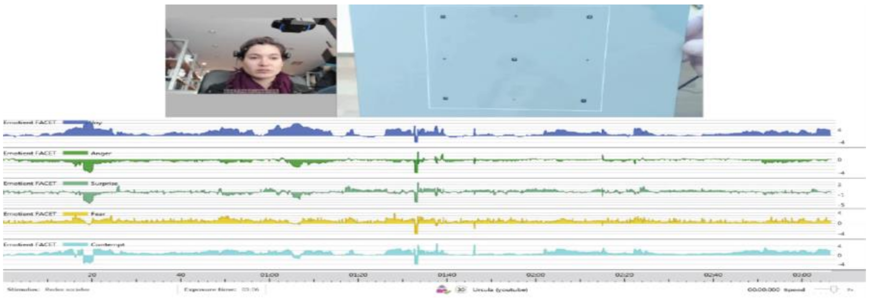


Source: iMotions (2020)[62]

62 https://imotions.com/

Software measures position and orientation of head and facial landmarks and activation of action units and emotion channels to interpret emotional valence and congruency of self-reports. The recorded values for the raw indicators are then transformed by the software underlying models into Ekman's seven basic emotions. An indicator for each emotion is provided based on the probability of appearance of the emotion, so the range of values for each of them is from 0 (no expression) to 100 (expression fully present). A value of 50 is proposed by AFFDEX as an initial threshold to determine if an emotional response has been detected.

Image 27: FACET output for emotions



Source: Neurologyca (2020)[63]

Software also detects emotional valence (positive, neutral, negative).

Image 28: Emotional valence

Source: Neurologyca (2020)[64]

[63] https://neurologyca.com/

[64] https://neurologyca.com/

A new algorithm with Artificial intelligence and deep learning named Kopernica has been developed by Neurologyca. Kopernika is an artificial intelligence that detects 32 emotions analyzing human being facial image reaction to a stimulus, calculating 140 facial coding points compare to actual 60 points of most advanced algorithms and developing a 3D facial human being model. Software KPNTest can segment all captured frames (captures data each 200 milliseconds versus AFFDEX 20 ms) and select high quality information ones generating a csv file for each participant. Kopernica has been trained with more than 20 mill images from participants in laboratory studies.

Kopernica use a double data filter system that other algorithms like Facet and affective does not. This system erases images that don't have the minimum quality. Kopernica erases all images that may point out a wrong emotion base on a wrong face and only accept high quality images. This means that probably we can have less data but more accuracy. This situation usually happens with mobile images.

KPN QUALITY erases all images that face are not clear due to: reflections, darkness, images excess, hand hidden the face.

KPN FILTER erases all images that face is find but it's not clear like high turn up or down faces, that could give data error in emotions.

Image 29: Kopernica dashboard

Source: Neurologyca (2020)[65]

Emotion's measurement is based on understanding the seven basic emotions proposed by Ekman and colleagues (Ekman et al., 1987; Ekman and Rosenberg, 2005): two positive (joy and surprise) and five negatives (anger, contempt, disgust, fear, and sadness). Hill (2018)

[65] https://neurologyca.com/

classifies these emotions into three classes: approach emotions (happiness, anger, sadness), spurning emotions (contempt, disgust) and reactive emotions (surprise, fear).

According to Ekman and colleagues (Ekman et al., 1987; Ekman and Rosenberg, 2005), the micro-expressions generated for certain number of muscle groups to reflect human emotions are universal, regardless of demographic characteristics, and people reveal their real reactions through micro expressions even if they want to hide them. However, Hu et al. (2015) suggest differential emotion attribution to neutral faces of different races and Girard and McDuff (2017) collected a large number of smile responses, a globally common facial expression, and showed that there are cultural and geographical differences in the expression of smiles.

Researchers have two theories about how the different emotions could be distinguished from each other (Eerola and Vuoskoski, 2011):

- Discrete emotion theory. It assumes that the seven basic emotions from Ekman are mutually exclusive, each with different action programs, facial expressions, physiological processes, and cognitions.
- Dimensional models. It accepts that emotions can be grouped and arranged along two or more dimensions. These models usually use valence (positive vs negative emotions) and arousal (activating vs calming emotions). Based on valence and arousal more emotional classifications are possible splitting up basic emotions.

Based on previous communication research, we can make a resume of which metrics and constructs research used in facial coding:

- Construct's measure: Emotional valence and responsiveness to stimuli.
- Metrics: Muscle contraction onset, offset and duration; AU activity.

In next table we have resume advantages and disadvantages of facial coding based on marketer's research.

Table 9: Facial coding advantages and disadvantages

Advantages	**Disadvantages**
Real-time data	Subjectivity: Probabilistic result.
Non-intrusive	Requires specialist training
Objective and quantitative measurement	Intensive task
Could be done in remote	Many sources of noise in non-control environment.
Low cost	Require high quality video equipment

Reliable to describe facial expressions	Difficult to compare: Each software uses a different database.

Source: Author

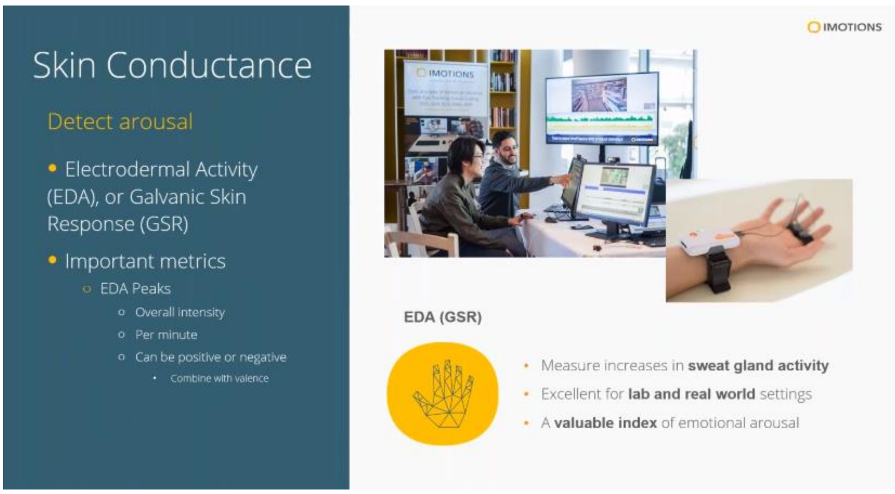
Galvanic Skin response

GSR (Galvanic Skin Response) is a method of measuring the electrical resistance of the skin, which varies with its moisture level. GRS has been mentioned with different names: ElectroDermal Response (EDR), PsychoGalvanic Reflex (PGR), and Skin Conductance Resistance (SCR). In combination with HR sensors, GSR can help determine wellness and emotional responses to external stimuli. So that, GSR measures the skin conductivity to determine response to the stimulus from the nervous system.

The number of sweat glands varies across the human body but is the highest in hand and foot regions (200–600 sweat glands per cm2), where the GSR signal is typically collected from. Therefore, generally, skin conductance is captured using reusable electrodes attached to two fingers of the hand, which are easy to apply. Sweat glands are controlled by the sympathetic nervous system so skin conductance is not under conscious control. A change in the electrical resistance of the skin that is a physiochemical response to emotional stimulation increases the sympathetic nervous system activity. Data is acquired with sampling rates between 1 – 10 Hz and is measured in units of micro-Siemens (µS).

When there are significant changes in GSR activity in response to a stimulus, it is referred to as an Event-Related Skin Conductance Response (ER-SCR).

Image 30: iMotions GSR measurement



Source: iMotions (2020)[66]

[66] https://imotions.com/

There are different software providers to measure GSR. One of most known software providers is *iMotions* software that has been used by many researchers and practitioners (Taggart et al., 2016).

Image 31: IMotions GSR software output

Source: iMotions (2020)[67]

The time course of the signal is the result of two processes: (1) a tonic base level driver, which fluctuates very slowly (seconds to minutes), and (2) a faster-varying phasic component (fluctuating within seconds). Changes in phasic activity can be identified in the continuous data stream as these bursts have a steep incline to a distinctive peak and a slow decline relative to the baseline level.

These responses, otherwise known as GSR peaks, can provide information about emotional arousal to stimuli. Arousal is a crucial dimension for determining the emotional state of the participants. In fact, the GSR is considered a sensitive and convenient measure for indexing changes in sympathetic arousal associated with emotion, cognition, and attention (Critchley, 2002). The higher the arousal, the higher the skin conductance. The GSR signal is not representative of the type of emotion, but the intensity of it.

Westerink et al. (2008) found that the GSR method correlated with sympathetic activity that is also demonstrated to be correlated with the emotional arousal; Boucsein (2012) suggests that the arousal level correlates with the GSR measure that measures the electrical resistance of the skin through giving very low levels of amperes (at milliampere level) and measuring the voltage and Lei et al. (2017) posit that there is a slightly higher correlation between emotion and GSR compared to emotion and heart rate. However, Taggart et al. (2016) point out that skin

[67] https://imotions.com/

conductance response was not as efficient due to some possible factors such as room temperature or body temperature.

An important issue is delay, not because of slow cognitive responses but because of the physiological latency of the GSR. The identification of a time window that the GSR rise is assumed to happen is quite critical, as it is the basis on which the response is determined and Lei et al. (2017) point out that a standard, widely used approach is to use a window between 1 and 4- or 5-seconds following stimulus presentation.

Table 10: GSR advantages and disadvantages

Advantages	Disadvantages
Easy to set up	More informative if combined with other neurometric tools.
Non-intrusive	Variations based in factor such as room or body temperature.
Easy transport	medications and hydration can also change measurements.
	different measurement locations can lead to different responses.
	Signals are delayed 1-5 seconds.

Source: Author

Based on previous communication research, we can make a resume of which metrics and constructs research used in Galvanic Skin Response.

- Construct's measure: Emotional arousal, engagement, and congruency of self-reports.
- Metrics: Skin conductance response.

<u>Heart rate</u>

HRV (Heart Rate Variability) is used in assessments of the ANS (Autonomic Nervous System) to evaluate human emotions. More precisely, variability in heart rate has been used to capture the arousal and attention of ad viewers. Sung-Nien and Chen (2015) proposed an emotion recognition system that is capable of differentiating four kinds of emotions, namely neutral, happiness, stress, and sadness, based on the heart rate variability.

Researchers have used heart rate decelerations to measure in television commercials response to cuts, edits, and movement, video graphics. Lang (2000) demonstrated heart rate decelerations to negative video images and to changes in content (for example, breaks between program and commercials) while Azarbarzin et al. (2014) point out that heart rate response to arousal appears to be most strongly related to arousal intensity and the increase in heart rate for a given arousal intensity varies considerably among subjects. Quintana et al. (2012) suggest that HRV is positively associated with performance on an emotion recognition task.

Okada et al. (2018) measured heart rate from the RGB facial images of participants watching a video that evokes the five basic emotions amusement, anger, disgust, sadness and surprise, and estimated each emotional state with an accuracy of 94%.

Based on previous communication research, we can make a resume of which metrics and constructs research used in HRV:

- Metrics: Heart rate variability
- Construct's measure: Emotional arousal, stress, attention, and cognitive workload.

Multi-technique approach

Multi-technique approach has a key objective: to understand consumer behavior using metric from different technologies. Researchers suggest that consumer neuroscience technologies complement each other to get a better understanding of the results, so many new studies combine different technologies. Alcañiz et al. (2017) point out that identifying correlation between metrics from different technologies (i.e., correlation between an emotion form FAE or eye-movement from eye-tracking) give us a practical value, better studies and less cost, while Muñoz-Leiva et al. (2019) comment that these methodologies can be used to gauge marketing efforts measuring the nonverbal body responses and opens an infinite number of possibilities for studying the attention consumers pay to online advertising and marketing in general.

In table 11 we can see what it's measured with each technique and where we can see different technologies for the same measure.

Table 11: Technologies and what they measure

Technology	What they measure
EEG	Attention Excitement Emotional valence Cognition Memory encoding Recognition Approach Withdrawal Mental workload

	Recall
ET	Visual search Fixation position Eye movement patterns Spatial resolution Excitement Visual attention Pupil dilation Speed of recognition
FEA	Unconscious reactions Emotions Valence
GSR	Emotion Valence Arousal
HR	Emotion Valence Arousal Ad recognition

Source: Author

In a research done about the most effective technique, for an average study, Lozano and García (2017) suggest fMRI, but most demanded are eye tracking and EEG.

Next table resume studies conducted using the multi-technique approach in marketing and their results.

Table 12: Multi-technique marketing research

Study	**Multi-technique**	**Results**
(Guixeres et al., 2017)	EEG, heart rate variability and eye tracking	A significant correlation between neuroscience metrics and self-reported of ad effectiveness and the direct number of views on the YouTube channel.
(Pham and Wang, 2017)	Facial expressions and physiological signals	Marketeers have shown improvements in accuracy when combining facial

		expressions and physiological signals into a multimodal system.
(Okada et al., 2018)	FAE, HR and machine learning	Ad liking can be predicted better than when only single-mode features are used
(Cherubino et al., 2019)	HR, GSR, EEG and ET	Measure cognitive and emotional responses and lead synergy for new insights, particularly in relation to consumer behavior and marketing communications
(Gountas et al., 2019)		A combination of different research methods (e.g., qualitative, surveys, behavioral experiments and neuroscientific tools) is likely to provide a more comprehensive understanding of how consumers process advertising information and what are the prospects of future behavioral change
(Wilson, 2020)		Eye-Tracking, Facial expression and skin conductance work very well together and complement each other
(Cerci and Koyluoglu, 2020)		Synchronizing electroencephalography with other instruments may give more accurate results on a subject’s

		response to a marketing stimulus
(Zito et al., 2021)	EEG, SC and ET	Detection of the emotional responses through neuromarketing tools, associated with the non-profit communication, resulted particularly effective

Source: Author

Based on the demand, software companies specialized in consumer neuroscience have develop solutions that work simultaneously with all these technologies. As an example, Taggart et al. (2016) point out that iMotions software is an excellent platform for collecting data from multiple biometrics sources, as long as the experiment is taking place locally. In this line, a study conducted in 2016 by iMotions with CBS highlighted the power of using a multi-technique, or multimodal, approach vs unitary technique explaining percentage of store sales variance. However, the iMotions platform is not intended to provide higher analytical capabilities.

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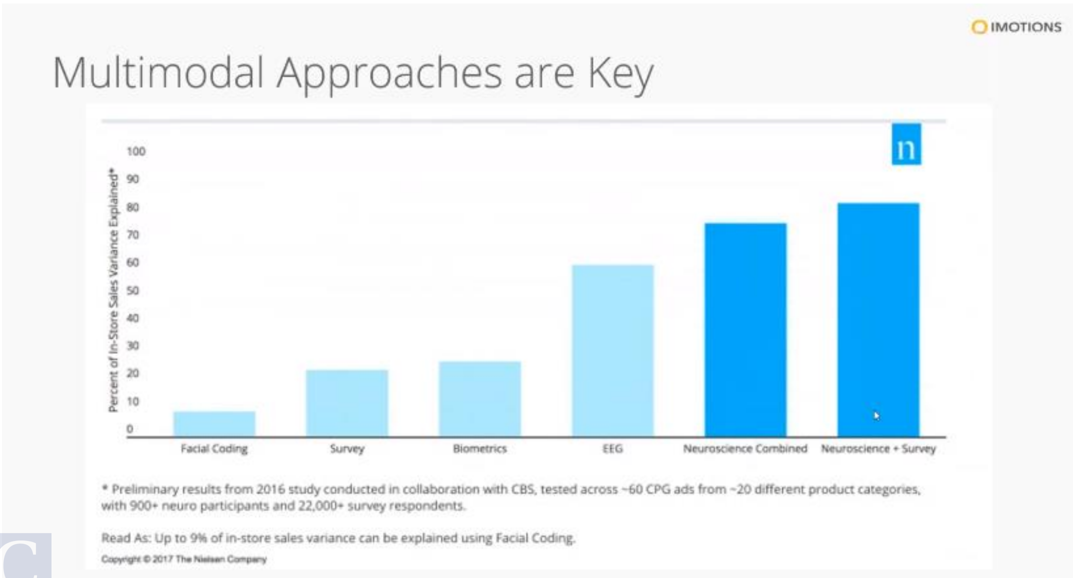
Image 32: Multimodal approaches



Source: iMotions (2017)[68]

[68] https://imotions.com/blog/neuromarketing-research/#fmcg

2.2.4 Research done in consumer neuroscience

People use not only the rational part but also the emotional part of the brain in order to take decisions (Damasio, 1994), thus researches begun to investigate how brain respond to different marketing stimuli in order to understand consumer behavior. However, it was not until nearly the end of the century, that biomedical imaging technology finally progressed to the point of allowing researchers to noninvasively measure and track neural activity at a spatiotemporal scale that reflects core features of cognitive and behavioral operations of the human brain (Hsu, 2017).

Consumer's neuroscience is increasingly becoming a field of interest both for researchers and for the business area, because it provides additional and better information than the traditional marketing methods (Vlăsceanu, 2014). This interest has been confirmed by the increase in the number of papers from 2006 to 2018 focused on consumer neuroscience (Casado, 2018) and this researcher suggests that coming years will see large numbers of publications in consumer neuroscience.

Currently, consumer neuroscience is becoming an essential part of any consumer research study and it's applied to a wide variety of use cases: video advertising, driving and in-vehicle experiences, sensory evaluations, shopper experiences, and many more (Murray, 2019).

Complementing the bibliometric analysis done by Casado (2018), table 23 shows studies done in the last three years, in order to understand which are the new directions in consumer neuroscience research. We must point out that there are a lot of practitioner's studies that have been done in last 10 years for companies around the world and most of them are not published as papers.

Table 13: Studies in consumer neurosciences done by marketers 2018-2020.

Studies	Neuroscientific technology	Marketing variable
(Yang, 2018)	EEG	Advertising
(Juarez, 2018)	ET, EEG, SCR	Packaging
(Valencia, 2018)	ET	Communication
(Aliagas and Torres, 2018)	ET	Advertising
(Daugherty et al., 2018)	EEG	Advertising
(Muñoz-Leiva et al., 2019)	ET	Advertising
(Al-Azawi, 2019)	ET	Consumer behavior
(Sachse, 2019)	ET	Communication

(Wang et al., 2019)	ET	Communication
(Alsakaa et al., 2020)	EEG, HR, SCR.	Advertising
(Chan, 2020)	fMRI	Advertising
(Malygina and Perepelkina, 2020)	ET, PPG	Advertising
(Eijlers et al., 2020)	EEG	Advertising
(Otamendi and Sutil, 2020)	FEA	Advertising
(Marques dos Santos et al., 2020)	EEG EDA/SCR, ET, HR	Communication
(Cerci and Koyluoglu, 2020)	ET	Advertising
(Zhang et al., 2020)	EEG	Advertising
(Zito et al., 2021)	EEG, SC, ET	Advertising
(Alimardani and Kaba, 2021)	EEG	Advertising

Source: Author

CHAPTER 3. HYPOTHESES

This Doctoral Thesis posits several hypotheses divided in two groups. First group considers the effect of several video advertising in consumer engagement using traditional survey and consumer neuroscience techniques. Second group analyzes how video ads in mobile affect metrics related to engagement, such as cognitive workload, attention, recall memory, emotional intensity, and valence, compare those same video ads in PC or TV.

3.1 Hypotheses about video ads effectiveness measured through traditional and neuroscience techniques

During last 10 years, as consumers spend more time in mobile, online advertising spend in mobile had a huge development. MMA (2020) posits that the role played by a mobile device to influence a consumer to purchase in a physical store has become significant today.

As video mobile consumption is increasing, so does advertising in mobile, and one of the reasons is that advertisers are looking for new media, such as mobile devices, to gain more consumers attention by avoiding actual clutter in communication media with lots of competitors, platforms, and media.

From time spent in mobile, 63% of mobile traffic is video (Appannie, 2020; Ericsson, 2020; Kemp, 2021) and main driver is the rapid diffusion of video content such as embedded video in web browsing, social media, plus increased video streaming and sharing services and forecast is 30% increase each year.

In this line, a survey in 2017 *Bain and Company* (2017) shows that some companies are misled by their own metrics, and those they use to calculate mobile's effectiveness are often incomplete. While 94% of smartphone owners use their devices to search for a store, that activity is captured by conventional metrics only when a consumer uses his or her phone to buy something.

Some researchers suggest that metrics such as incidence of site visitation, minimum time on screen, click and conversion rates (Ghose et al., 2013), recurrent usage, demographics, social shares, revenue leads generated, number of downloads, and tagging of geospatial-location information currently are among the measures with the most utility for generating success metrics for stakeholders in mobile (Fulgoni and Lipsman, 2017).

A recent survey Sterling (2019) found that most marketers are using traffic to their websites as the principal measure of campaign effectiveness, reflecting a general lack of measurement sophistication.

Researchers (Clark et al., 2018; Grewal et al., 2016) posit that one of the main problems in mobile advertising is the lack of standardize metrics in the advertising industry. The only measurement is the direct behavioral response and usually requires the additional design and implementation of a post-campaign survey. However, all actors in the advertising industry, publishers, advertisers, and agencies cite engagement as a crucial variable in the success of ad campaigns. Also, researchers and marketers have identified engagement as a good variable to measure advertising effectiveness (Addis, 2020; Calder and Malthouse, 2008; Grewal et al., 2016; Marbach et al., 2019; Mersey et al., 2010; Rasool et al., 2020).

If engagement is a good variable to measure advertising effectiveness, we propose to study first engagement, its dimensions, its metrics, and data collection methodologies to establish hypotheses related to the measurement of advertising effectiveness in mobile.

Together with the consumer engagement metrics associated with conducting surveys, this Doctoral Thesis proposes using a class of brain-based measures –based-neuroscience- which have potential to serve as a marker of engagement. The intuition of these measures is that, as engaging content triggers similar behavioral and psychological responses across individuals, this will be reflected in similar neural responses across people. This class of measures obviates the need to pinpoint a precise “engagement” module of the brain and instead focuses on complementing and building upon existing measures.

However, given that companies that are dedicated to the measurement of advertising effectiveness use their own algorithms, with characteristics that differentiate one from the other, we consider it interesting to analyze the degree to which, for three video ads, the measurement results of metrics related to the consumer engagement dimensions converge with each other. We also consider it of interest to check to what degree data associated with the engagement dimensions obtained through surveys are correlated with those obtained through neuroscience techniques in the corresponding dimensions. Thus, the first group of hypotheses proposed deals with these issues, while the second group of hypotheses examines the differences, or not, in the adverting effectiveness in three devices: mobile, PC and TV. To do so, we use various metrics related to the cognitive and affective dimensions of consumer engagement.

3.1.1 Consumer engagement: concept and dimensions

The study of engagement has been developed in a wide spectrum of academic disciplines such as education, psychology, sociology, political science, computer systems, and organizational behavior (Ballesteros-Herencia, 2018; Brodie et al., 2011; Hollebeek, 2011; Vivek, 2009). Rosado-Pinto and Loureiro (2020) in their systematic review analysis about engagement found 648 papers from 2005 till 2018.

In marketing literature, Hirschman and Holbrook (1982) were the pioneers but it has been in the last fifteen years that most of studies about engagement in marketing have been done. Organizations like the MSI (Marketing Science Institute), IAB or the MMA have also contributed to boost the interest of academics on this topic by considering it a priority (Vivek et al., 2012).

Kumar and Pansari (2017) suggest that engagement has become a popular word due to the fact that satisfaction is no longer enough to ensure loyal and profitable customers and the goal of organizations evolved from relationship marketing to engaging customers in all possible ways. Engaging customers is important because it increases customer value.

Marketers are making significant investments in providing consumers seamless digital experiences and immediate customized solutions to engage them with their brands (Kaur et al., 2019).

To resume this interest, next tables detail articles in chronological order about engagement, types of engagement and engagement in mobile.

Table 14: Articles about engagement in marketing

Engagement	Author
Strength of engagement	(Higgins, 2006)
Engagement with an advertisement	(Heath, 2007)
Engagement or satisfaction	(Calder et al., 2009)
The concept of engagement	(Gambetti and Graffigna, 2010)
Engagement with facebook	(Hart et al., 2015)
Engagement index	(Ballesteros-Herencia, 2018)
Engagement with social media	(Voorveld et al., 2018)
Engaging brands	(Addis, 2020)
Advertising engagement	(Wang, 2006)

Source: Author

Table 15: Articles about different types of engagement in marketing

Engagement type	Author
Customer engagement	(Vivek, 2009) (Patterson, 2006) (Bowden, 2009) (van Doorn et al., 2010) (Verhoef et al., 2010) (Kumar et al., 2010) (Van Doorn, 2011) (Brodie et al., 2011) (Cheung et al., 2011) (Gummerus et al., 2012) (Sashi, 2012) (Vivek et al., 2012) (Brodie et al., 2013) (Vivek, 2013) (Verleye et al., 2013) (Wirtz et al., 2013) (Oviedo-García et al., 2014) (Jaakkola and Alexander, 2014) (Wallace at al., 2014) (Schamari and Schaefers, 2015) (Dessart et al., 2015) (Lujja and Özata, 2016) (Gatautis et al., 2016)

	(Scholz and Smith, 2016) (Hollebeek et al., 2016a) (Masłowska et al., 2016) (Islam and Zillur, 2016) (Hollebeek et al., 2016b) (Harmeling et al., 2017) (Romero, 2017) (Kumar and Pansari, 2017) (Fehrer et al., 2018) (Lee et al., 2018) (Gavilanes et al., 2018) (Hollebeek et al., 2019b) (Marbach et al., 2019) (Mclean and Alan, 2019) (Do et al., 2019) (Malthouse et al., 2019) (Hollebeek et al., 2019a) (Rasool et al., 2020) (Shawky et al., 2020) (Kay et al., 2020) (Kang et al., 2020) (Rosado-Pinto and Loureiro, 2020) (Mkumbo et al., 2020) (Wang, 2020) (Prateeksha and Jagrook, 2020) (Azer and Alexander, 2020) (Mateus and Guerra, 2020)
Social media engagement	(Dolan et al., 2015) (Dessart, 2017)
Media engagement	(Calder and Malthouse, 2008)
Online engagement	(Calder et al., 2009) (Pletikosa and Michahelles, 2013) (Luarn et al., 2015)
Brand engagement	(Sprott et al., 2009) (Mollen and Wilson, 2010) (Kabadayi and Price, 2014) (Yang et al., 2016)
Customer brand engagement	(Hollebeek, 2011) (Hollebeek et al., 2014) (De Villiers, 2015) (Dwivedi, 2015) (Solem, 2015) (Leckie et al., 2016) (Algharabat et al., 2019) (Kumar, 2020)
Customer engagement behavior	(Jaakkola and Alexander, 2014; Azer and Alexander, 2020)
Actor engagement	(Brodie et al., 2019)
Negative customer engagement	(Hollebeek and Chen, 2014) (Juric et al, 2016) (Naumann et al., 2017) (Azer and Alexander, 2020) (Khac et al., 2020)

Source: Author

Table 16: Articles about engagement and mobile.

Engagement and mobile	Author
Engagement	(Bellman et al., 2011) (Kim et al., 2015) (Parise et al., 2016)

	(Gill et al., 2017) (Liu et al., 2019)
Consumer engagement	(Tarutė et al., 2017) (Clark et al., 2018) (Grover and Kar, 2018; O'Brien and Toms, 2008) (Mclean and Alan, 2019) (Rasool et al., 2020) (Wang, 2020)
Digital engagement	(van Heerde et al., 2019)

Source: Author

Engagement conceptualization

There is no consensus on exactly how to define engagement (Cheung et al., 2011; Masłowska et al., 2016; Ra et al., 2019; Rosado-Pinto and Loureiro, 2020). Marketing research on this concept has propose different definitions based on context (Ballesteros-Herencia, 2018; Bowden, 2009).

Next table resumes engagements definitions to facilitate the analysis.

Table 17: Engagement definitions

Concept	Engagement definition	Author
Media engagement	"is turning on a prospect to a brand idea enhanced by the surrounding context" (ARF definition)	(Wang, 2006, p. 1)
Engagement	"a collection of experiences with the site"	(Calder et al., 2009, p. 323)
Consumer engagement	"as a psychological process that leads to the formation of loyalty"	(Bowden, 2009, p. 65)
Customer engagement	"the behavioral manifestation from a customer toward a brand or a firm which goes beyond purchase behavior"	(van Doorn et al., 2010, p. 254)
Consumer engagement	"level of a customer's physical, cognitive, and emotional presence in connections with a particular online social platform"	(Cheung et al., 2011, p. 3)
Customer engagement	"the intensity of an individual's participation in and connection with an organization's offerings or organizational activities, which either the customer or the organization initiates."	(Vivek et al., 2012, p. 133)
Customer brand engagement	"A consumer's positively valenced brand-related cognitive, emotional and behavioral activity during, or related to, focal consumer/brand interactions"	(Hollebeek and Chen, 2014, p. 149)
Ad engagement	"A spectrum of consumer advertising activities and experiences—cognitive, emotional, and physical— that will have a positive impact on a Brand."	(IAB, 2015, p. 6)
customer engagement	"the readiness of a customer to actively participate and interact with the focal object (e.g. brand/organization/community/website/organizational activity), [which] varies in	(Islam and Zillur, 2016, p. 8)

	direction (positive/negative) and magnitude (high/low) depending upon the nature of a customer's interaction with various touch-points (physical/virtual)"	
customer engagement	"an ecosystem with four components of customer engagement: customer brand experience, brand dialogue behaviors, brand consumption and shopping behaviors. All of these components affect each other as part of a dynamic, nonlinear, iterative process".	(Masłowska et al., 2016, p. 10)
customer engagement	"as the mechanics that customers use to add value to the firm".	(Kumar and Pansari, 2017, p. 2)
engagement initiatives	"as organizational initiatives that facilitate firm-customer interactions or interactions among customers, with the primary goal of fostering an emotional and psychological bond between customers and the firm"	(Gill et al., 2017, p. 3)
Customer engagement	"a customer's cognitive, emotional, behavioral, and social investment in their brand interactions"	(Hollebeek et al., 2019, p. 4)

Source: Author

Maslowska et al. (2016) doing an analysis of all these definitions in the last fifteen years, point out that they can be divided into two broad groups – those focusing on the psychological versus behavioral components, although some definitions include both.

The IAB (2015) includes experiences in their definition of ad engagement and emphasizes that engagement is not a single "event," but more of a continuum, or inter-connected gears. Regarding experiences, Calder et al. (2009) point out that experiences is a first-order construct while engagement is a second-order construct (divided in personal engagement and social-interactive engagement).

Bijmolt et al. (2010) distinguish between three general manifestations of customer engagement: WOM (Word of mouth), customer cocreation, and complaining behavior; all of which affecting the brand or firm in ways other than purchase. Addis (2020) suggests that customer engagement is related with customer experience, customer satisfaction, customer loyalty and what she defines as customer well-being.

Khac et al. (2020) posit out that while there is little consensus on customer engagement conceptualization, there is broad agreement on the interactive, experiential and value co-created nature of customer engagement based on relationship marketing theory and service dominant logic.

As we can see many academics have different definitions for the term engagement and there is no consensus for a unique definition, but we must mention that most of these definitions include "interactions" or "experiences" to define it and these interactions or experiences lead us to the dimensions of engagement.

Consumer engagement in the mobile environment occurs when mobile device users interact with mobile devices to meet their needs (Gill et al., 2017).

In-app engagement

IAB (2013) points out that digital ad engagement is characterized by an limited consensus on what they mean or how to use them wisely and consistently. Too often engagement is used as a catchall for multiple behaviors ranging from softer metrics such as brand awareness through more concrete metrics such as conversions.

Regarding mobile area practitioners use a new term for engagement “in-app engagement” which refers to engagement in mobile apps using behavioral metrics to measure it: dwell time, bounce rates and number of downloads, logins, visits and specific interactions, such as clicking on links, watching videos, completing modules.

In 2017, Tarutė et al. (2017, p. 146) pointed out, “despite growing interest from academic research, consumer engagement in a mobile environment specifically with regard to mobile applications is, to the best of our knowledge, not explored.” In the same line, Rasool et al. (2020) posit that, due to the fact that mobile apps are becoming very important to engage users, studies investigating customer engagement through mobile apps has transpired into marketing literature relatively recently.

Mobile apps have generated substantial interest among marketers, primarily because of their high level of user engagement and the positive impact this presumably has on a user's attitude toward the sponsoring brand. Bellman’s et al. (2011) results show, that using these apps has a positive persuasive impact, increasing interest in the brand and the brand's product category. The relevance of the product category makes no difference, but apps with an informational/user-centered style were more effective at shifting purchase intention, most likely because this style focuses attention on the user, and therefore encourages making personal connections with the brand.

Regarding consumer’s motivation to engage with the mobile device and mobile application some academics (Hamka et al., 2014; Kim and Han, 2014) suggest that is based on lifestyle decisions, timetable or organization of meetings, collecting information when travelling, playing games, giving priority to activities or tasks, functionality or goals (utilitarian aspects) or on the need to have a good time (hedonic aspects).

Clicks remain an important signal in digital advertising that an interaction or engagement has taken place; however, clicks are not the only indication of engagement, nor the “best” indication of engagement, nor appropriate in every use case (IAB, 2015).

Studying whether the use of the apps to main interactive features, information lookups and check-in influences adopters spending levels, Kim et al. (2015) found that app adoption and continued use of the branded app increase future spending. Furthermore, consumers who adopt both features show the highest increase. However, they also observe “the recency effect” – when consumers discontinue using the app, their spending levels decrease. They suggest that sticky apps which attract continuing uses can be a persuasive marketing tool because they provide portable, convenient, and interactive engagement opportunities, allowing customers to interact with the brand on a habitual basis.

Testing how digital technology (location-based mobile apps and augmented reality) can transform the customer experience, Parise et al. (2016) conclude that emotional triggers are one of the key reasons behind shoppers’ return visits to a store and loyalty to a retail brand. What provides these emotional triggers are personalized experiences, content-in-context, and highly immersive engagement with products.

Based on the four mobile application features that might have an impact on consumer behavior (functionality, design solutions, nature of supported interaction and perceived quality of information), Taruté et al. (2017) suggest that perception of design solutions and information quality will result in higher engagement leading to continuous usage of mobile applications. Moreover, consumer engagement positively influenced users' intention to continuous usage of mobile applications. Inconsistent with expectation, consumer interaction and functionality features are not found to be positively related to consumer engagement with mobile applications.

Liu et al. (2019) posit that apps enable customers to engage more with retailers and therefore are more likely to lock-in customers. Their results show that app adopters have higher purchase incidence, buy more frequently, and spend more in each order than non-adopters. They also found that app adoption has a stronger positive effect on the order size of customers who have a lower spending share of high-price products and customers who are less loyal to the focal retailer.

Wang (2020) posits that mobile apps facilitate customer engagement by providing a richer, portable, and deeper shopping experience to customers than websites and O´Brien et al. (2020) point out that "downloading a mobile health app on your smartphone does not mean you will ever use it. Telling another person about an app does not mean you like it. Using an online intervention does not mean it has had an impact on your well-being" (p. 1). They conclude that user engagement measurement should not rely only in behavioral metrics like downloads, clicks, likes, and other usage and popularity metrics to measure app engagement.

Dimensions of engagement

Scholars debate between unidimensionality, usually behavioral or emotional, or multidimensionality of engagement. IAB (2013) points out that multiple ad sellers price inventory on a cost per engagement basis consider behavioral dimension. For example, "engagement as a mouse rollover on a unit plus a 3s countdown before beginning to play the ad or the amount of time a video play" (p. 14).

Due to the fact that the unidimensional nature of engagement (Romero, 2017; van Doorn et al., 2010) merits simplicity but it does not reflect engagement rich conceptual scope, it seems that most scholars consider engagement a multidimensional concept (Dessart, et al., 2016; Hollebeek, et al., 2014; Islam & Zillur, 2016; Marbach et al., 2019) and highly context specific (Voorveld et al., 2018).

Some researchers define two dimensions, experiential and social (Gambetti et al., 2012) or behavioral and emotional (Kumar et al., 2013). Vivek et al. (2012) point out that customer engagement refers to the combination of behavioral responses with an emotional context. So, the emotional context is confidence and trust, commitment, the behavioral context is action.

But most scholars identify three dimensions in engagement: cognitive, emotional, and behavioral (Algharabat et al., 2019; Brodie et al., 2013; Calder et al., 2013; Cheung et al., 2011;

Dessart et al., 2015; Hollebeek, 2011; Hollebeek et al., 2014; Leckie et al., 2016; Vivek, 2009; Wirtz et al., 2013).

IAB (2015) identify these three dimensions and define subdimensions in the cognitive dimension:

- Cognitive, which maps to changes in awareness, interest, and intent.
- Emotional, or affective: measure feelings.
- Physical/behavioral, or user-initiated interaction.

Dessart et al. (2015), in the context of online brand communities, conceptualize these three dimensions:

- Cognitive engagement: Is defined as a set of enduring and active mental states experienced by the consumer. Like the overall mental activity focused on something, involving attention and absorption.
- Emotional or affective engagement: Captures the summative and enduring level of emotions experienced by a consumer with respect to his or her engagement focus. It is composed of enthusiasm and enjoyment about an engagement object.
- Behavioral engagement: Represents the active manifestations of the concept, including sharing, learning, and endorsing behaviors.

Gatautis et al. (2016), one year later than Dessart et al. (2015), conceptualized also these three dimensions:

- Cognitive engagement dimension refers to the consumer's level of engagement object related through processing, concentration, and interest in specific object (business enterprise, brand, online social network, brand community). For example, in the brand engagement context, cognitive engagement refers to consumer concentration or interest regarding specific brand.
- Emotional engagement dimension refers to a state of emotional activity also known as the feeling of inspiration or pride related to and caused by engagement object. For example, in the brand engagement context, emotional engagement refers to consumer association, dedication or commitment regarding specific brand.
- Behavioral dimension refers to a state of consumer behavior related to engagement object and understood as endeavor and energy given for interaction. For example, in the brand engagement context, behavioral engagement refers to consumer intention to act towards specific brand or obtain/purchase specific brand.

Scholz and Smith (2016), in their research about AR (Augmented Reality) and consumer engagement, mention the need to focus on consumer engagement and the dimensions that drive it, such as affordance, sociability, and artifacts, which are different from the traditional three dimensions.

There is a controversy between academics about social as a fourth dimension of engagement. Hollebeek (2011) points out that two related but conceptually distinct constructs, involvement and social interaction are included as antecedents of customer engagement in an online social platform and Cheung et al. (2011) demonstrated that they are different from the concept of customer engagement. Vivek et al. (2012) mention that in the evolving marketing, relationships are not just between buyers and sellers, but between any combination of (and among) prospects, potentials, society, buyers, sellers and suggest a fourth dimension named "social". However, Dessart et al. (2015) suggest that Vivek notion of "social dimension" is not very adaptable to all engagement contexts, and thus foci.

Table 18: Vivek model of dimensions

Experiences and feelings of customers	Participation of customers
Cognitive	Behavioral
Affective	Social

Source: (Vivek et al., 2012)

Another aspect to take care about is that as researchers accept the three dimensions, they are not considered to be equally important, but there is no consensus on the level of importance of each one (Cheung et al., 2011; Tarutė et al., 2017).

Although the dimensionality of engagement remains unclear (Dessart et al., 2015), based on the number of academics –mentioned before- that support the three dimensions of engagement model, we will use those three dimensions in our analysis, in order to measure advertising effectiveness.

Table 19 resume the dimensions and sub-dimensions based on Dessart et al. (2016) analysis.

Table 19: Dimensions and sub-dimensions.

D1 Cognitive:	**Set of enduring and active mental states that a consumer experience**
	S1 Attention: Cognitive availability and amount of time spent thinking about, and being attentive to, the engagement partner.
	S2 Absorption: Level of consumer's concentration and immersion with an engagement partner
D2 Affective:	**Summative and enduring level of emotions experienced by a consumer**
	S3 Enthusiasm: Intrinsic level of excitement and interest regarding the engagement partner
	S4 Enjoyment: Pleasure and happiness derived from interactions with the engagement partner
D3 Behavioral:	**Behavioral manifestations towards an engagement partner, beyond purchase, which results from motivational drivers**
	S5 Sharing: The act of providing content, information, experiences, ideas, or other resources to the engagement partner

S6 Learning: The act of seeking content, information, experiences, ideas, or other resources from the engagement partner
S7 Endorsing: The act of sanctioning, showing support, referring resources shared by the engagement partner

Source: (Dessart et al., 2016)

3.1.2 Consumer engagement: metrics

According to the WARC (2018) study, the biggest barriers to growth in mobile are metrics and measurement. As we mention the debate about engagement dimensions, in this Doctoral Thesis we assume the three dimensions model that identifies cognitive, affective, and behavioral dimensions, model that most researchers accept. Consequently, we must pay attention to the metrics of possible use in each engagement dimension.

<u>Cognitive metrics</u>

The IAB (2015) proposes the following cognitive metrics, based in attention, used in surveys:

- Campaign awareness: The extent an ad or campaign is recognize by a potential customer.
- Brand message recall: The extent which a consumer can remember the key messages of an ad.
- Attribute recall: The extent to which a consumer can remember the brand attributes communicated in an ad.
- Change in message/attribute recall and association: The pre-post delta in measuring to which extent the consumer can remember and associate those advertising messages or attributes with the correct brand.
- Change in brand awareness/familiarity: The pre-post delta in measuring to what extent a brand is recognize by a potential customer.
- Change in purchase intent: The pre-port delta in planning or willingness to purchase a brand in the future.
- Change in brand consideration: The pre-post delta in a brand's inclusion in a set which a consumer would select from in.

Academic studies using surveys have utilized the following cognitive metrics:

- Absorption (Cheung et al., 2011)
- Cognitive processing (Hollebeek et al., 2014)
- Absorption and attention (Dessart et al., 2015).

Comparing practitioners and academics we can see that while first ones use awareness and recall academics use absorption and attention.

<u>Emotional metrics</u>

The IAB (2015) propose the following emotional metrics, based in affect used in surveys:

- Change in baseline brand perception: The pre-post delta in measuring what the potential customer thinks and feels about the brand.
- Change in baseline brand favorability: The pre-post delta in measuring what the potential customer likes and values about the brand.
- Change in baseline brand loyalty: The pre-post delta in measuring customer loyalty in terms of weight and frequency of usage and likelihood to switch.
- Physiological response: Extent to which the ad results in changes respiration, circulation or other non- conscious physical reactions that correlate with emotion.

Using surveys, academic researchers have used the following emotional metrics in their studies:

- Dedication (Cheung et al., 2011)
- Affection (Hollebeek et al., 2014)
- Enthusiasm and enjoyment (Dessart et al., 2015).

Comparing practitioners and academics we can see that while first ones use perception, favorability, and loyalty, second ones use dedication, affection and affective.

Many studies revealed that emotions and their dynamics have a profound impact on cognition and behavior. Unobtrusively measuring emotions is difficult (Eijlers et al., 2019).

<u>Behavioral metrics</u>

Most practitioners use this dimension as synonymous of engagement without using the other two dimensions, so there is a large list of metrics about behavioral dimension. For example, to measure engagement in social media, many practitioners use the following formula:

$$\textbf{Engagement} = \frac{\substack{\textbf{Total interactions} \\ \text{(Likes, shares, comments, clicks, page likes,...)}}}{\textbf{Estimated reach from total posts}} \text{ X } 100$$

IAB (2015) comments that clicks remain an important signal in digital advertising that an interaction or engagement has taken place; however, clicks are not the only indication of engagement, nor the "best" indication of engagement, nor appropriate in every use case. IAB (2015) posits 19 metrics to measure behavioral:

- Gaze time: Amount of time a user looked at an ad.
- Gaze rate: The percentage of users who intentionally looked at an ad, of all those who could have seen it.

- Total interactions: Total number of times a user "interacted" within an ad (clicks, hovers, taps, swipes, video plays, shares)
- Interaction rate: The percentage that total represents of possible interactions or the percentage of users who purposely enter the frame of an ad continuously for at least 0,5 seconds.
- Interaction time: The average amount of time users spends with an ad.
- Clicks: The number of users who clicked on an ad.
- CTR: The number of clicks on an ad divided by the number of times the ad was served.
- Taps: The number of users who tapped on a mobile ad.
- Swipes: The number of users who swiped an ad.
- Total video starts, pauses, stops completes: The number of times a user played a video, and how.
- Video completion view - through rate: Percentage of times a video ad was viewed to completion, of total times it was served.
- Display view through: Number of brand site visits that could have been influenced by display media within a particular look-back window.
- Search for more information: After seeing an ad, number of users who visited the brands web site.
- Offline word of mouth: After seeing an ad, number of users who had an offline conversation about the brand.
- Social: Read a brand post/viewed a brand video: Number of users who read/saw a brand post/paid brand ad/brand video on social media site.
- Liked a brand post/video: Number of users who then liked the brand post/video.
- Followed a brand: Number of users who then followed the brand.
- Shared a brand post/video: Number of readers who shared the brand post/video with someone else.
- Recommend a brand: Number of sharers who also recommended the brand.

Depending on the type of ad, practitioners use some of them, for example, regarding video, metrics used are: Play rate, completion rate, median viewing time and share rates. Regarding mobile, metrics used are: Click to call, click to play, click to download, map location, interaction rates, and share rates.

Academic studies using surveys have utilized the following behavioral metrics:

- Vigor (Cheung et al., 2011)
- Activation (Hollebeek et al., 2014)
- Sharing, learning, and endorsing (Dessart et al., 2015).

As we can see there are many behavioral metrics used by practitioners and researchers and there is no consensus on which ones should be used.

3.1.3 Consumer engagement: scales used

There has been much theorizing on the dimensions of consumer engagement, but work on generating and validating scales to measure these dimensions is still in its infancy (Khac et al., 2020) and, consequently, the study of consumer engagement in an online social platform has been hampered by a lack of validated scales in the literature (Cheung et al., 2011).

As any other construct, practitioners and academic are proposing solutions to measure consumer engagement because once consumer engagement is measured, it can be optimized.

Consulting companies have developed some indexes to measure brand's ability to create a superior customer experience and engage consumers. The most important for brands are probably: Forrester Customer Experience Index, Capgemini Customer Experience Index, and Net Promoter Score. Addis (2020) analyzes these indexes and concludes that although they might be useful for the industry, they are far from having met the scientific standards.

Different scales have been developed to measures consumer engagement based on different conceptualizations of engagement. (e.g., Addis, 2020; Baldus et al., 2015; Sprott et al., 2009; Tarutė et al., 2017). Five scales incorporate the three dimensions of engagement previously indicated. These scales are those proposed by:

1. Cheung et al. (2011). This scale has 18 items.
2. Vivek (2013). This scale has 10 items.
3. Hollebeek et al. (2014). This scale has 10 items.
4. Dessart et al. (2016). This scale has 22 items.
5. Schivinski et al. (2016). This scale has 17 items.

Appendix 6.1 shows in detail the different items included in these five scales that we mention above.

3.1.4 Consumer engagement and metrics used in consumer neuroscience

This Doctoral Thesis aims to examine ad effectiveness using consumer neuroscience. To do this, we must resort to neuroscience metrics. Researchers have proposed different metrics. Table 20 shows these metrics.

Table 20: Metrics proposed in consumer neuroscience to measure advertising effectiveness.

Author	Metrics
(Pradeep and Patel, 2010)	Attention, emotional engagement and memory. Based on these metrics and how they combine, deliver an overall effectiveness score and measure three market performance indicators: Purchase Intent/Persuasion, Novelty, and Awareness/Understanding/Comprehension
(Steele et al., 2013)	Emotional engagement (attention plus emotional intensity)
(Vlăsceanu, 2014)	Emotional engagement, memory retention, purchase intention, novelty, awareness and attention.
(Clark et al., 2018)	Attention, engagement, and affect
(Ciceri et al., 2019)	Memorization, visual attention and cognitive response.
(Muñoz-Leiva et al., 2019)	Visual attention and recall

Source: Author

In a synthetic way, we can relate the dimensions of consumer engagement and traditional consumer neuroscience metrics as follows:

- Cognitive dimension: Workload, attention, and recall metrics. Software companies have developed their own metrics, based on these traditional ones, like EEG-engagement, a cognitive metric develop by *iMotions* or Interest, a cognitive metric develop by *Neurologyca*.

- Affective dimension: Arousal and valence metrics. Also in affective dimension, software companies have developed their own, like affective engagement, develop by *iMotions*.

If engagement is a good variable to measure advertising effectiveness, it is important examine:

- First, if neuroscience technologies and algorithms provide results similar, or not,

- Second, if results of some neuroscience algorithms and results derived from survey data in cognitive and affective engagement dimensions are correlated.

Stöckli et al. (2018) comparing data from Facet and AFFDEX found a large variance in accuracy across emotions and databases, with a performance advantage for Facet over AFFDEX. In this line, some marketers point out that one of the problems of consumer neuroscience data are the different results that different technologies achieve. Then, we propose that, for the same stimulus, results of three algorithms -Kopernica, AFFDEX, and Facet-, are different. Since the stimuli considered in this Doctoral Thesis are video advertisements, we propose a hypothesis 1a regarding video ads; hypothesis that we disaggregate into two sub-hypotheses:

H1a1: Results corresponding to the cognitive dimension of consumer engagement provided by the various algorithms of consumer neuroscience technologies are not correlated.

H1a2: Results corresponding to the affective dimension of consumer engagement provided by the various algorithms of consumer neuroscience technologies are not correlated.

When using survey and neuroscience techniques to obtain consumer engagement data it is expected a positive relationship between both results. A positive association between the results of survey data and data from neuroscience technologies would indicate that both methodologies are convergent in the measurement of engagement, strengthening the research results. On the contrary, the non-correlation between the results raises several questions. First, do the various methodologies really measure engagement? Second, if so, which one provides the best results? Third, should the various methodologies be used in a complementary way to have a more complete view of the ad's effectiveness? In line with this, our proposal is that traditional survey metrics of engagement and at the same time consumer neuroscience metrics of engagement are related, but since the results of the various algorithms of neuroscience techniques may be different, we propose a hypothesis 1b regarding video ads; hypothesis that we disaggregate into two sub-hypotheses:

H1b1: There is a correlation between consumer engagement cognitive results measured through a survey and through some neuroscience algorithms.

H1b2: There is a correlation between consumer engagement affective results measured through a survey and through some neuroscience algorithms.

3.2 **Hypotheses about video ads effectiveness in mobile, PC and TV**

Online advertising may be divided in three periods corresponding to the three types of devices. First period starts with a banner in a PC in 1996 and since then practitioners continue to place ads in PC. Second period was during last 10 years, with companies spending money on mobile advertising as consumers spend more time in mobile. Third period starts a couple of years ago with connected TV implementing new strategies to target consumers.

Some researchers suggest that mobile advertising is unique in terms of establishing direct, pervasive, and individualized links with customers due to several inherent characteristics of mobile handsets such as being ''exceptionally personal,'' ''always on,'' ''always connected,'' and ''always with the user'' (Balasubramanian et al., 2002; Gauba et al., 2017; Kavassalis et al., 2003). Thus, difference between advertising in mobile devices and advertising in PC or TV are based in:

- Interactivity. Traditional advertising is a one-way communication but not in the mobile environment where users can, and use to, interact with the brands using a two-way communication channel. Traditional advertising as a mass media communication channel doesn't fit with the personalize advertising that mobile requires. In this line, in 2017 a Bain and Company (2017) survey found, that people interact with their devices an average of 200 times per day for communication, information, entertainment, socializing and to make a purchase, so, there`s a conventional idea that if companies want to reach consumers, mobile is the easiest way compare to TV, print or PC (Beaudin et al., 2016). Therefore, interactivity is changing the strategies that brands are using in their communication models.

- Personalization. Traditional advertising as a mass media communication channel doesn't fit with the personalize advertising that mobile requires. Users expect a high level of advertising personalization that fit their needs of information (MMA, 2020; Rivero and Mendez, 2020). As consumers may perceive these personalize services as more attractive and favorite (Shareef et al., 2017), many brands use advanced internet and computing technologies to exploit user data in order to implement online personalized advertising on their platforms (Kim and Kim, 2017). In this line, location-based marketing is the most popular use for location data as marketeers seek to reach mobile consumers and synced advertising, showing a message on a second screen device simultaneously with relevant TV content (or other medium) with the aim to persuade the data.

- Repetition. Repetition does not make sense in mobile as users get irritated (Schmidt and Eisend, 2015).

- Screen size. Compare to other devices like PC or TV mobile screen sizes must face with small screen size.

These main characteristics main explain different behavior in consumers between different devices regarding advertising effectiveness. Many ads are not suited to the mobile medium, they are often repurposed from ads produced for television, meaning it is too long and too slow for mobile users' short attention spans (Beaudin, 2017). Simple transfer of traditional broadcast advertising content into mobile has been found ineffective, because this strategy accounts neither for the contextual environment that mobile maintains nor for the differences in the attention and engagement of a mobile audience (Clark, et al., 2018). One essential feature of advertising which is repetition does not make sense in mobile as users get irritated and frustrated.

Also, Varun (2019) suggests that all the advertising happening on mobile phones is only an adaptation of digital and it does not make sense to have same banner ads on PCs than on mobile phones, considering the size of the mobile screen, while Advertising Research Foundation (2015) indicates that most mobile advertisements are not taking advantage yet of the interactive aspect afforded through the mobile platform. Consequently, mobile advertising should be different from traditional advertising to gain effectiveness.

As each device facilitates different user behavior by level of engagement, level of attention, and psychological attitude toward advertising (Ciceri et al., 2019; Segijn, 2019) and as the device chosen to convey the advertising message plays an important role in mediating advertising effectiveness (Royne et al., 2002), comparison of video ads in mobile versus other devices, such as PC and TV, is an important research topic that is taking place in various fields (Park et al., 2019).

Moreover, there is a lack of agreement about this topic. While Fulgoni and Lipsman (2017) posit that mobile advertisements performed better than PC at reaching their target audiences and were significantly less affected by invalid traffic, practitioners like Gemius Global (2018) suggest that advertising on mobile is less effective than on TV. To analyze this question, this Doctoral Thesis compares video ads effectiveness in mobile, PC, and TV, considering neuroscience and survey metrics such as cognitive workload, attention, recall memory, emotional intensity, and valence. To our knowledge, previous research was based on banners in webs but not video ads that have high demand and does not compare mobile to other devices such as PC or TV.

3.2.1 Cognitive workload

Cognitive workload, as its name indicates, it is a metric of the cognitive dimension of consumer engagement. Elkin et al. (2017, p. 127) define cognitive workload as “a measure of the amount of mental effort exerted on a given task a composite of working memory, attentional load, and executive function”. They suggest that measures of neurophysiological activity are perhaps the most direct measure of cognitive workload. Cognitive workload is measured as electrical activity over medial frontal areas during a demanding task and a time series of frequencies can be collected. As functional and experiential executional elements engage different brain areas, the extent to which these particular brain areas are activated is associated with higher ad effectiveness (Couwenberg et al., 2017).

Although cognitive workload has been studied for a long time it is in last 20 years when EEG has been used mostly to measure it (Antonenko et al., 2010; Berka et al., 2007; Gevins and Smith, 2003; Knoll et al., 2011). The MMA and Facebook recently released a whitepaper on short-form video strategy titled ‘From a Blink to a Heartbeat’. The most important insight from this study is that the cognitive process is faster than we thought, and that the human brain needs less than half-a-second to engage with mobile advertising and trigger a reaction, positive or negative (MMA, 2019). Also, they conclude that cognitive workload correlates with emotional activation, long term memory and active perception.

Two waves are used to measure cognitive workload:

- Beta and alpha waves. High Beta means alert and active attention and low alpha means relax and paying attention.
- P300: Tells me if there are attention level changes.

Eye-tracking technology has also been used to measure cognitive workload. For example, researchers have used parameters like blink rate and duration, pupil diameter, saccadic extent, fixation frequency, and dwell time, to estimate the cognitive requirements of different but, as Pomplun and Sunkara (2003) point out, we should be advised that these measures are subject to external factors that can be difficult to control. For example, pupil dilation occurs automatically in response to low light conditions; therefore, it is not always possible to accurately assess cognitive workload in low-light settings.

Smaller screen size of mobile screens is expected to imply higher cognitive workload. Although mobile vendors are increasing screen size in new mobile phones and actual mobile advertising is video with less text and full-size view, so it is possible that actually cognitive workload in mobile is higher to cognitive workload in devices with a larger screen size like PC or TV. For example, Hancock et al. (2015) suggest that increasing screen size would be accompanied by indications of reduced cognitive effort as reflected in subjective workload response. In line with previous research, Babiloni (2019) posits, regarding cognitive workload of advertising in mobile compared to PC or widescreen, that size screen matters in advertising effectiveness and cognitive workload is different based on different devices screen size.

Thus, as previous research that compare effectiveness ads among mobile, PC and/or TV considers that cognitive workload of video ads is higher in mobile than PC or TV, we propose the following hypothesis 2a regarding video ads, which we decompose into two sub-hypotheses:

H2a1: Cognitive workload of video ads is higher in mobile than PC.

H2a2: Cognitive workload of video ads is higher in mobile than TV.

3.2.2 Attention

Attention is one of the subdimensions of the cognitive dimension (Dessart et al., 2016). For cognitive researchers is highly relevant to determine if a stimulus captures or not our attention. A great number of studies argue that the cognitive response directly depends on the degree of attention focused on the stimulus (Muñoz-Leiva et al., 2019).

Attention is the first step in the recognition phase and the fact that a product does not attract visual attention means that the product is not perceived or considered. Thus, attention is an important key to interpreting the information processing of consumers (Reynolds et al., 2000) in areas such as advertising effectiveness and product selection (Lee, et al., 2015).

Two neuroscience technologies are used to measure attention. These are EEG and Eye-tracking. Some researchers have used them separately but most of them use both together.

Armstrong et al. (2006) suggest that the prefrontal cortex directs towards and focuses on attention and has been shown to connect with the neurons responsible for processing visual stimuli in the occipital lobe, the vision center of the brain. Casado (2018) posits that occipital and parietal regions and right frontal gyri correlates with attention and Clark et al. (2018) point out that frontal alpha asymmetry (FAA) captured by EEG has been shown to reflect motivation in attending to or avoiding a stimulus.

Pradeep and Patel (2010) use the moment-to-moment fluctuations (wax and wane on a subsecond-by-subsecond basis) of the attention circuit brainwave patterns to measure which stimulus trigger attention.

Casado (2018) posits that occipital and parietal regions and right frontal gyri correlates with attention and Clark et al. (2018) point out that frontal alpha asymmetry (FAA) captured by EEG has been shown to reflect motivation in attending to or avoiding a stimulus.

Using EEG methodology, researchers use EEG-engagement to measure attention because this metric measures the level of immersion in the moment and is a mixture of attention and concentration. EEG-engagement is characterized by increased physiological arousal and beta waves along with attenuated alpha waves. EEG-engagement is experienced as alertness and the conscious direction of attention towards task-relevant stimuli.

Table 21: EEG brain zones of attention.

Researcher	Measure
(Armstrong et al., 2006)	prefrontal cortex
(Pradeep et al., 2010)	attention circuit brainwave patterns: AI, DLPFC, PPC and PRC.
(Casado, 2018)	Occipital and parietal regions and right frontal gyri.
(Clark et al., 2018)	FAA

Source: Author

EEG-engagement is characterized by increased physiological arousal and beta waves along with attenuated alpha waves. EEG-Engagement level is projected to a continuous scale with the extreme poles with values zero (low EEG-engagement) and one (high EEG-engagement).

iMotions (2017) provided an EEG-engagement metric defining "cognitive state" that is projected to a continuous scale with the extreme poles with values zero (low engagement) and one (high engagement).

In Eye-tracking technology visual attention is considered. Steel et al. (2013) defined visual attention per advertisement as "total time spent in fixation measured using state-of the-art eye tracking technology" (p. 421). Regarding visual attention, the longer time a user spends looking at a point, gaze span time metric, the more important that point to the user is. Also, the more fixations in a region of interest, number of gaze points in a fixation point metric, the more important that region is. In contrast, the large number of saccades indicates that the region is not important or not of interest to the user. Eye-tracking studies usually analyze AOI to understand responses to different stimulus but its worth's its breakdown AOI to explain what its visually attended or ignored.

Several studies have analyzed the attention in banners and other formats. For example, Lapa (2007) showed that when the structure and design of websites remained the same, the duration of eye fixations on the banner decreased progressively for each page viewed, while Hervet et al. (2011), using eye-tracking with a PC in a web banner, found that, even internet user avoids looking at ads, most participants in their study fixate ads at least once during their website visit. Simola et al. (2013) concluded that banners are viewed less when users are reading text on webpages.

Table 22 shows different metrics used to measure visual attention.

Table 22: Eye Tracking measures of visual attention

(Pieters & Wedel, 2004)	Fixation duration is a good indicator of the amount of attention that is paid to that object
(Lapa, 2007)	Total time spent in fixation (fixation during the task starting at the time of entrance into an AOI and stopping when they exited)
(Hervet et al., 2011)	Fixation duration
(Steele et al., 2013)	Total time spent in fixation
(Simola et al., 2013)	Fixation and entry counts. Time of first entry and the total gaze duration
(Lagun & Navalpakkam, 2014)	Fixation time spent
(Lee, J. et al., 2015)	Gaze duration. Time to first fixation. Percentage of participant's fixation.
(Li et al., 2016)	Entry into an area of interest was counted as a contact and the duration of this contact was counted as time spent between entry and exit from the area.
(Tangmanee, 2016)	Fixation duration and fixation count
(Segijn et al., 2017)	Number of switches between media, average gaze duration in seconds, prevalence of gaze duration per second, and total viewing time in seconds.
(Clark et al., 2018)	Amount of time fixation in the AOI.
(Ahn, et al., 2018)	Eye-fixation and eye saccade. Eye-fixation considered to occur when eyes are fixated stably on a specific area of the display for a certain period (100 milliseconds) and eye

	saccade defined as rapid eye-movement between any two eye-fixations
(Muñoz-Leiva et al., 2019)	TFF, FB, FD and TFD
(Park et al., 2019)	Fixation duration and fixation count

Source: Author

Lee et al. (2015) indicated that visual attention wear-out occurs with static but not with animated banner ads, which consequently influences the downstream effects. Compared to a static banner ad, an animated ad barely attracts consumers' attention initially, resulting in worse memory performance and attitude in the beginning.

Ahn et al. (2018) found that consumers' attention span decreases exponentially, instead of linearly, as they maneuver from the top to the bottom of a search result webpage. The total number of available options significantly influences the speed and pattern of attention decay.

Ciceri et al. (2019), comparing digital and print ads, found that using in a tablet a PDF version of a newspaper yielded the highest memory performance, the greatest visual attention, and the highest electroencephalography frustration index (defined as a "state of perceived irritation") while participants watched advertising messages. Also, the website had the lowest performance in terms of visual attention and memorization.

Other studies have examined the attention to web pages or ads in TV and PC. For example, Brasel and Gips (2011) point out that gaze duration on the TV (around 1.5 seconds) were shorter than the gazes on the PC and computer dominated the TV in terms of viewing time.

A third type of studies analyzes the attention to web pages or ads in TV and online advertising. Differences in engagement with advertisements between platforms often are driven by the low levels of visual attention to online display advertising (Steele et al., 2013). This finding is consistent with prior eye-tracking based data that have suggested that a typical banner advertisement had about 16 percent of the value of a 30-second commercial (McPheters & Company, 2009) and that impressions from TV advertising appear to be as effective as ever, even possibly increasing in effectiveness (Rubinson, 2009). On the other side, Draganska et al. (2014) indicate that internet ads perform on par with television ads on the brand-building metrics that advertisers use and trust.

There are also a few studies that analyze the attention to different parts of web pages or ads in mobile and other devices. For example, Lagun and Navalpakkam (2014), regarding attention comparing mobile and PC, suggest that unlike PC where engagement (both clicks and attention) in a web page has been widely reported to decrease from top to bottom positions, on mobile phones they found, that the second result of a SERP, gets more viewport (visible portion of a web page in mobile) and gaze time than the first result, probably due to short scrolls. Also different on mobile phones than PC is that, unlike in desktop, on mobile phones, they found that on average, user attention is focused on the center and top half of the screen. In PC, attention is focused on the top-left and decreases towards the bottom and right of the search result page, while on mobile phones, they found that on average, user attention is focused on the center and top half of the screen.

Other type of studies considers ads in multiscreen. For example, Voorveld et al. (2018) point out that 50% of all the gazes on screens have a duration of 10 seconds or shorter and Segijn (2019) that people who are watching television without distractions also have short gazes toward media, such as television. That means that people spent their attention only a limit amount of time towards a media message. It is difficult to process information of the same modality (visual-visual) simultaneously because the information needs to be processed through the same sensory channel (Brasel & Gips, 2011; Jeong & Hwang, 2014; Kahneman, 1973; Salvucci & Taatgen, 2011; Segijn & Eisend, 2019; Wang, et al., 2012).

Multiscreening decreases advertising effectiveness although an additional mobile advertising impression of the same brand can attenuate the effect, but only when the additional mobile advertisement does not lead to high levels of distraction from the PC advertisement (Hoeck & Spann, 2020).

Comparing attention to ads in devices of different screen size, Troscianko et al. (2012) posit that bigger size screen produces higher subjective presence scores leading to the conclusion that attention varies with screen size and Segijn at al. (2019) point out that first reason of greater attention to TV compared to the tablet could be explained by screen size. However, as visual attention is defined, Steel et al. (2013) as total time spent in fixation, Kim et al. (2015) measuring time spent, confirmed that the time spent on mobile situations is longer than for PCs and suggest as an explanation, that consumers normally had more difficulty extracting information on a small screen.

An MMA (2020) research points out that comparing visual attention across mobile and PC platforms, mobile is superior at generating attention and this difference may be due to a difference in screen size, in that a mobile screen has less space in which content can be presented, and the PC can have more distracting materials within the screen.

Based on the last results of the previous research, we propose the following hypothesis 2b regarding video ads, which we decompose into two sub-hypotheses:

H2b1: Attention to a mobile video ad is higher than in PC.

H2b2: Attention to a mobile video ad is higher than in TV.

3.2.3 Memory

The memory process represents a key factor in marketing because people do not buy a product during or right after advertising exposure. Memory process generates consistent and measurable brainwave patterns that indicate when memory processing is active. Memorization measures widely used in advertising effectiveness research are recognition and recall tests, two metrics related to the cognitive dimension of consumer engagement.

Ciceri et al. (2019) point out that recognition is a more effective measure of memorization than recall, because the latter may mask the amount of actual memory and comment the relation between visual attention and cognitive processing, such as eye movements and memorizing. Other researchers (Mehta & Purvis, 2006; Muñoz-Leiva et al., 2019; Pradeep & Patel, 2010; Silberstein & Nield, 2008) have use recall and recognition in combination as a valid measure of advertising effectiveness.

Memory is one of the most deeply studied aspects of the brain, both in memory encoding and memory retrieval mechanisms. Table 23 shows results of studies that have analyzed the relationship between advertising forms and memorization.

Table 23: Studies and results about advertising forms and memorization.

Studies	**Results**
(Danaher and Mullarkey, 2003)	The longer a person remains on a website, the more likely they are to recall the ad and subjects who have the objective of performing a task on the website are less likely to recall banners than people who surf without any specific purpose
(Mehta and Purvis, 2006)	the longer and deeper the visual attention to advertising is, the greater is the extent to which users can learn from it, recognize it, and recall it
(Silberstein and Nield, 2008)	level of memory encoding at branded moments is an important predictor of advertising effectiveness. Brain is encoding into conscious and unconscious long-term memory. Commercials that integrated their brand/product with the narrative saw a 17% uplift in memory encoding
(Hervet et al., 2011; Lee and Ahn, 2012)	there is a small amount of recall of banner promotions amongst viewers
(Simola et al., 2013)	the ad recognition results showed that congruent ads were better recognized than incongruent ads
(Nihel, 2013)	banners located on the top of the screen are more frequently recalled than those on the inside or on the bottom of the page
(Li et al., 2016)	banner properties, especially animation speed and format, have no significant effects on recall and attitudes

(Tangmanee, 2016)	less than 10% were able to correctly recall the ad content viewed but about half of viewers were able to correctly recall clip details
(Segijn et al., 2017)	memory is only impaired for the screen that receives the least attention thus, when most of the attention is focused on the mobile device, memory should not be impaired for the information presented on the mobile device
(Muñoz-Leiva et al., 2019)	participants in research works in general do not recall most ads
(Ginai, 2020)	LTME (Long Term Memory Encoding) was higher in users of premium sites than users of social media. LTME is proven to drive brand recall and future purchase decisions in consumers
(Malygina and Perepelkina, 2020)	recall as a metric for prediction. Ad recall metric generally represents how many people out of a hundred remember a particular ad

Source: Author

To our knowledge there is not too much research about recall in mobile video ads. About learning, Nipan et al. (2008) point out that if an m-learning environment that relies heavily on video-based material is displayed on a mobile device with a small screen, such as an average mobile phone, then the effectiveness of the learning experience may be inhibited.

Kim's (2011) study on the effects of screen-size shows that participants exposed to a larger screen remembered better than those exposed to the same content on a smaller screen specifying that is for fixed screens and the effects of screen-size may be different on mobile devices. In this line, a study from *Hub Entertainment Research* (2016) shows that TV outperforms PC and mobile in recall.

Based on previous research we propose the following hypothesis 2c regarding video ads, which we decompose into two sub-hypotheses:

H2c1: Recall memory in mobile video ads is lower than in PC.

H2c2: Recall memory in mobile video ads is lower than in TV.

3.2.4 Emotional intensity

Emotions have demonstrated to be necessary for the human function because they are strongly correlated with attention, decision-making, and memory (LeBlanc et al., 2014).

Emotions have been proposed to be a good predictor of advertising effectiveness (McDuff et al., 2015; Otamendi & Sutil, 2020; Poels & Dewitte, 2006) and it is known that they have an important impact also in the cognitive process (Hamelin et al., 2017). Emotion-eliciting messages are remembered better than messages that do not elicit emotion (Lang, 2000).

Emotional intensity is related to affective dimension of consumer engagement. Steele et al. (2013) use “emotional engagement” (attention plus emotional intensity) to measure ads effectiveness and suggest that television’s heightened ability to sustain nonconscious emotional response over online viewing. In this line, Du Plessis (2008) points out that the vast majority of emotional processing occurs below conscious awareness and emotional and memory systems are dynamic and change moment-to-moment in response to the environmental context.

Inducing emotion is important for reducing the frequency of "zapping," or skipping advertisements, and concentrate the attention of viewers of online video advertisements (Teixeira et al., 2012)

One of the first methodologies proposed to measure emotions was IAPS (International affective picture system) using images in order to associate them with emotional states (Eijlers et al., 2020). IAPS is limited to academic use and also tailored to the dimensions that measure arousal, valence (positive or negative) and dominance which is basically the amount of control an individual has over an emotion in a specific context.

Usually, in consumer neuroscience, emotional response is measured by EEG fMRI, facial coding and biometrically by four channels of medical-grade, biologically based activity: heart rate variability, skin conductance level, respiratory response, and movement (Marci, 2006). Moses and Tullman (2019) developed a new methodology based on the selection of 32 basic discrete emotional associations with images. They use implicit association based on reaction time and frequency. Today, there is a database of 2000 images associated with these 32 emotions statistically validated.

For most researchers (e.g., Cherubino et al., 2019), two metrics are linked to emotional intensity: arousal and valence.

<u>Arousal</u>

Arousal refers the propensity of brain to be more or less activated by a stimulus (Pradeep and Patel, 2010). Other marketers (Bradley and Lang, 2007; Eijlers et al., 2020) consider arousal as the intensity or level of activation of one’s (emotional) response. By analyzing brain responses to stimulus, we can identify peaks in arousal in terms of states of low arousal (e.g., quietness) with states of high arousal. (e.g., surprised).

Lang (2000) points out that higher levels of emotional arousal recruit more cognitive resources to media information processing, including the encoding, storage, and retrieval of TV advertising. He suggests that emotional arousal should improve awareness measures of TV advertising effectiveness, such as unaided recall and social TV’s social context may accentuate this effect. Measuring the amygdala activation, Bakalash and Riemer (2013) found that TV commercials that require more social cognition are more memorable, reinforcing the association between ad-elicited emotional arousal and memory for the ad.

Previous literature (Detenber and Lang, 2011; Kim et al., 2011; Lombard et al., 2000) shows that bigger size screens elicit more arousal than smaller size screens and Reeves et al.

(1999) posit that this higher arousal of bigger size screens could positively affect memory. In video gaming, Bakdash et al. (2006) show that bigger screen size led to a higher immersion in the game environment.

Although these studies show that arousal is higher in big screen sizes, Werlen and Moser (2017) posit that, using text, there were no differences in arousal on the different screen sizes. In fact, Bracken et al (2010) comparing an iPod with a TV conclude that participants felt more immersed when watching a fast-paced action scene on the iPod than on the TV. Also, a comprehensive study by *Yahoo Advertising* found that not only is mobile use on the rise (while TV is declining), but mobile ads achieve a more emotional response than traditional television spots (Lafferty, 2016). Based on this latest study we propose the following hypothesis 2d regarding video ads, which we decompose into two sub-hypotheses:

H2d1: Arousal in mobile video ads is higher than in PC.

H2d2: Arousal in mobile video ads is higher than in TV.

<u>Valence</u>

A key measure of advertising effectiveness is advertisement likability (McDuff and Berger, 2019; Smit et al., 2006) and it is measured with valence that contrasts states of arousal pleasure (positive valence) with states of displeasure (negative valence).

Timme and Brand (2020) posit that a positive valence in commercial advertising reflects approaching behavior, whereas a negative valence is a sign of distancing behavior. In this line, in order to demonstrate ad liking, out of the seven emotions, the predominant one must be joy (Lewinski et al., 2014; Shehu et al., 2016).

Valence is usually measured by facial expression. Zygomatic and corrugator muscle activity - smiling and frowning respectively – have been shown to capture the valence of emotions (Hazlett and Hazlett, 1999; Lewinski et al., 2014). The range of valence is from −100 to 100, providing an indication of negative, neutral, or positive experience. The initial thresholds are usually arbitrarily set at ±50 (iMotions, 2020; Otamendi and Sutil, 2020).

Heart rate and heartbeat patterns can indicate arousal, valence and attention in real-time and continuous manner. However, because it captures a variety of phenomena it is recommended for use in tandem with other measures (e.g., skin conductance) to secure validity (Lewinski et al., 2014).

Although Detenber and Lang (2011) posit that, the bigger the screen the bigger the arousal, but no effect was detected on valence, several previous studies (e.g., Burgoon et al, 1998; Kim et al., 2011) point out that larger screen-size was key to greater enjoyment. Regarding reading text on screen, Werlen and Moser (2017) posit that valence was more negative on the small screen compared to the large screen. In this line, Sheen et al. (2018) found students were unhappy with the smallest size device when reading with the Kindle app.

Recently, Timme and Brand (2020) posit that a positive valence in commercial advertising reflects approaching behavior, whereas a negative valence is a sign of distancing behavior. In this line, in order to demonstrate ad liking, out of the seven emotions, the predominant one must be joy (Lewinski et al., 2014; Shehu et al., 2016). Although these findings were for fixed screens and are not clear for mobile devices, based on previous research we propose the following hypothesis 2e regarding video ads, which we decompose into two sub-hypotheses:

H2e1: Valence of a mobile video ad is more negative that in PC.

H2e2: Valence of a mobile video ad is more negative that in TV.

3.2.5 Intrusiveness

Intrusiveness has been studied by many researchers as a mayor cause of advertising annoyance (Hairong et al., 2014). Merisavo et al. (2007) posited that intrusiveness would become a major issue specially on mobile phones and Chatterjee (2008) suggested that consumer perceptions of online advertising have become increasingly negative, due to certain advertising formats being considered intrusive by consumers. It seems that the mobile context heightens the sensitivity of consumers to the intrusiveness. So, IAB (2018b) points out consumer annoyance with intrusive ads, especially on mobile devices while Segijn (2019), in her research about synced advertising, found that syncing ads on different devices might create feelings of being watched and perceived as intrusive to one’s privacy.

Regarding the size of the devices screen, Truong and Simmons (2010) point out that the smaller size of the screen made participants more sensitive to advertising intrusiveness on mobile phones than on other digital receiving devices, such as computers, while regarding personalization, Xu (2006) posits that it is the most effective way to prevent mobile advertising from being perceived as intrusive and irritating.

Based on smaller size of mobile screen and in the fact that the ads used in the research are not personalized, intrusiveness perception may be higher in mobile than other devices. Thus, we propose the following hypothesis 2f regarding video ads, which we decompose into two sub-hypotheses:

H2f1: Mobile video ads are more intrusive than video ads in PC.

H2f2: Mobile video ads are more intrusive than video ads in TV.

CHAPTER 4. RESEARCH METHODOLOGY, DATA ANALYSIS AND RESULTS

Hypotheses discussed in the previous chapter must be contrasted. To do this, this chapter presents the sample and the research methodology used.

We use survey and several consumer neuroscience technologies: ET, EEG, FEA, and GSR. Regarding survey, we used Google forms software. Researchers agree that data collected via online tools not only maximize response rates but also yield comparable results to data collected through traditional surveys (e.g., Deutskens et al., 2006). In addition, a multi-technique approach was selected, using.

Regarding consumer neuroscience techniques software, we select *iMotions* software to carry out the biometric measurements based on the huge amount of previous research done with it. This software, that has been used by prestigious institutions or brands like Harvard, MIT, Stanford, Yale, P & G, Nestlé, and Kraft, combines several technologies as such Eye-tracking, FEA, EEG, EDA, and others. Using various sensor technologies to track different aspects of human responses to stimuli in many kinds of environments, *iMotions* integrates all of them, synchronizing and managing multiple data streams from different devices.

The combination of multiple data sources increases research accuracy. The software records several raw indicators per frame based on biometric measurements or action units while an experimental subject is watching a stimulus on the computer or mobile screen. *iMotions* (2020) Version 9.0 was used in this research.

4.1 **Sample**

Sample sizes in consumer neuroscience studies are between 30 and 100 participants, far away from normal surveys size (see table 24). In this line, Muñoz-Leiva et al. (2019) point out that samples of this size are common in Eye-tracking studies and are not intended to be representative.

Table 24: Sample sizes in consumer neuroscience vs traditional surveys.

Research	Sample size consumer neuroscience	Sample size questionnaire

Understanding wechat users' motivations, attitudes and intention of reading promotional material		364
The Halo Effect	50	
The Mental Image Revealed by Gaze Tracking	30	30
The influence of snippet length on user behavior in mobile web search	31	31
The Application of Eye-Tracking in Consumer Behaviour	30	
Neuro-inspired Eye Tracking with Eye Movement Dynamics	20	
Measuring advertising effectiveness in Travel 2.0 websites through eyetracking technology	60	60
Implicit measurement of emotional experience and its dynamics	40	40
Evaluating the Effect of YouTube Advertising towards Young Customers' Purchase Intention		240
Do Mobile Devices Change Shopping Behavior?	80	80
Attention to online channels across the path to purchase: an eye-tracking study	58	58
Attention and Cognitive Process in Mobile	869	
Understanding consumers' reactance of online personalized advertising: A new scheme of rational choice from a perspective of negative effects		308
Towards incorporating personality into the design of an interface: a method for facilitating users' interaction with the display	87	
The strides of consumer neuroscience. Chapter 5	30	
The strides of consumer neuroscience. Chapter 6	68	
The strides of consumer neuroscience. Chapter 7	30	
The Forensic biometric analysis of changes in facial response provoked by emotional arousal during initial and subsequent exposure to stimuli	11	11
Purchase intention of Consumers from Melaka towards Mobile Advertising		250
Optimization of menu-labeling formats to drive healthy dining: An eye tracking study	95	95
Measuring consumer neural activation to differentiate cognitive processing of advertising	23	
In-Store Mobile Phone Use and Customer Shopping Behavior: Evidence from the Field	393	393
Incentivizing Advertisement Interaction within Mobile Applications		90

How Advertisers Can Keep Mobile Users Engaged and Reduce Video-Ad Blocking	144	144
The influence of an in-store gift on emotional arousal and shopper behavior	60	
Exploring the potential of a mobile eye tracker as an intuitive indoor pointing device: A case study in cultural heritage	22	
Etourism advertising effectiveness: banner type and engagement as moderators	84	84
Emotional or rational product labeling using galvanic skin response	12	
Customer Attitude towards Mobile Advertising		150
A comparison of the Affectiva iMotions Facial Expression Analysis Software with EMG for identifying facial expressions of emotion	20	
A Case - Study in Neuromarketing: Analysis of the Influence of Music on Advertising Effectivenes through Eye-Tracking, Facial Emotion and GSR	19	19
Predicting consumer liking and preference based on emotional responses and sensory perception: A study with basic taste solutions	102	102
How smartphone advertising influences consumers' purchase intention		303
El procesamiento cognitivo en una app educativa con electroencefalograma y «Eye Tracking»	22	22
Attitudes toward mobile search ads: a study among Mexican millennials		1240
Neuromarketing aplicado a dos anuncios de moda infantiles	35	35
Predictors of avoidance towards personalization of restaurant smartphone advertising		159
Mobile location-based advertising: How information privacy concerns influence consumers' attitude and acceptance		224
Explain the intention to use smartphones for mobile shopping		400
Customer's Attitude Towards Mobile Advertising in Bangladesh		150
Why smartphone advertising attracts customers: A model of Web advertising, flow, and personalization		256
¿Qué factores fomentan la compra por impulso en el comercio móvil?		447

Attitudes toward mobile advertising: a study of mobile web display and mobile app display advertising		237
Attitude towards mobile advertising and purchase intention of Swedish customers		104
An empirical examination of users' adoption of mobile advertising in China		346
Want to be loved? go mobile!		300
2011 Mobile advertising: An investigation of factors creating positive attitude in Iranian customers		652
2011 Attitudes towards Mobile Advertising – A Research to Determine the Differences between the Attitudes of Youth and Adults		380
Understanding the Acceptance of Mobile SMS Advertising among Young Chinese Consumers		262
An Empirical Study of the Drivers of Consumer Acceptance of Mobile Advertising		4062
Consumer attitude toward mobile advertising in an emerging market: an empirical study		318

Source: Author

Also, Meng-Hsien et al. (2018) point out that these small sample sizes may be perceived as resulting in low statistical power but this perceived limitation is often due to some misperceptions regarding neuroscience data:

- the common fundamental biological composition of the brain does not vary as widely as other behavioral variables
- the experimental design used for conducting neuroscience studies, whether it is the procedures or the stimuli, is much more controlled in comparison to behavioral experiments
- in the case of EEG studies, the number of trials per subject included in a study is relatively large.

In this study, sampling technique was not probabilistic, using convenience sampling to get participants and the final sample comprised in our research was 60 participants. Study was done between April 20th and June 5th 2021 in *Neurologyca* laboratory in Santiago de Compostela. Spain. Table 25 collects main data of the study.

Table 25: Study data sheet

Information collection	Survey and consumer neuroscience techniques: EEG, ET, GSR, FEA (3 engines: Kopernica, iMotions-Facet and AFFDEX).
Population	Population from Galicia
Geographical scope	Spain
Sample size	180 valid cases (60 participants x 3 experiment each one, 1 per device: MOBILE, PC y TV)
Sample procedure	Not probabilistic, using convenience sampling
Field research date	April 20th till June 5th 2021
Stimulus	3 spots from 3 brands in 3 devices (MOBILE, PC, TV).
Statistic Software	IBM SPSS Statistics 24

Source: Author

The sample of 60 participants was distributed as follows: 27 men and 33 women (45% and 55%, respectively). Age was between 20 and 58 years old, with the average being 28,37.

4.2 **Methodology**

In this Doctoral Thesis several technologies, devices, stimuli, and platforms were used. The experiments were carried out in a laboratory according to a rigorous procedure.

4.2.1 Technologies and algorithms

Used technologies in this Doctoral Thesis were Eye-tracking, FEA, EEG, GSR/HR.

<u>Eye tracking</u>

To measure visual attention Tobii pro x2 30 device was selected. Eye tracking was fixed in PC screen to get ocular movements at 30 Hz.

Image 33: Tobii pro x2 30

Source: Neurologyca (2020)[73]

Next table details Eye-tracker Tobii pro X2-30 characteristics a model that is usually proposed for eye tracking studies.

Table 26: Tobii pro X2-30 characteristics

Model	Tobi pro X2-30
Sample rate	30 Hz (±2 Hz)
Accuracy	0.4°
Precision	0.32°
Mount type	On screen, stand
Screen size	Up to 25" when mounted (16:9)
Operation distance	40-90 cm
Head movement	50 x 36 cm
Pupil size	Yes
Connection type	USB 2.0
Dimensions	18.4 x 2.8 x 2.3 cm
Weight	200 g

Source: Neurologyca (2020)[74]

Mobile support device was used for mobile test with Tobii eye-tracker. Users can perform efficient, natural, and high-quality research into how subjects experience mobile websites and apps or how they consume ads on smaller screens.

It's interesting to comment that although fixing the mobile into a support device gives a better control of the experiment, we lose the natural way a consumer handles the device in a real situation.

[73] https://neurologyca.com/
[74] https://neurologyca.com/

Image 34: Mobile support for eye tracker.

Source: Neurologyca (2020)[75]

Camera used for facial recognition was Logitech HD Pro Webcam C920 with autofocus and a wide angle lens that offers a 78-degree field of view.

Image 35: Logitech HD Pro Webcam C920

Source: Neurologyca (2020)[76]

Table 27 details Logitech HD Pro Webcam C920 specifications.

Table 27: Logitech HD Pro Webcam C920 specifications

Model	Logitech HD Pro Webcam C920
Max. Resolution:	1080p / 30 fps - 720p / 30 fps
Focus Type:	automatic
Built-in Microphone:	stereo

[75] https://neurologyca.com/
[76] https://neurologyca.com/

Universal Clip	Compatible with Tripods for Monitors, LCD Displays or Laptops
Cable Length:	1.5 m
Dimensions:	29 mm x 94 mm x 24 mm

Source: Logitech (2020)[77]

EEG

To measure cognitive workload with EEG we selected B-alert ABM X10. It allows metric generation based in frequencies like Power spectral density. PSD values are available for each sampling point, each channel for frequencies between 1 and 40 Hz.

Image 36: ABM X10 placed in a participant

Source: Neurologyca (2020)[78]

Table 28 details ABM B-Alert X10 EEG pro specifications.

Table 28: ABM B-Alert X10 EEG specifications

Model	B-Alert X10
Number of channels	10
Sampling rate[79]	256 Hz
Communication	Bluetooth
Operating type	8+ hours

[77] https://www.logitech.com/en-us/products/webcams/c920s-pro-hd-webcam.html
[78] www.neurologyca.com
[79] Sampling rate: Number of samples per second.

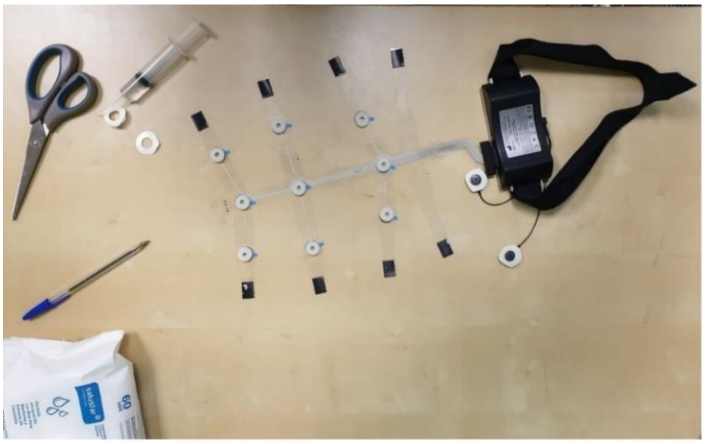
Weight	110 g
Onboard storage	Yes
Accelerometer	Yes
Medically certified	No

Source: iMotions (2020)[80]

For frequency-based analyses, like prefrontal lateralization of alpha or beta bands, a sampling rate of 256 Hz is more than sufficient.

Headset sensors compile signals from all the sensors placed in a participant and make conversion, coding, format and transmission from analogue to digital of all signals using a radio transmitter from 2,4 to 2,48 GHz. X10 use system bidirectional capacities to monitor electrode impedance in the scalp and control battery capacity. A BT receptor unit is used as base unit in the PC.

Image 37: EEG sensors preparation.



Source: Author

<u>GSR/HR</u>

To measure arousal, we selected, Shimmer GSR + compiles biophysiological signals: Galvanic skin conductance (GSR) and optic heart rate (HRV).

Image 38: Shimmer 3 GSR

[80] https://imotions.com/

Source: Neurologyca[81]

Table 29 details Shimmer GSR + specifications.

Table 29: Shimmer GSR + specifications

Model	Shimmer3 GSR
Channel	1 Channel GSR (Analog)
Measurement Range	10k-4.7MΩ (.2uS - 100uS) +/- 10%. 22k-680kΩ (1.5-45uS) +/- 3%
Frequency Range	DC-15.9Hz
Input Protection	RF/EMI filtering, Current limiting
Current Draw	60µA
Jacks	2 x Hospital-Grade 1mm Touchproof IEC/EN 60601-1 DIN42-802
Auxiliary input	2 Channel Analog/I2C Digital input: via 3.5mm 4-position jack

Source: Shimmer (2020)[82]

Algorithms

Regarding software, we have used the three algorithms mention before: Kopernica, Facet, and AFFDEX to measure emotions, valence, and intensity.

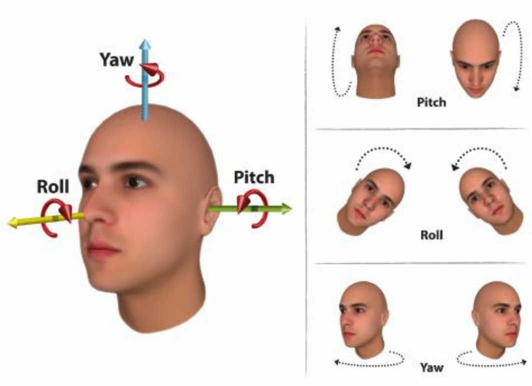
Kopernica configuration was:

- Origin = internal. Original Kopernica platform was used, without any API83 (Application Programming Interfaces) with external platform.
- Adjust =Yes (Final data adjust based on baseline.
- Quality. Stimulus = Yes. Filters apply.

[81] https://neurologyca.com/
[82] https://www.shimmersensing.com/products/shimmer3-wireless-gsr-sensor
[83] API: Is the acronym for Application Programming Interface, which is a software intermediary that allows two applications to talk to each other.

- Face_size =64 Minimum pixel size of the face to be recognize.
- ir_size=120 Framework pixel size of the image where face should be centered.
- pitch=150 Threshold face is not detected.
- roll=25 Threshold face is not detected.
- yaw=25 Threshold face is not detected.

Image 39: Pitch, Roll and Yaw.



Source: Neurologyca (2020)[84]

Configurations from *iMotions* were not available as *iMotions* do not publish internal configurations.

4.2.2 Devices

To validate hypothesis between the three devices we use: PC with secondary screen, smartphone and smart TV.

Mobile

A Samsung Galaxy S6 Edge was selected.

PC

Laptop was an ASUS TUF GAMING FX504 SERIES with OS: Microsoft Windows 10 Pro, version: 10.0.1363 compilation 18363 and Processor: Intel® Core™ i7-8750H CPU.

Secondary screen was ASUS MB168B/MB168B+ Resolution: 1366x768

Smart TV

[84] https://neurologyca.com/

A Samsung Smart TV 32 inches was selected.

4.2.3 Stimuli and platforms

Stimuli were presented in the three devices -PC, Smartphone, and Smart TV- and in three selected platforms –*Atresplayer*, *YouTube,* and *Facebook* video. To have a good exposition control in each of the platforms and devices, stimuli were recorded in video and users have a natural navigation in each platform and device so all of them have the same opportunity to see all ads.

Same video ads were included in the 3 devices (PC, Smart TV and mobile) to avoid bias and obtain a homogeneous comparative base.

Each participant was exposed randomly to a unique device (PC, mobile or Smart TV) in each of the 3 platforms.

These platforms were selected based in their popularity and that they are also used frequently.

Atresplayer: 1 pre-roll video ad

Participants saw an *Atresplayer* landing page with a pre-established content and 1 pre-roll video ad (Dominos extra hot days) appear to them while they see content in the platform. Video length was 20".

Image 40: Dominos advertising

Source: Author

YouTube: 1 pre-roll ad without skip-add

Participants saw a *YouTube* landing page with a pre-established content and a video ad appear to them (Oreo Stay Playful and Oreo Doble Crema) while they see content in the platform. Video length was 20”.

Image 41: Oreo advertising

Source: Author

Facebook video: 1 ad in *Facebook* wall

Participants saw a *Facebook* video landing page with a first audiovisual content and a second audiovisual content that was the ad. (Galaxy S21 Ultra _ Official TVC _ Samsung). Video length was 30”.

Image 42: Samsung advertising

Source: Author

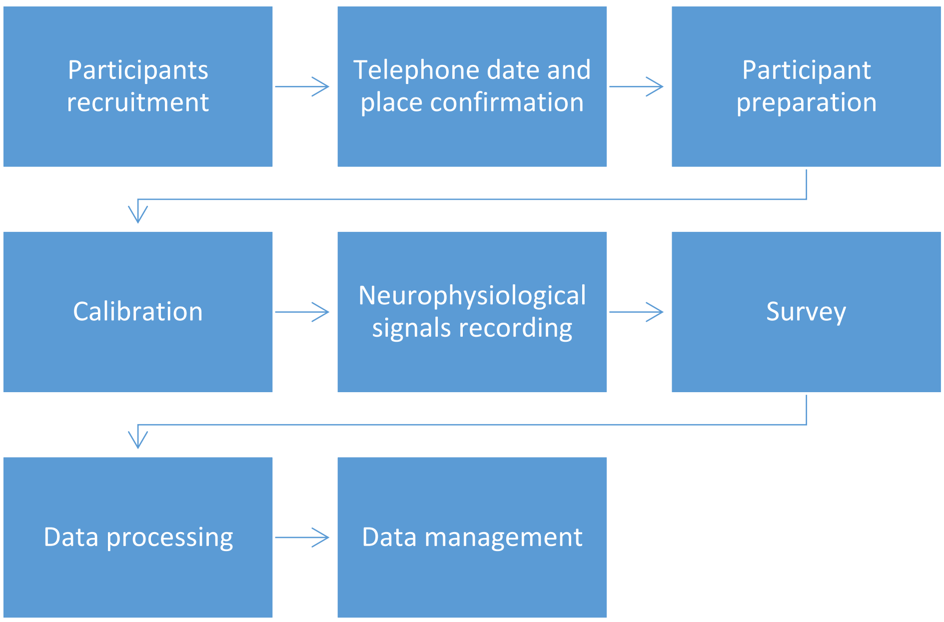
4.2.4 Laboratory

Laboratory used was Neurologyca lab in Santiago de Compostela. All material was supply by Neurologyca. This company has been doing Consumer Neuroscience projects for a long time and develop hundreds of experiments with this material so they have a huge background using it.

4.2.5 Study procedure

Eight main steps formed the study procedure conducted.

Image 43: Research procedure



Source: Author

<u>Step1: Participant's recruitment</u>

Email was sent to several potential participants proposing them to participate in the experiment and encouraging them to get more participants.

<u>Step 2: Telephone date and place confirmation</u>

As soon as a participant confirms his/her interest, an email was sent with the proposing date. Once the participant confirms the date an email was sent to the laboratory to book in the agenda. A final email was sent one day before the experiment to remember date. In some cases, agenda was changed due to participants or lab problems.

Laboratory used was *Neurologyca* lab in Santiago de Compostela and homogeneous and controlled environment, isolated from outside noise, with an ambient light of 200 Lux, as recommended in *International Telecommunication Union* to simulate a "home environment".

Image 44: Neurologyca lab in Santiago de Compostela.

Source: Author

Step 3: Participant preparation

Once the participant arrived to *Neurologyca* lab, we welcome him/her, check identity, explain basic instructions and anti-covid protocol. Participant signed an authorization for data collection, analysis, and management. Once the participant was ready, he enters the lab, and we show them the devices we are going to use and where they must sit. Meanwhile we clean all electrode sites with alcohol.

We placed first gel in participant scalp to get a better EEG sensors fixation. Next, we ask participant to sit in front of the first device selected randomly (Smartphone, smart TV, or PC). Finally, we placed GSR device.

Participants in this study did the experiment one participant at a time. For each participant, when they arrive to the laboratory, we enter personal data and ad timing in a control datasheet as we can see in image 44.

Image 45: Participant control data

FECHA	HORA	ID	PARTICIPANTE	GÉNERO	EDAD
20/04/2021	17h	ID1	marivi	mujer	58

PC				
A3 Dominos	YT Oreo	FB Samsung	INICIO SPOT	FIN SPOT
1			30	50

MOVIL				
A3 Dominos	YT Oreo	FB Samsung	INICIO SPOT	FIN SPOT
		2	20	50

SMART TV				
A3 Dominos	YT Oreo	FB Samsung	INICIO SPOT	FIN SPOT
	3		35	55

Source: Author

This control datasheet allows us to extract from all consumer neuroscience technology data just the ones that correspond in timing to the exact moment when participants see the ads.

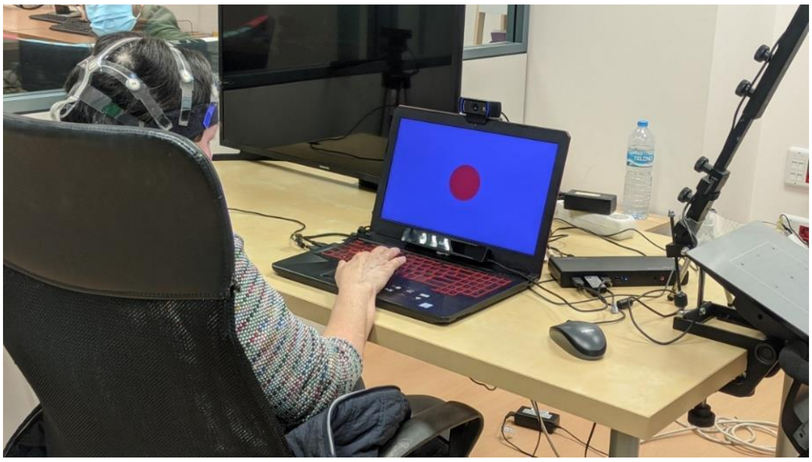
Step 4: Calibration

To calibrate sensors, we plug and play them to devices, configure to study setup and control data quality of data streams. We explain each participant what they must do in order to calibrate each device, as we can see in next images.

Image 46: Smart TV calibration

Source: Author

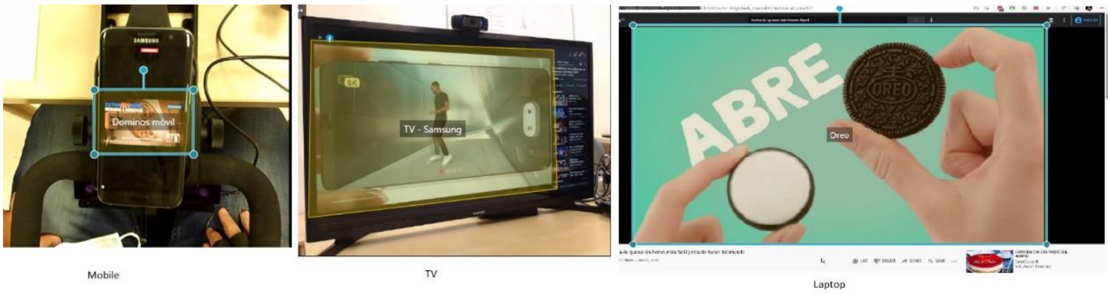
Image 47: PC calibration.



Source: Author

Regarding Eye-tracking, AOI were defined for each device and ad to get attention data.

Image 48: AOI defined for devices

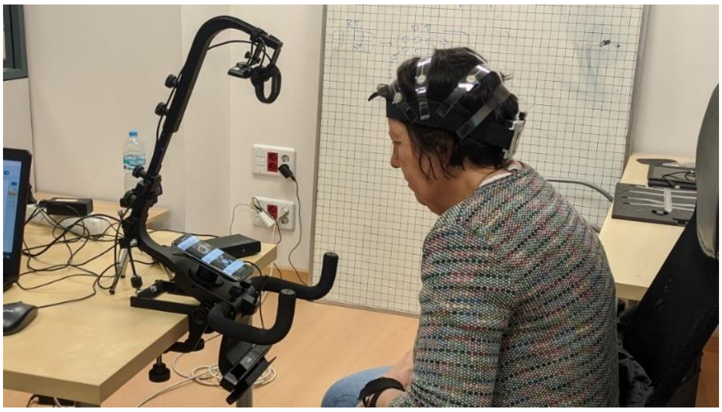


Source: Author

Step 5: Neurophysiological signals recording

Once calibration was finished, we started the platform and during navigation participant saw the ad. Then we do the calibration with second device and do the same procedure and finally we do the third device.

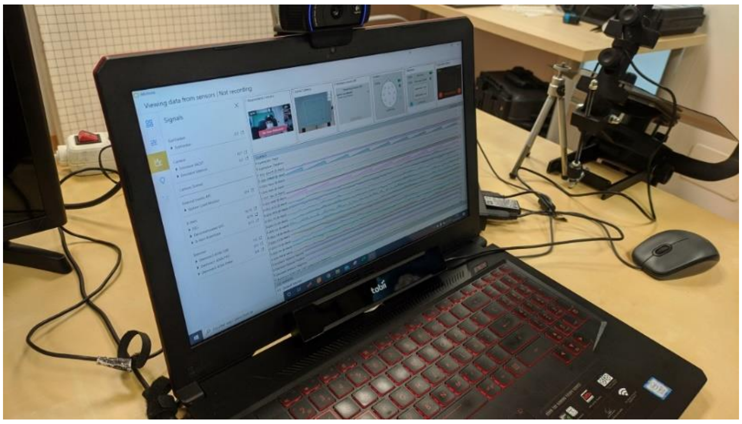
Image 49: Mobile data experiment



Source: Author

Data from different technologies was recorded at the same time and we were monitoring that all sensors were working properly.

Image 50: Viewing data from sensors.



Source: Author

Step 6: Survey

Once participant finished experiment, we take out all sensors and propose him/her to go to another room where a PC had the online survey in Google forms. An example of the questionnaire is in appendix 6.3.

Step 7: Data processing

Regarding FEA we have used AFFDEX, Facet, and Kopernica to measure emotions, valence and intensity, using them simultaneously, but with *iMotions* we only can use one at the same time. Our solution was to use Facet with *iMotions* and video recorded all experiments. After we use recorded videos with AFFDEX and the same procedure with Kopernica.

<u>Step 8: Data management</u>

Data output was in csv files like the one show in next image.

Image 51: CSV files

```
#METADATA,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,
#Device,,SlideEvents,SlideEvents,SlideEvents,SlideEvents,SlideEvents,SlideEvents,Affectiva AFFDEX,Affectiva AFFDEX,Affectiva AFFDEX,Affectiva AFFDEX,Affectiva AFFDEX,Affectiva AFFDEX,Affectiva AFFDEX,Affectiva AFFDEX,Affectiva AFFDEX,Affectiva AFFDEX,Affectiva AFFDE
#Category,Timestamp,Event Source,Slideshow,Slideshow,Slideshow,Slideshow,Slideshow,Event Source,Counter,FEA(Emotions),FEA(Emotions),FEA(Emotions),FEA(Emotions),FEA(Emotions),FEA(Emotions),FEA(Emotions),FEA(Emotions),FEA(Emotions),FEA(Act
#Description,iMotions synchronization timestamp. Relative to data recording start,Can be used to filter data from: SlideEvents,Slide & Media events: Start/Stop,Type of stimulus,Stimulus duration fx video length,Reason slide was changed,Name of stimulus,C
#Unit,Millisecond,,,,Millisecond,,,,Index,Index,Index,Index,Index,Index,Index,Index,Index,Index,Index,Index,Index,Index,Index,Index,Index,Index,Index,Index,Index,Index,Index,Index,Index,Index,Index,Index,Index,Index,Index,Degrees,Degrees,Degrees,Pixel
#Short unit,ms,,,,ms,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,
#Group,,Event Source,,,,,,Event Source,Other,Emotion,Emotion,Emotion,Emotion,Emotion,Emotion,Emotion,Emotion,Emotion,Facial Expression,Facial Expression,Facial Expression,Facial Expression,Facial Expression,Facial Expression,Facial Expression,Facial Expression,Facial
#Display name,,,,,,,,,,Anger,Contempt,Disgust,Fear,Joy,Sadness,Surprise,Engagement,Valence,Attention,Brow Furrow,Brow Raise,Cheek Raise,Chin Raise,Dimpler,Eye Closure,Eye Widen,Inner Brow Raise,Jaw Drop,Lip Corner Depressor,Lip Press,Lip Pucker,Lip
#Provided By,iMotions,iMotions,iMotions,iMotions,iMotions,iMotions,iMotions,iMotions,iMotions,Affectiva,Affectiva,Affectiva,Affectiva,Affectiva,Affectiva,Affectiva,Affectiva,Affectiva,Affectiva,Affectiva,Affectiva,Affectiva,Affectiva,Affectiva,Affectiva,Affectiva,Affectiva,Affectiva,Af
#Channel identifier,iMotions_Synchronization_Timestamp,Eventsource_Slideevents,SE_SlideEvent,SE_StimulusType,SE_Duration,SE_CollectionPhase,SE_SourceStimuliName,Eventsource_Affectiva_AFFDEX,Imotions_Sample_Counter_Affectiva_AFFDEX,FEA_
#,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,
#DATA,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,
Row,Timestamp,EventSource,SlideEvent,StimType,Duration,CollectionPhase,SourceStimuliName,EventSource,SampleNumber,Anger,Contempt,Disgust,Fear,Joy,Sadness,Surprise,Engagement,Valence,Attention,Brow Furrow,Brow Raise,Cheek Raise,Chin Raise
1,0,1,StartSlide,TestImage,49170.033300000003,StimuliDisplay,FaceRecording-1,,,,,,,,,,,,,,,,,,,,,,,,,,,,
2,0,1,StartMedia,TestImage,49170.033300000003,StimuliDisplay,FaceRecording-1,,,,,,,,,,,,,,,,,,,,,,,,,,,,
3,36,,,,,,FaceRecording-1,1,0,0.00055437820265069604,0.19266054034233093,0.42694789171218872,0.27025279402732849,0.00020891393069177866,0.00061467883642762899,9.3877239227294922,8.3783950805664063,0,92.625465393066406,0.005
4,70,,,,,,FaceRecording-1,1,1,0.0011735946172848344,0.19265963137149811,0.4277116060256958,0.52478176355361938,0.00032279791776090086,0.00077145686373114586,5.164426326751709,3.4567394256591797,0,92.137466430664063,0.0020926
5,103,,,,,,FaceRecording-1,1,2,0.0021863293368369341,0.19266603887081146,0.42676609754562378,1.4122087955474854,0.00041148436139337718,0.00072957394877448678,3.8698899745941162,2.0402014255523682,0,90.761856079101563,0.0019
6,136,,,,,,FaceRecording-1,1,3,0.0020893241744488478,0.19267235696315765,0.4266238808631897,1.7935202121734619,0.00036922190338373184,0.00059644092107191682,4.6845221519470215,2.5619204044342041,0,91.257347106933594,0.0014
7,170,,,,,,FaceRecording-1,1,4,0.0020020338706672192,0.1926732063293457,0.42666861414909363,2.3045585155487061,0.00033132222597487271,0.00048532785149291158,5.6767368316650391,3.2265820503234863,0,91.185523986816406,0.0014
8,203,,,,,,FaceRecording-1,1,5,0.0018730122828856111,0.19267109036445618,0.42694872617721558,1.4877368211746216,0.00035725350608117878,0.00061838008696213365,4.8664054870605469,2.760857105255127,0,91.302513122558594,0.0012
9,236,,,,,,FaceRecording-1,1,6,0.0022170383017510176,0.19267256557941437,0.42682346701622009,2.1512091159820557,0.00037054929998703301,0.00056928227422758937,4.7583646774291992,2.5469584465026855,0,92.208992004394531,0.0012
10,270,,,,,,FaceRecording-1,1,7,0.0021853912621736526,0.19267283380031586,0.42681047320365906,2.2933692932128906,0.00036043717409484088,0.00054367794655263424,5.0068926811218262,2.7018618583679199,0,91.53802490234375,0.0013
11,303,,,,,,FaceRecording-1,1,8,0.0024138542357832193,0.19267155230045319,0.4267924427986145,1.5973310470581055,0.00043463514884933829,0.00075534038478508592,3.6076226234436035,1.8127418756484985,0,91.075302124023438,0.0012
12,336,,,,,,FaceRecording-1,1,9,0.0032611861824989319,0.19267301261425018,0.4266200065612793,2.6351950168609619,0.00048232733388843137,0.00070754368789494038,3.2058901786804199,1.4458842277526855,0,90.88525390625,0.0013204602
13,370,,,,,,FaceRecording-1,1,10,0.0030586174689233303,0.19267410039901733,0.4267117977142334,1.9370005130767822,0.00049892143579919991,0.00081409187987446785,2.9473850727081299,1.3451927900314331,0,92.075614929199219,0.0016
14,403,,,,,,FaceRecording-1,1,11,0.0034037765581160784,0.19267457723617554,0.42681795358657837,2.1854932308197021,0.00052681914530694485,0.00082668557297438383,2.737865686416626,1.1989239454269409,0,90.962684631347656,0.001
15,436,,,,,,FaceRecording-1,1,12,0.0034372077789157629,0.19267530739307404,0.42669576406478882,1.8356393575668335,0.00055773602798581123,0.00093282241141423583,2.4539763927459717,1.0585001707077026,0,92.426216125488281,0.00
```

Source: Author

From each participant we get:

- PC: 1 AFFDEX csv file, 1 *iMotions* csv file and 1 Kopernica csv file.
- Smart TV: 1 AFFDEX csv file, 1 *iMotions* csv file and 1 Kopernica csv file.
- Smartphone: 1 AFFDEX csv file, 1 *iMotions* csv file and 1 Kopernica csv file.

First, we convert csv data into Excel files with metrics in columns as we can see in next image.

Image 52: Excel data transformation

Row	Timestamp	EventSource	SlideEvent	StimType	Duration	CollectionPha	SourceStimul	EventSource	SampleNumb	Anger	Contempt	Disgust	Fear	Joy	Sadness	Surprise	Engagemen
1	0	1	StartSlide	TestImage	84733,3	StimuliDisplay	FaceRecordin	1	0	0,0168533	0,19267374	0,42618132	5,0429163	0,00177597	0,00305304	0,44811079	0,0845641
2	0	1	StartMedia	TestImage	84733,3	StimuliDisplay	FaceRecording-1										
3	33						FaceRecordin	1	1	0,00808565	0,19267356	0,42617121	0,44433442	0,00182657	0,00646187	0,32557532	0,0795288
4	66						FaceRecordin	1	2	0,00679365	0,19267356	0,42630658	0,2581912	0,00182852	0,00765683	0,3072221	0,0795020
5	100						FaceRecordin	1	3	0,00985364	0,19267356	0,42668161	0,87385213	0,00183008	0,00544418	0,35460719	0,079765
6	133						FaceRecordin	1	4	0,01317881	0,19267356	0,42702937	2,53546691	0,00183038	0,00430548	0,40905225	0,080149
7	166						FaceRecordin	1	5	0,01643521	0,19267356	0,42742756	5,02425957	0,00183167	0,0034901	0,44245449	0,0804643
8	200						FaceRecordin	1	6	0,01673619	0,19267356	0,42770511	5,58834648	0,00183264	0,00347843	0,45171222	0,0806887
9	233						FaceRecordin	1	7	0,01437865	0,19267356	0,42777982	3,74493527	0,0018327	0,00408771	0,43603677	0,0807768
10	266						FaceRecordin	1	8	0,01571004	0,19267356	0,42815596	4,32249165	0,00183362	0,00360719	0,43476406	0,0811266
11	300						FaceRecordin	1	9	0,01829206	0,19267356	0,42846143	6,60307789	0,00183421	0,0030828	0,4547053	0,0814161
12	333						FaceRecordin	1	10	0,01764195	0,19267356	0,42822608	6,23932648	0,0018324	0,00323943	0,45547301	0,0813207
13	366						FaceRecordin	1	11	0,01847099	0,19267356	0,42820331	7,0421567	0,00183063	0,0030784	0,4614239	0,081461
14	400						FaceRecordin	1	12	0,019614	0,19267356	0,42832169	8,15931892	0,00183048	0,00287632	0,4672628	0,0816060
15	433						FaceRecordin	1	13	0,02213014	0,19267356	0,42821696	10,5259199	0,00183026	0,00249265	0,47417822	0,0815071
16	466						FaceRecordin	1	14	0,02252406	0,19267356	0,42827553	10,9986639	0,00183056	0,00244613	0,47621983	0,0815409
17	500						FaceRecordin	1	15	0,02451633	0,19267356	0,42832065	13,5427151	0,00183201	0,00224125	0,48615843	0,0814501
18	533						FaceRecordin	1	16	0,02412691	0,19267356	0,42832127	13,0966425	0,00183201	0,00228274	0,48451912	0,0814534
19	566						FaceRecordin	1	17	0,02718383	0,19267356	0,42892304	18,6531982	0,0018341	0,00205465	0,51110059	0,0819566
20	600						FaceRecordin	1	18	0,03055516	0,19267356	0,42933664	24,9465847	0,00183569	0,00183467	0,53274202	0,0822832
21	633						FaceRecordin	1	19	0,03157363	0,19267356	0,42927018	26,26161	0,00183553	0,00176127	0,53363949	0,0822240
22	666						FaceRecordin	1	20	0,03255693	0,19267356	0,42897373	26,9643822	0,00183399	0,00168183	0,53007984	0,0820275
23	700						FaceRecordin	1	21	0,03147055	0,19267356	0,42927098	25,8312817	0,00183406	0,00175529	0,53125	0,0823667
24	733						FaceRecordin	1	22	0,03190165	0,19267356	0,42943144	26,7410049	0,00183369	0,0017302	0,53495699	0,082594
25	766						FaceRecordin	1	23	0,03382602	0,19267356	0,42958948	30,1906071	0,00183402	0,00162656	0,54380161	0,0827513
26	800						FaceRecordin	1	24	0,0340391	0,19267356	0,42954093	31,09375	0,00183406	0,00162834	0,54798204	0,0826917
27	833						FaceRecordin	1	25	0,03416307	0,19267356	0,42902365	30,5777493	0,00183291	0,00161289	0,54247224	0,0821984

Source: Author

Once we have data in Excel, we select timing where ad was executed (based on control datasheet) and extract metrics. With these data we calculate means for each metric.

Finally, we develop a datasheet with all means from all participants for each device (PC, smart TV, and smartphone).

Regarding Kopernica some frames are not available due to Kopernica filters that erase images that have low quality as we comment before. In our experiment this happened especially in mobile Kopernica data. Also, with AFFDEX, due to high sensibility, most of the data with Facial expressions were neutral, especially in mobile. For this reason, AFFDEX results are not collected in Doctoral Thesis.

Study procedure took a media of 45 min.

- Welcome, instructions and anti-covid protocol (5 minutes)
- Placing equipment and calibration (15 minutes)
- Test ads (15 minutes)
- Survey (5-10min)

4.3 **Data analysis**

Data come from the survey scales and consumer neuroscience metrics. Data from survey scales in Mobile, PC and TV were:

- Free brand recall, cued brand recall, and intrusiveness degree (Furnham, 1990)
- Consumer engagement scale (Dessart, 2016):
    - Cognitive dimension: 2 dimensions
        - Attention (2 items)
        - Absorption (4 items)
    - Affective dimension: 2 dimensions
        - Enthusiasm (3 items)
        - Enjoyment (3 items)
    - Behavioral dimension: 3 dimensions
        - Sharing (3 items)
        - Learning (3 items)

        - Endorsing (4 items)

Data from consumer neuroscience technologies, specifically of algorithms Kopernica, Facet, and AFFDEX in Mobile, PC and TV.

- KOPERNIKA (*Neurologyca*): 4 metrics
    - Engagement cognitive dimension.
        - Interest (rank 0 a 100, transformation to rank 0 a 1)
    - Engagement Affective dimension.
        - Intensity or Arousal (rank 0 to 100, transformation to rank 0 to 1)
        - Valence + (rank 0 to 100, transformation to rank 0 to 1)
        - Valence – (rank 0 to 100, transformation to rank 0 to 1)
- *iMotions* (Facet, EEG and Eye-tracking): 6 metrics
    - Engagement cognitive dimension.
        - Workload (EEG) (rank 0 to 1)
        - Visual attention (Eye Tracking): not available. Data aggregate.
        - Cognitive state or attention (EEG-Engagement) (rank 0 to 1)
    - Engagement affective dimension
        - Valence+ (logarithmic scale: antilogarithmic transformation, base power 10)
        - Valence– (logarithmic scale: antilogarithmic transformation, base power 10)
- iMotions (AFFDEX): 1 metric
    - Engagement affective dimension
        - Valence (rank 0 to 100).

4.3.1 Survey data descriptive analysis

Tables 30, 31 and 32 show results of free brand recall, cued brand recall and intrusiveness degree, respectively. Participants that match free or brand recall with the real ad where count as “yes” and the participants that don’t match answers with real ad were count as “non”.

Table 30: Free brand recall survey analysis

Device			Frequency	Percentage	valid percentage	cumulative percentage
Mobile	Valid	No	9	15,0	**15,3**	15,3
		Yes	50	83,3	**84,7**	100,0
		Total	59	98,3	**100,0**	
	Lost	System	1	1,7		
	Total		60	100,0		
PC	Valid	No	9	15,0	**15,5**	15,5
		Yes	49	81,7	**84,5**	100,0
		Total	58	96,7	**100,0**	
	Lost	System	2	3,3		
	Total		60	100,0		
TV	Valid	No	11	18,3	**18,6**	18,6
		Yes	48	80,0	**81,4**	100,0
		Total	59	98,3	**100,0**	
	Lost	System	1	1,7		
	Total		60	100,0		

Source: Author

As can be seen, free brand recall of the experimental subjects (yes) was higher in mobile device than PC or TV, and the lowest one is TV, although values are very similar.

Table 31: Cued brand recall survey analysis

Device			Frequency	percentage	valid percentage	cumulative percentage
Mobile	Valid	No	6	10,0	**10,2**	10,2
		Yes	53	88,3	**89,8**	100,0
		Total	59	98,3	**100,0**	
	Lost	System	1	1,7		
	Total		60	100,0		
PC	Valid	No	2	3,3	**3,4**	3,4
		Yes	56	93,3	**96,6**	100,0
		Total	58	96,7	**100,0**	
	Lost	System	2	3,3		
	Total		60	100,0		
TV	Valid	No	6	10,0	**10,2**	10,2
		Yes	53	88,3	**89,8**	100,0
		Total	59	98,3	**100,0**	
	Lost	System	1	1,7		
	Total		60	100,0		

Source: Author

As can be seen, free cued brand recall of the experimental subjects (yes) was higher in PC device than mobile or TV, and it’s the highest value in both free and cued brand recall. Also it’s interesting to mention that cued brand recall (yes) values are higher than free brand recall.

Table 32: Intrusiveness survey analysis

Device		N	Minimum	Maximum	Mean	Standard deviation
Mobile	Intrusiveness (Survey)	59	1	4	**2,12**	1,001
	N valid (by list)	59				
PC	Intrusiveness (Survey)	58	1	5	**2,00**	,973
	N valid (by list)	58				
TV	Intrusiveness (Survey)	59	1	5	**2,15**	1,186
	N valid (by list)	59				

Source: Author

As can be seen, intrusiveness of the experimental subjects was higher in TV than mobile or PC, and the lower mean is clearly PC, although all the mean and standard deviation values are very similar. All mean values for intrusiveness in all devices are low they don't reach the 2,5-mean value.

Tables 33 and 34 show results of cognitive engagement dimension, aggregate data and by device.

Table 33: Descriptive statistics. Cognitive engagement. Aggregate date

	N	Minimum	Maximum	Mean	standard deviation
Engagement (1.Cognitive; 1.Attention): 01 (Pienso muchas veces acerca de esta marca.)	176	1	5	**2,05**	,987
Engagement (1.Cognitive; 1.Attention): 02 (Parte de mi tiempo pienso en esta marca.)	176	1	4	**1,68**	,829
Engagement (1.Cognitive; 2.Absorption): 01 (Cuando interactúo con esta marca, me olvido de todo lo demás.)	176	1	4	**1,80**	1,005
Engagement (1.Cognitive; 2.Absorption): 02 (El tiempo vuela cuando interactúo con esta marca)	176	1	4	**1,86**	1,040
Engagement (1.Cognitive; 2.Absorption): 03 (Cuando interactúo con esta marca, me dejo llevar)	176	1	5	**2,03**	1,136
Engagement (1.Cognitive; 2.Absorption): 04 (Cuando interactúo con esta marca me es difícil desconectar)	176	1	4	**1,70**	,884
N valid (by list)	176				

Source: Author

As can be seen, cognitive engagement items score is very low, not exceeding the mean value of 2.5 in any of the items. The highest scores are reached in item 1 of attention and in item 3 of absorption, in both cases slightly exceeding level 2. Lower values are in item 2 of attention and item 4 of absorption.

Table 34: Descriptive statistics. Cognitive engagement. Survey by device

Device		N	Minimum	Maximum	Mean	Standard deviation
Mobile	Engagement (1.Cognitive; 1.Attention): 01 Pienso muchas veces acerca de esta marca.	59	1	4	**2,05**	1,007
	Engagement (1.Cognitive; 1.Attention): 02 Parte de mi tiempo pienso en esta marca.	59	1	4	**1,53**	,774
	Engagement (1.Cognitive; 2.Absorption): 01 Cuando interactúo con esta marca, me olvido de todo lo demás.	59	1	4	**1,85**	,997
	Engagement (1.Cognitive; 2.Absorption): 02 El tiempo vuela cuando interactúo con esta marca	59	1	4	**1,83**	1,020
	Engagement (1.Cognitive; 2.Absorption): 03 Cuando interactúo con esta marca, me dejo llevar.	59	1	4	**1,93**	1,032
	Engagement (1.Cognitive; 2.Absorption): 04 Cuando interactúo con esta marca me es difícil desconectar.	59	1	4	**1,69**	,856
	N valid (by list)	59				
PC	Engagement (1.Cognitive; 1.Attention): 01 Pienso muchas veces acerca de esta marca.	58	1	5	**2,05**	1,083
	Engagement (1.Cognitive; 1.Attention): 02 Parte de mi tiempo pienso en esta marca.	58	1	4	**1,81**	,907
	Engagement (1.Cognitive; 2.Absorption): 01 Cuando interactúo con esta marca, me olvido de todo lo demás.	58	1	4	**1,83**	,994
	Engagement (1.Cognitive; 2.Absorption): 02 El tiempo vuela cuando interactúo con esta marca	58	1	4	**1,93**	1,057
	Engagement (1.Cognitive; 2.Absorption): 03 Cuando interactúo con esta marca, me dejo llevar.	58	1	5	**2,14**	1,191
	Engagement (1.Cognitive; 2.Absorption): 04 Cuando interactúo con esta marca me es difícil desconectar.	58	1	4	**1,76**	,961
	N valid (by list)	58				
TV	Engagement (1.Cognitive; 1.Attention): 01 Pienso muchas veces acerca de esta marca.	59	1	4	**2,05**	,879
	Engagement (1.Cognitive; 1.Attention): 02 Parte de mi tiempo pienso en esta marca.	59	1	4	**1,71**	,789
	Engagement (1.Cognitive; 2.Absorption): 01 Cuando interactúo con esta marca, me olvido de todo lo demás.	59	1	4	**1,71**	1,035
	Engagement (1.Cognitive; 2.Absorption): 02 El tiempo vuela cuando interactúo con esta marca	59	1	4	**1,81**	1,058
	Engagement (1.Cognitive; 2.Absorption): 03 Cuando interactúo con esta marca, me dejo llevar.	59	1	5	**2,03**	1,189
	Engagement (1.Cognitive; 2.Absorption): 04 Cuando interactúo con esta marca me es difícil desconectar.	59	1	4	**1,66**	,843
	N valid (by list)	59				

Source: Author

Table 34 shows that cognitive engagement items score by device, between mobile and PC, the major differences are found in item 2 of attention and item 3 of absorption, in both cases with higher scores on the PC than on the mobile. A similar result is observed when the means corresponding to mobile, and TV are compared. It’s interesting to comment that lowest value is in item 2 attention in mobile and has also the lowest standard deviation. All values are low and don’t reach the 2,5-mean value.

Tables 35 and 36 show results of affective engagement dimension, aggregate data and by device.

Table 35: Descriptive statistics. Affective engagement. Aggregate date

	N	Minimum	Maximum	Mean	Standard deviation
Engagement (2.Affective; 1.Enthusiasm): 01 Estoy entusiasmado con esta marca	176	1	4	**2,10**	1,020
Engagement (2.Affective; 1.Enthusiasm): 02 Estoy interesado en todo lo que tenga que ver con esta marca	176	1	5	**2,02**	1,042
Engagement (2.Affective; 1.Enthusiasm): 03 Esta marca me parece interesante.	176	1	5	**2,80**	1,173
Engagement (2.Affective; 2.Enjoyment): 01 Cuando interactúo con esta marca me siento contento.	176	1	5	**2,49**	1,171
Engagement (2.Affective; 2.Enjoyment): 02 Obtengo placer al interactuar con esta marca.	176	1	5	**2,47**	1,287
Engagement (2.Affective; 2.Enjoyment): 03 Interactuar con esta marca es un regalo para mí.	176	1	5	**1,82**	1,003
N válid (by list)	176				

Source: Author

As can be seen in table 35, affective engagement items score is low, although somewhat higher than that achieved by the cognitive engagement items, since the scores are above 2, except for item 3 of enjoyment that is in line with cognitive values. The highest scoring item is enthusiasm item 3.

Table 36: Descriptive statistics. Affective engagement. Survey by device

Device		N	Minimum	Maximum	Mean	Standard deviation
Mobile	Engagement (2.Affective; 1.Enthusiasm): 01 Estoy entusiasmado con esta marca	59	1	4	**2,03**	1,017
	Engagement (2.Affective; 1.Enthusiasm): 02 Estoy interesado en todo lo que tenga que ver con esta marca	59	1	4	**2,02**	1,008
	Engagement (2.Affective; 1.Enthusiasm): 03 Esta marca me parece interesante.	59	1	5	**2,83**	1,147
	Engagement (2.Affective; 2.Enjoyment): 01 Cuando interactúo con esta marca me siento contento.	59	1	5	**2,41**	1,161

	Engagement (2.Affective; 2.Enjoyment): 02 Obtengo placer al interactuar con esta marca.	59	1	5	**2,31**	1,193
	Engagement (2.Affective; 2.Enjoyment): 03 Interactuar con esta marca es un regalo para mí.	59	1	4	**1,73**	,962
	N valid (by list)	59				
PC	Engagement (2.Affective; 1.Enthusiasm): 01 Estoy entusiasmado con esta marca	58	1	4	**2,12**	1,061
	Engagement (2.Affective; 1.Enthusiasm): 02 Estoy interesado en todo lo que tenga que ver con esta marca	58	1	5	**2,07**	1,057
	Engagement (2.Affective; 1.Enthusiasm): 03 Esta marca me parece interesante.	58	1	5	**2,72**	1,225
	Engagement (2.Affective; 2.Enjoyment): 01 Cuando interactúo con esta marca me siento contento.	58	1	5	**2,48**	1,173
	Engagement (2.Affective; 2.Enjoyment): 02 Obtengo placer al interactuar con esta marca.	58	1	5	**2,55**	1,300
	Engagement (2.Affective; 2.Enjoyment): 03 Interactuar con esta marca es un regalo para mí.	58	1	4	**1,97**	1,042
	N valid (by list)	58				
TV	Engagement (2.Affective; 1.Enthusiasm): 01 Estoy entusiasmado con esta marca	59	1	4	**2,15**	,997
	Engagement (2.Affective; 1.Enthusiasm): 02 Estoy interesado en todo lo que tenga que ver con esta marca	59	1	4	**1,98**	1,075
	Engagement (2.Affective; 1.Enthusiasm): 03 Esta marca me parece interesante.	59	1	5	**2,83**	1,162
	Engagement (2.Affective; 2.Enjoyment): 01 Cuando interactúo con esta marca me siento contento.	59	1	5	**2,59**	1,191
	Engagement (2.Affective; 2.Enjoyment): 02 Obtengo placer al interactuar con esta marca.	59	1	5	**2,56**	1,368
	Engagement (2.Affective; 2.Enjoyment): 03 Interactuar con esta marca es un regalo para mí.	59	1	5	**1,76**	1,006
	N valid (by list)	59				

Source: Author

Table 36 shows that affective engagement items score by device, between mobile and PC. The scores of all the items are higher in PC than in mobile, except in item 3 of enthusiasm. A similar result is observed when the means corresponding to mobile and TV are compared, although in this case, the exception is given in item 2 of enthusiasm. Lowest value is item 3 enjoyment in mobile.

Tables 37 and 38 show results of behavioral engagement dimension, aggregate data and by device.

Table 37: Descriptive statistics. Behavioral engagement. Aggregate date

	N	Minimum	Maximum	Mean	Standard deviation
Engagement (3.Behavioral; 1.Sharing): 01 Comparto mis ideas con esta marca	176	1	4	**1,78**	,951
Engagement (3.Behavioral; 1.Sharing): 02 Comparto contenido interesante con esta marca.	176	1	5	**1,68**	,940
Engagement (3.Behavioral; 1.Sharing): 03 Ayudo a esta marca	176	1	4	**1,65**	,881
Engagement (3.Behavioral; 2.Learning): 01 Hago preguntas a esta marca	176	1	4	**1,33**	,721
Engagement (3.Behavioral; 2.Learning): 02 Busco ideas o información sobre esta marca	176	1	5	**1,84**	1,068
Engagement (3.Behavioral; 2.Learning): 03 Busco ayuda de esta marca	176	1	4	**1,27**	,580
Engagement (3.Behavioral; 3.Endorsing): 01 Promuevo esta marca	176	1	5	**1,63**	,930
Engagement (3.Behavioral; 3.Endorsing): 02 Intento que otros se interesen por esta marca	176	1	4	**1,55**	,918
Engagement (3.Behavioral; 3.Endorsing): 03 Defiendo a esta marca de aquellos que la critican	176	1	5	**1,86**	1,163
Engagement (3.Behavioral; 3.Endorsing): 04 Digo cosas positivas sobre esta marca a otras personas	176	1	5	**2,31**	1,282
N valid (by list)	176				

Source: Author

In behavioral engagement dimension, items score is also low, in the line of cognitive items because only one item reaches a score greater than 2. The highest scoring item is endorsing item 4.

Table 38: Descriptive statistics. Behavioral engagement. Survey by device

Device		N	Minimum	Maximum	Mean	Standard deviation
Mobile	Engagement (3.Behavioral; 1.Sharing): 01 Comparto mis ideas con esta marca	59	1	4	**1,73**	,962
	Engagement (3.Behavioral; 1.Sharing): 02 Comparto contenido interesante con esta marca.	59	1	4	**1,64**	,943
	Engagement (3.Behavioral; 1.Sharing): 03 Ayudo a esta marca	59	1	4	**1,68**	,918
	Engagement (3.Behavioral; 2.Learning): 01 Hago preguntas a esta marca	59	1	4	**1,37**	,763
	Engagement (3.Behavioral; 2.Learning): 02 Busco ideas o información sobre esta marca	59	1	5	**1,92**	1,179
	Engagement (3.Behavioral; 2.Learning): 03 Busco ayuda de esta marca	59	1	4	**1,34**	,685
	Engagement (3.Behavioral; 3.Endorsing): 01 Promuevo esta marca	59	1	5	**1,63**	,981
	Engagement (3.Behavioral; 3.Endorsing): 02 Intento que otros se interesen por esta marca	59	1	4	**1,59**	,985

	Engagement (3.Behavioral; 3.Endorsing): 03 Defiendo a esta marca de aquellos que la critican	59	1	5	**1,95**	1,238
	Engagement (3.Behavioral; 3.Endorsing): 04 Digo cosas positivas sobre esta marca a otras personas	59	1	5	**2,37**	1,351
	N valid (by list)	59				
PC	Engagement (3.Behavioral; 1.Sharing): 01 Comparto mis ideas con esta marca	58	1	4	**1,78**	1,044
	Engagement (3.Behavioral; 1.Sharing): 02 Comparto contenido interesante con esta marca.	58	1	5	**1,74**	1,036
	Engagement (3.Behavioral; 1.Sharing): 03 Ayudo a esta marca	58	1	4	**1,60**	,877
	Engagement (3.Behavioral; 2.Learning): 01 Hago preguntas a esta marca	58	1	4	**1,31**	,706
	Engagement (3.Behavioral; 2.Learning): 02 Busco ideas o información sobre esta marca	58	1	5	**1,79**	1,005
	Engagement (3.Behavioral; 2.Learning): 03 Busco ayuda de esta marca	58	1	3	**1,22**	,497
	Engagement (3.Behavioral; 3.Endorsing): 01 Promuevo esta marca	58	1	4	**1,57**	,797
	Engagement (3.Behavioral; 3.Endorsing): 02 Intento que otros se interesen por esta marca	58	1	4	**1,55**	,902
	Engagement (3.Behavioral; 3.Endorsing): 03 Defiendo a esta marca de aquellos que la critican	58	1	5	**1,78**	1,140
	Engagement (3.Behavioral; 3.Endorsing): 04 Digo cosas positivas sobre esta marca a otras personas	58	1	5	**2,17**	1,258
	N valid (by list)	58				
TV	Engagement (3.Behavioral; 1.Sharing): 01 Comparto mis ideas con esta marca	59	1	4	**1,83**	,854
	Engagement (3.Behavioral; 1.Sharing): 02 Comparto contenido interesante con esta marca	59	1	4	**1,64**	,846
	Engagement (3.Behavioral; 1.Sharing): 03 Ayudo a esta marca	59	1	4	**1,68**	,860
	Engagement (3.Behavioral; 2.Learning): 01 Hago preguntas a esta marca	59	1	4	**1,31**	,701
	Engagement (3.Behavioral; 2.Learning): 02 Busco ideas o información sobre esta marca	59	1	5	**1,81**	1,025
	Engagement (3.Behavioral; 2.Learning): 03 Busco ayuda de esta marca	59	1	3	**1,25**	,544
	Engagement (3.Behavioral; 3.Endorsing): 01 Promuevo esta marca	59	1	5	**1,68**	1,008
	Engagement (3.Behavioral; 3.Endorsing): 02 Intento que otros se interesen por esta marca	59	1	4	**1,49**	,878
	Engagement (3.Behavioral; 3.Endorsing): 03 Defiendo a esta marca de aquellos que la critican	59	1	5	**1,86**	1,121
	Engagement (3.Behavioral; 3.Endorsing): 04 Digo cosas positivas sobre esta marca a otras personas	59	1	5	**2,39**	1,246
	N valid (by list)	59				

Source: Author

Table 38 shows that behavioral engagement items score by device. Unlike what happened with the cognitive and affective dimensions, the difference between the scores of the behavioral items between mobile and PC is generally favorable to mobile phones since in 8 of the 10 items their scores are higher than those obtained for PC. This advantage is not so clear in the comparison between mobile and TV, since in this case the mobile scores more in 5 items and the TV in 3. The TV scores more in a sharing item and 2 in endorsing, while the mobile scores more in the 3 learning items and in 2 endorsing items.

Exploratory factor analysis. Survey. Cognitive engagement

Tables 39 and 40 show total variance explained, rotated component matrix, and reliability of main components: absorption and attention. These components will be used in the hypothesis analysis.

Table 39: Total variance explained

	Extraction sums of square loadings			Rotation sums of square loadings		
Component	Total	% of variance	% cumulative	Total	% of variance	% cumulative
1 Absorption	3,597	59,948	59,948	2,789	46,491	46,491
2 Attention	1,019	16,988	76,937	1,827	30,446	76,937

Extraction method: Principal component analysis.

Source: Author

Table 40: Rotated[a] component matrix

	Component	
	1	2
Engagement (1.Cognitive; 2.Absorption): 03 Cuando interactúo con esta marca, me dejo llevar.	**,841**	,265
Engagement (1.Cognitive; 2.Absorption): 01 Cuando interactúo con esta marca, me olvido de todo lo demás.	**,819**	,262
Engagement (1.Cognitive; 2.Absorption): 04 Cuando interactúo con esta marca me es difícil desconectar.	**,818**	,073
Engagement (1.Cognitive; 2.Absorption): 02 El tiempo vuela cuando interactúo con esta marca	**,795**	,376
Engagement (1.Cognitive; 1.Attention): 01 Pienso muchas veces acerca de esta marca.	,176	**,906**
Engagement (1.Cognitive; 1.Attention): 02 Parte de mi tiempo pienso en esta marca.	,283	**,849**

Extraction methodology: Principal component analysis.
Rotation methodology: Varimax with Kaiser normalization.
a. Rotation converge in 3 iterations.

Reliability test Cronbach's alpha

	Cronbach's alpha	N of items
1 Absorption	0,876	4
2 Attention	0,790	2
Complete	**0,864**	**6**

Source: Author

Rotated component matrix of principal component analysis shows that the two dimensions of cognitive engagement are clearly identified, assigning the items corresponding to each one appropriately and with high scores. Also, Cronbach's alpha of the Reliability test shows correct values.

Exploratory factor analysis. Survey. Affective engagement

Tables 41 and 42 show total variance explained, rotated component matrix, and reliability of main components: affective enjoyment and enthusiasm. These components will be used in the hypothesis analysis.

Table 41: Total variance explained

	Extraction sums of square loadings			Rotation sums of square loadings		
Component	Total	% of variance	% cumulative	Total	% of variance	% cumulative
1 Enjoyment	4,073	67,885	67,885	2,642	44,035	44,035
2 Enthusiasm	,833	13,876	81,761	2,264	37,726	81,761

Extraction method: Principal component analysis.

Source: Author

Table 42: Rotated[a] component matrix

	Component 1	Component 2
Engagement (2.Affective; 2.Enjoyment): 02 Obtengo placer al interactuar con esta marca.	**,913**	,250
Engagement (2.Affective; 2.Enjoyment): 03 Interactuar con esta marca es un regalo para mí.	**,877**	,260
Engagement (2.Affective; 2.Enjoyment): 01 Cuando interactúo con esta marca me siento contento.	**,801**	,463
Engagement (2.Affective; 1.Enthusiasm): 02 Estoy interesado en todo lo que tenga que ver con esta marca	,279	**,860**
Engagement (2.Affective; 1.Enthusiasm): 03 Esta marca me parece interesante.	,225	**,851**
Engagement (2.Affective; 1.Enthusiasm): 01 Estoy entusiasmado con esta marca	,519	**,675**

Extraction methodology: Principal component analysis.
Rotation methodology: Varimax with Kaiser normalization.
a. Rotation converges in 3 iterations.

Reliability test Cronbach's alpha

	Cronbach's alpha	N of items
1 Enjoyment	0,914	3
2 Enthusiasm	0,834	3
Complete	**0,902**	**6**

Source: Author

Rotated component matrix of principal component analysis shows, as in the case of cognitive engagement, that the two dimensions of affective engagement are clearly identified, assigning the items corresponding to each one appropriately and with high scores. Also, Cronbach's alpha of the Reliability test shows right values.

Exploratory factor analysis. Survey. Behavioral engagement

Tables 43 and 44 show total variance explained, rotated component matrix, and reliability of main components: behavioral endorsing, learning, and sharing. These components will be used in the hypothesis analysis.

Table 43: Total variance explained

	Extraction sums of square loadings			Rotation sums of square loadings		
Component	Total	% of variance	% cumulative	Total	% of variance	% cumulative
1 Endorsing	5,980	59,800	59,800	3,219	32,192	32,192
2 Learning	1,076	10,755	70,556	2,334	23,340	55,532
3 Sharing	,787	7,870	78,426	2,289	22,894	78,426

Extraction method: Principal component analysis.

Source: Author

Table 44: Rotated[a] component matrix

	Component		
	1	2	3
Engagement (3.Behavioral; 3.Endorsing): 03 Defiendo a esta marca de aquellos que la critican	**,867**	,287	,110
Engagement (3.Behavioral; 3.Endorsing): 01 Promuevo esta marca	**,835**	,288	,224
Engagement (3.Behavioral; 3.Endorsing): 04 Digo cosas positivas sobre esta marca a otras personas	**,775**	,143	,360
Engagement (3.Behavioral; 3.Endorsing): 02 Intento que otros se interesen por esta marca	**,747**	,375	,292
Engagement (3.Behavioral; 2.Learning): 03 Busco ayuda de esta marca	,235	**,841**	,224
Engagement (3.Behavioral; 2.Learning): 02 Busco ideas o información sobre esta marca	,332	**,759**	,213
Engagement (3.Behavioral; 2.Learning): 01 Hago preguntas a esta marca	,244	**,697**	,406
Engagement (3.Behavioral; 1.Sharing): 02 Comparto contenido interesante con esta marca.	,253	,275	**,860**
Engagement (3.Behavioral; 1.Sharing): 01 Comparto mis ideas con esta marca	,209	,363	**,811**
Engagement (3.Behavioral; 1.Sharing): 03 Ayudo a esta marca	,526	,173	**,596**

Extraction methodology: Principal component analysis.
Rotation methodology: Varimax with Kaiser normalization.
a. Rotation converges in 5 iterations.

Reliability test Cronbach's alpha

	Cronbach's alpha	N of items
1 Endorsing	0,903	4
2 Learning	0,789	3
3 Sharing	0,846	3
Complete	**0,919**	**10**

Source: Author

Rotated component matrix of principal component analysis shows, as in the case of cognitive and affective engagement, that the three dimensions of behavioral engagement are clearly identified, assigning the items corresponding to each one appropriately and with high scores, perhaps with the exception of item 3 of sharing. Also Cronbach's alpha of the Reliability test shows right values.

Exploratory factor analysis. Survey. Comparative by devices.

Tables 45, 46 and 47 show the factorial scores of the three dimensions of consumer engagement, respectively. Since the aggregate mean equals 0, a positive mean value indicates that the score of each one of the devices is above the mean and a negative score, that it is below the mean.

Table 45: Factorial scores. Cognitive dimension

Device		N	Minimum	Maximum	Mean	Standard deviation
Mobile	Factorial Engagement: 1.Cognitive 2.Absorption	59	-1,34143	1,99267	**,0012199**	,92336893
	Factorial Engagement: 1.Cognitive 1.Attention	59	-1,68403	2,43760	**-,1001462**	,97923557
	N valid (by list)	59				
PC	Factorial Engagement: 1.Cognitive 2.Absorption (survey)	58	-1,71607	2,38784	**,0621732**	1,04620564
	Factorial Engagement: 1.Cognitive 1.Attention (survey)	58	-1,97204	2,39368	**,0664767**	1,08562636
	N valid (by list)	58				
TV	Factorial Engagement: 1.Cognitive 2.Absorption (survey)	59	-1,71607	2,48016	**-,0623394**	1,03977701
	Factorial Engagement: 1.Cognitive 1.Attention (survey)	59	-1,44339	2,39368	**,0347962**	,94033075
	N valid (by list)	59				

Source: Author

Table 45 shows cognitive engagement factorial score by device. As can be seen, between mobile and PC, the attention and absorption scores are higher on PC than on TV. In the comparison between mobile and TV, the results are different: factorial score of attention is higher in TV than in mobile, but the factorial score of absorption is higher in mobile than in TV.

Table 46: Factorial scores. Affective dimension

Devices		N	Minimum	Maximum	Mean	Standard deviation
Mobile	Factorial Engagement: 2.Affective 2.Enjoyment (survey)	59	-1,83609	2,43554	**-,1362813**	,92527724
	Factorial Engagement: 2.Affective 1.Enthusiasm (survey)	59	-1,47602	2,09066	**,0462173**	,99364422
	N valid (by list)	59				
PC	Factorial Engagement: 2.Affective 2.Enjoyment (survey)	58	-1,59462	2,84206	**,1013051**	1,04546665
	Factorial Engagement: 2.Affective 1.Enthusiasm (survey)	58	-1,84249	2,06505	**-,0508963**	1,01096065
	N valid (by list)	58				
TV	Factorial Engagement: 2.Affective 2.Enjoyment (survey)	59	-1,59776	2,95111	**,0366932**	1,02782420
	Factorial Engagement: 2.Affective 1.Enthusiasm (survey)	59	-2,63871	1,76475	**,0038163**	1,01030412
	N valid (by list)	59				

Source: Author

Regarding the affective dimension of engagement, table 46 shows factorial score by device. As can be seen, between mobile and PC, factorial score of enjoyment is higher in PC than in mobile, but the factorial score of enthusiasm is higher in mobile than in PC. The same happens in the comparison between mobile and TV.

Table 47: Factorial scores. Behavioral dimension

Devices		N	Minimum	Maximum	Mean	Standard deviation
Mobile	Factorial Engagement: 3.Behavioral 3.Endorsing	59	-1,25982	3,50890	**,0477654**	1,08990701
	Factorial Engagement: 3.Behavioral 2.Learning	59	-1,50553	3,69998	**,1158848**	1,14964055
	Factorial Engagement: 3.Behavioral 1.Sharing	59	-2,98018	2,37231	**-,0906071**	1,08084871
	N valid (by list)	59				
PC	Factorial Engagement: 3.Behavioral 3.Endorsing	58	-1,55848	2,39198	**-,0836547**	,88814285
	Factorial Engagement: 3.Behavioral 2.Learning	58	-1,69653	2,80690	**-,0505350**	,85354029
	Factorial Engagement: 3.Behavioral 1.Sharing	58	-1,14316	2,96560	**,0633161**	1,02551629
	N valid (by list)	58				
TV	Factorial Engagement: 3.Behavioral 3.Endorsing	59	-1,33284	3,19147	**,0344715**	1,02157652
	Factorial Engagement: 3.Behavioral 2.Learning	59	-1,71423	2,55528	**-,0662063**	,97924685
	Factorial Engagement: 3.Behavioral 1.Sharing	59	-2,07699	2,62345	**,0283641**	,89569959
	N valid (by list)	59				

Source: Author

Regarding the behavioral dimension of engagement, table 47 shows factorial score by device. As can be seen, between mobile and PC, factorial score of sharing is higher in PC than in mobile, but the factorial score of learning and endorsing is higher in mobile than in PC. In the comparison between mobile and TV, factorial scores of sharing and endorsing are higher in TV than in mobile, but the factorial score of learning is higher in mobile than in PC.

4.3.2 Consumer neuroscience data descriptive analysis

To facilitate understanding of the results, these are presented for each of the 2 algorithms used: Kopernica and Facet iMotions. Although they were also calculated for AFFDEX iMotions, the results were neutral, thus lacking value from the point of comparison between the various devices.

<u>Kopernica: Engagement cognitive and affective dimensions</u>

The first algorithm of neuroscience technology used in this Doctoral Thesis is Kopernica. With this algorithm we measure, corresponding to the cognitive dimension: Interest (rank 0 a 100), while in affective dimension we measure: Arousal (rank 0 to 100), Valence + (rank 0 to 100), and Valence – (rank 0 to 100). To place all measures between rank (0-1), we divide raw scores by 100.

Tables 48, 49, 50, and 51 show the means of interest, arousal, valence +, and valence -, respectively. As stated above, all means are in the range 0-1.

Interest is a mix of focalize attention, immersion, and concentration. This metric is based on focus, a variable that measures how oriented and focus is the user face to the screen using pitch, roll and jaw, blinks rate and distance from face to screen. Distance to screen is measure using eye trackers. Leaning forwards or backwards in front of a remote device is tracked directly and can reflect approach-avoidance behavior. Low interest corresponds to lower mean and high interest to high mean.

Table 48: Cognitive engagement. Interest (Kopernica)

Device		N	Minimum	Maximum	Mean	Standard deviation
Mobile	Engagement Cognitive: Interest (Kopernica)	49	,16980	,73990	**,4976531**	,13479603
PC	Engagement Cognitive: Interest (Kopernica)	59	,32500	,76950	**,5934610**	,09659479
TV	Engagement Cognitive: Interest (Kopernica)	49	,27590	,73650	**,5591939**	,10053718

Source: Author

Interest (Kopernica) by device is in table 48. As can be seen, the means are around the middle of the 0-1 scale. PC mean is the highest, followed by the TV mean and, lastly, the one corresponding to mobile.

Table 49 resumes Kopernica Arousal or intensity that indicate the level of activation of our nervous system in terms of quietness low mean or surprise high mean. When a stimulus is relevant intensity mean has a high value while if a stimulus is neutral intensity mean has a low value.

Table 49: Affective engagement: Intensity/Arousal (Kopernica)

Device		N	Minimum	Maximum	Mean	Standard deviation
Mobile	Engagement Affective: Intensity or Arousal (Kopernica)	49	0,0010714	0,9933333	**0,433932658**	0,388231558
	N valid (by list)	49				
PC	Engagement Affective: Intensity or Arousal (Kopernica)	59	0,0007576	0,99	**0,492145631**	0,352214363
	N valid (by list)	59				
TV	Engagement Affective: Intensity or Arousal (Kopernica)	48	0,0131881	0,9830357	**0,487599035**	0,320677533
	N valid (by list)	48				

Source: Author

Regarding arousal (Kopernica) by device, table 49 shows a result like those obtained for the interest. As can be seen, the means are slightly below the middle of the 0-1 scale. PC mean is the highest, followed by the TV mean and, lastly, the one corresponding to mobile intensity. Therefore, when the video ads are seen on PC or TV arousal increases more than in mobile phones.

Another metric used by Kopernica is valence, positive and negative. When a stimulus is positive and consumers like it, positive valence has a high value meaning an approach behavior to the stimulus.

Table 50: Affective engagement: Valence + (Kopernica)

Device		N	Minimum	Maximum	Mean	Standard deviation
Mobile	Engagement Affective: Valence + (Kopernica)	49	0,0914651	0,9902597	**0,505290388**	0,334926721
	N valid (by list)	49				
PC	Engagement Affective: Valencia + (Kopernica)	59	0,0921718	0,9936808	**0,431259441**	0,318387209
	N valid (by list)	59				
TV	Engagement Affective: Valencia + (Kopernica)	48	0,0927967	0,9675873	**0,438359119**	0,288277629
	N valid (by list)	48				

Source: Author

Regarding valence+ (Kopernica) by device, table 50 shows different results to those obtained for interest and arousal. As can be seen, the means are around, slightly below, the middle of the 0-1 scale. Mobile mean is the highest, followed by the TV mean and, lastly, the one corresponding to PC. Therefore, when the video ads are seen on mobile phones, they like something more than when they are seen on the other two devices, even if they have less arousal as we saw in table 49.

Opposite to what happens with valence+, if a stimulus is negative and consumers do not like it, negative valence has a high value meaning an avoid behavior to the stimulus. If stimulus is neutral values are close to cero.

Table 51: Affective engagement: Valence- (Kopernica)

Device		N	Minimum	Maximum	Mean	Standard deviation
Mobile	Engagement Affective: Valencia - (Kopernica)	49	0,0097403	0,9085349	**0,494709612**	0,334926721
	N valid (by list)	49				
PC	Engagement Affective: Valencia - (Kopernica)	59	0,0063192	0,9078282	**0,568740559**	0,318387209
	N valid (by list)	59				
TV	Engagement Affective: Valencia - (Kopernica)	48	0,0324127	0,9072033	**0,561640881**	0,288277629
	N valid (by list)	48				

Source: Author

Regarding valence- (Kopernica) by device, table 51 shows consistent results to those obtained for valence+. As can be seen, the means are around, slightly above, the middle of the 0-1 scale. Mobile mean is the lowest, followed by the TV mean and, lastly, the highest corresponding to PC. Therefore, when the video ads are seen on TV and PC, they are somewhat less liked than when they are seen on mobile.

Globally, in three devices, valence- has the highest means of the three affective engagement metrics (Kopernica).

<u>Facet iMotions:</u> <u>Engagement cognitive and affective dimensions</u>

Other neuroscience algorithms used in this Doctoral Thesis is Facet that appertains to iMotions. With this algorithm and EEG technology we measure, corresponding to the cognitive dimension: Workload (EEG) (rank 0 to 1) and Cognitive state (EEG-Engagement) (rank 0 to 1) corresponding to the cognitive dimension. In affective dimension we measure: Valence+ (logarithmic scale: antilogarithmic transformation, base power 10), Valencia– (logarithmic scale: antilogarithmic transformation, base power 10).

Tables 52, 53, 54, and 55, show the scores of cognitive workloads, cognitive state (EEG-engagement), valence+, and valence-, respectively.

Regarding to cognitive workload, a high value means that a consumer is experimenting a high mental effort with a stimulus and low value if it does not.

Table 52: Cognitive engagement. Workload (iMotions)

Device		N	Minimum	Maximum	Mean	Standard deviation
Mobile	Engagement Cognitive: Workload (EEG)	57	,34953	,79711	**,6261599**	,11231220
	N valid (by list)	57				
PC	Engagement Cognitive: Workload (EEG)	53	,27580	,76421	**,5645169**	,11343397
	N valid (by list)	53				
TV	Engagement Cognitive: Workload (EEG)	56	,34276	,70640	**,5200987**	,08972376
	N valid (by list)	56				

Source: Author

Regarding cognitive workload (*iMotions*) by device, table 52 shows, as can be seen, the means are around, slightly above, the middle of the 0-1 scale. Mobile mean is the highest, followed by the PC mean and, lastly, the one corresponding to TV. So, video ads in mobile require the highest mental effort from consumers.

Other metric of cognitive nature of *iMotions* is cognitive state (EEG-engagement). Table 53 shows their scores. A high value of this metric means that a consumer pay attention and is focus during visual scanning of the stimulus.

Table 53: Cognitive engagement: Cognitive state. EEG engagement. (iMotions)

Device		N	Minimum	Maximum	Mean	Standard deviation
Mobile	Cognitive Engagement Cognitive state. (iMotions)	57	,00000	,95070	**,3993299**	,19347951
	N valid (by list)	57				
PC	Cognitive Engagement Cognitive state. (iMotions)	54	,00000	,83093	**,4047085**	,18034175
	N valid (by list)	54				
TV	Cognitive Engagement Cognitive state. (iMotions)	56	,00000	,83314	**,3812887**	,18569564
	N valid (by list)	56				

Source: Author

Regarding cognitive state (EEG-engagement, *iMotions*) by device, Table 53 shows, as can be seen, PC mean is the highest, followed by the mobile mean and, lastly, the one corresponding to TV. Therefore, when the video ads are seen on mobile consumers pay a little less attention and focus than when the video ad is viewed on PC but somewhat greater than when viewed on TV device.

Valence+ (Facet-*iMotions*) measures the degree to which the consumer likes the stimulus. When a stimulus is positive and consumers like it, valence+ has a high value meaning an approach behavior to the stimulus.

Table 54 shows the scores of valences+, an affective engagement metric.

Table 54: Affective engagement. Valence + (Facet iMotions)

Device		N	Minimum	Maximum	Mean	Standard deviation
Mobile	Engagement Affective: Valence + (Facet iMotions)	60	,00000	11,88100	**,3146000**	1,62662153
	N valid (by list)	60				
PC	Engagement Affective: Valence+ (Facet iMotions)	58	,00000	,10600	**,0047345**	,01919683
	N valid (by list)	58				
TV	Engagement Affective: Valence+ (Facet iMotions)	57	,00000	1,63160	**,0753123**	,23932045
	N valid (by list)	57				

Source: Author

Regarding valence + (Facet-*iMotions*) by device, table 54 shows, as can be seen, mobile mean is the highest, with a score 4 times higher than that of the next device, TV. The lowest average corresponds to the PC. Therefore, video ads in mobile are liked more by consumers than on the other two devices.

Table 55 shows the scores of valences-, another affective engagement metric. Valence - (Facet-iMotions) measures the degree to which the consumer does not like the stimulus. When a stimulus is negative and consumers do not like it, negative valence has a high value meaning an avoid behavior to the stimulus. If stimulus is neutral values are close to cero.

Table 55: Affective engagement. Valence - (Facet iMotions)

Device		N	Minimum	Maximum	Mean	Standard deviation
Mobile	Engagement Affective: Valence - (Facet iMotions)	59	,13810	24,62010	**3,4107729**	4,07288628
	N valid (by list)	59				
PC	Engagement Affective: Valence - (Facet iMotions)	59	,00000	17,47660	**1,4475593**	2,57301431
	N valid (by list)	59				
TV	Engagement Affective: Valence - (Facet iMotions)	58	,04570	19,02090	**2,3867103**	3,59785720
	N valid (by list)	58				

Source: Author

Regarding valence - (Facet-*iMotions*) by device, table 55 shows, as can be seen, mobile mean is the highest, followed by the TV mean and, lastly, the one corresponding to PC. Therefore, when the video ads are seen on mobile, they are somewhat less liked than when they are seen on TV and PC.

iMotions (**AFFDEX**)

In affective dimension we measure (rank 0 to 100). Stimulus in the experiment were normal ads that do not have a high value of emotions, so AFFDEX detect them as neutral emotions (0 values). Thus, these results are not used in subsequent analysis.

4.3.3 Correlation analysis consumer neuroscience: Kopernica and Facet-iMotions metrics

This section shows the correlation between the various metrics corresponding to the Kopernica and Facet algorithms (see table 56).

Table 56: Correlation analysis. Kopernica and Facet-iMotions metrics

		1	2	3	4	5	6	7	8
1 Engagement Cognitive: Interest (Kopernica)	Correl.	1	-,025	,033	-,033	-,111	,015	-,178*	-,005
	Sig.		,756	,683	,683	,181	,852	,026	,951
	N		156	156	156	147	155	156	148
2 Engagement Affective: Intensity/Arousal (Kopernica)	Correl.		1	-,951**	,951**	,010	,117	,011	,089
	Sig.			,000	,000	,902	,149	,889	,285
	N			156	156	146	154	155	147
3 Engagement Affective: Valence + (Kopernica)	Correl.			1	-1,000**	-,012	-,074	-,008	-,051
	Sig.				,000	,882	,360	,918	,538
	N				156	146	154	155	147
4 Engagement Affective: Valence - (Kopernica)	Correl.				1	,012	,074	,008	,051
	Sig.					,882	,360	,918	,538
	N					146	154	155	147
5 Engagement Cognitive: Workload (iMotions)	Correl.					1	,070	,084	-,072
	Sig.						,376	,282	,356
	N						164	165	166
6. Engagement Affective: Valence + (iMotions)	Correl.						1	,030	-,018
	Sig.							,694	,815
	N							174	165
7. Engagement Affective: Valence - (iMotions)	Correl.							1	-,110
	Sig.								,158
	N								166
8. Engagement cognitive: EEG-Engagement (iMotions)	Correl.								1
	Sig.								
	N								

**. Correlation is significant at the level 0,01 (bilateral).
*. Correlation is significant at the level 0,05 (bilateral).

Source: Author

As can be seen in table 57, there is a significant positive correlation between:

- Intensity/Arousal (affective engagement) in Kopernica with negative valence (affective engagement) in Kopernica. This correlation shows that when intensity/arousal increases also negative valence increase, it suggests that ads that increase excitation of the participants are also ads that they generate an avoiding attitude to the ad.

Likewise, there is a significant negative correlation between:

- Interest (cognitive engagement) in Kopernica with negative valence (affective engagement) iMotions. This correlation explains that when interest in the ad increases decreases avoiding attitude in the participants.
- Intensity/Arousal (affective engagement) in Kopernica with positive valence (affective engagement) in Kopernica. According to this correlation when intensity/arousal increases the approach attitude of the participants to the ad decreases.
- Positive valence (affective engagement) in Kopernica with negative valence (affective engagement) in Kopernica. This correlation between the two valences is normal, one depends on the other.

4.4 **Results**

This Doctoral Thesis starts from the premise that consumer engagement, based on three dimensions, is a valid variable to measure video ads effectiveness. From this premise, two groups of hypotheses are articulated.

The first group integrates the hypothesis that refer to the proposition that the metrics associated with consumer neuroscience technologies complement the traditional survey technique to measure video advertising effectiveness. That is, video ads effectiveness can be measured using consumer neuroscience technologies as a compliment of traditional methods.

The second group is made up of hypothesis that propose that advertising videos inserted in different devices generate different results in various metrics related to the dimensions of consumer engagement. In other words, an advertising video has different effects depending on the device on which it communicates.

4.4.1 Results obtained through survey method and consumer neuroscience technologies

In chapter 3 of the Doctoral Thesis, the hypotheses were proposed, the first group of which integrated two, each in turn disaggregated into two sub-hypotheses:

H1a1: Results corresponding to the cognitive dimension of consumer engagement provided by the various algorithms of consumer neuroscience technologies are not correlated.

H1a2: Results corresponding to the affective dimension of consumer engagement provided by the various algorithms of consumer neuroscience technologies are not correlated.

H1b1: There is a correlation between consumer engagement cognitive results measured through a survey and through some neuroscience algorithms.

H1b2: There is a correlation between consumer engagement affective results measured through a survey and through some neuroscience algorithms.

Hypothesis 1a

To contrast Hypothesis 1a, formulated as: "Results corresponding to the cognitive and affective dimensions of consumer engagement provided by the various algorithms of consumer neuroscience technologies are not correlated", we performed correlation analysis between the metrics corresponding to the consumer neuroscience algorithms (Kopernica and Facet-iMotions). Specifically, we performed the following analysis:

- Interest (Cognitive engagement Kopernica) versus Workload (Cognitive engagement *iMotions)*
- Interest (Cognitive engagement Kopernica) versus Cognitive state (Cognitive engagement *iMotions*)
- Valence+/- (Affective engagement Kopernica) versus Valence +/- (Affective engagement *iMotions*)

Table 57 shows the results corresponding to correlations corresponding to cognitive dimension.

Table 57: Correlation algorithms. Interest vs. Workload and Cognitive State

		Cognitive Engagement: Interest (Kopernica)
Cognitive Engagement: Workload (iMotions)	Pearson correlation	-,111
	Sig. (bilateral)	,181
	N	147
Cognitive Engagement: Cognitive state (iMotions)	Pearson correlation	-,005
	Sig. (bilateral)	,951
	N	148

Source: Author

As table 57 shows, the correlations of interest (Kopernica) with workload (*iMotions*) are negative, but not significant. Table 57 also shows, the correlations of interest (Kopernica) with cognitive state (*iMotions*). As can be seen, this correlation is negative, but not significant. These results are in line with previous results from workload.

This result indicates that the cognitive dimension that these algorithms measure is different. This finding supports H1a1 ("Results corresponding to the cognitive dimension of consumer engagement provided by the various algorithms of consumer neuroscience technologies are not correlated").

Table 58 shows the results corresponding to each to affective dimension.

Table 58: Correlation algorithms. Valence+ and -.

		1	2	3	4
1. Affective Engagement: Valence + (Kopernica)	Pearson correlation			-,074	-,008
	Sig. (bilateral)			,360	,918
	N			154	155
2. Affective Engagement: Valence - (Kopernica)	Pearson correlation			,074	,008
	Sig. (bilateral)			,360	,918
	N				
3. Affective Engagement: Valence + (Facet iMotions)	Pearson correlation				
	Sig. (bilateral)				
	N				
4. Affective Engagement: Valence - (Facet iMotions)	Pearson correlation				
	Sig. (bilateral)				
	N				

Source: Author

As can be seen in table 58, neither of the two valence metric correlations with the algorithms considered is significant. This finding supports H1a2 ("Results corresponding to the affective dimension of consumer engagement provided by the various algorithms of consumer neuroscience technologies are not correlated").

Although the non-significance of the results has already been pointed out, it is striking that, for example, the valence + corresponding to the Kopernica algorithm is negatively correlated with the same construct measured by the *iMotions* algorithm. In this case, since the construct is the same, the question arises as to which of the two algorithms, if any, adequately measures the construct.

Since all the correlations examined show that the results obtained by different neuroscience algorithms are not significant, we conclude that hypothesis 1a. is supported. Therefore, there is no relationship between the results obtained with the various neuroscience algorithms considered. This finding raises questions about which is the best applicable neuroscience algorithm to measure the effectiveness of video ads.

<u>Hypothesis 1b</u>

To contrast Hypothesis 1b, we correlate Dessart et al. (2016) based-survey results, with based-consumer neuroscience technologies results. Specifically, first, for cognitive engagement dimension, we correlate Attention and Absorption (survey) with workload and cognitive state EEG-engagement (FACET *iMotions*). Tables 59 and 60 show the lineal correlations corresponding to cognitive dimension.

Table 59: Factors Attention and Absorption (Cognitive engagement survey) versus workload.

		Factorial Engagement: 1.Cognitive 2.Absorption (Survey)	Factorial Engagement: 1.Cognitive 1.Attention (Survey)	Engagement Cognitive: Workload (EEG iMotions)
Factorial Engagement: 1.Cognitive 2.Absorption (Survey)	Pearson correlation	1	,000	**,033**
	Sig. (bilateral)		1,000	**,680**
	N	176	176	**162**
Factorial Engagement: 1.Cognitive 1.Attention (Survey)	Pearson correlation	,000	1	**-,120**
	Sig. (bilateral)	1,000		**,129**
	N	176	176	**162**
Engagement Cognitive: Workload (EEG iMotions)	Pearson correlation	,033	-,120	1
	Sig. (bilateral)	,680	,129	
	N	162	162	166

Source: Author

As can be seen in table 59, the workload metric, measured by iMotions EEG technology, does not significantly correlate with neither of the two dimensions of cognitive engagement measured by surveys. Although the non-significance of the results has already been pointed out, it is interesting to consider the sign of the correlations. Both seem coherent, since higher workload can lead to less attention but, at the same time, greater absorption.

Table 60: Factors Attention and Absorption (Cognitive engagement survey) versus cognitive state (Cognitive engagement, iMotions EEG).

		Engagement Cognitive: Cognitive State (iMotions EEG)
Factorial Engagement: 1.Cognitive 2.Absorption (Survey)	Pearson correlation	**,073**
	Sig. (bilateral)	**,352**
	N	**163**
Factorial Engagement: 1.Cognitive 1.Attention (Survey)	Pearson correlation	**,133**
	Sig. (bilateral)	**,090**
	N	**163**

Source: Author

Regarding the correlation between attention and absorption with cognitive state (*iMotions* EEG technology), table 60 indicates this variable does not significantly correlate with neither of the two dimensions of cognitive engagement measured by survey.

These findings do not support H1b1 ("There is a correlation between consumer engagement cognitive results measured through a survey and through some neuroscience algorithms").

After correlating the cognitive metrics, the ones corresponding to the affective dimension of consumer engagement are considered below. Tables 61 and 62 show their linear correlations.

Table 61 shows results of the correlations between enthusiasm and enjoyment, measured by survey, and arousal (or emotional intensity), valence + and valence -, affective metrics provided by Kopernica.

Table 61: Factors Enthusiasm and Enjoyment (Affective engagement survey) versus Intensity or Arousal, Valence+ and Valence- (Affective engagement Kopernica)

		Factorial Engagement: 2.Affective 2.Enjoyment (Survey)	Factorial Engagement: 2.Affective 1.Enthusiasm (Survey)	Engagement Affective: Intensity or Arousal (Kopernica)	Engagement Affective: Valence + (Kopernica)	Engagement Affective: Valence - (Kopernica)
Factorial Engagement: 2.Affective 2.Enjoyment (Survey)	Person correlation	1	,000	**,000**	**,039**	**-,039**
	Sig. (bilateral)		1,000	**,999**	**,638**	**,638**
	N	176	176	**152**	**152**	**152**
Factorial Engagement: 2.Affective 1.Enthusiasm (Survey)	Person correlation	,000	1	**-,062**	**,039**	**-,039**
	Sig. (bilateral)	1,000		**,448**	**,633**	**,633**
	N	176	176	**152**	**152**	**152**
Engagement Affective: Intensity or Arousal (Kopernica)	Person correlation	,000	-,062	1	-,951**	,951**
	Sig. (bilateral)	,999	,448		,000	,000
	N	152	152	156	156	156
Engagement Affective: Valence + (Kopernica)	Person correlation	,039	,039	-,951**	1	-1,000**
	Sig. (bilateral)	,638	,633	,000		,000
	N	152	152	156	156	156
Engagement Affective: Valence - (Kopernica)	Person correlation	-,039	-,039	,951**	-1,000**	1
	Sig. (bilateral)	,638	,633	,000	,000	
	N	152	152	156	156	156

**. Correlation is significant at the level 0,01 (bilateral).

Source: Author

Table 61 show that neither of the two dimensions of affective engagement measured by survey is significantly correlated with any of the metrics used by Kopernica. As in previous correlations, however the non-significance of the results already pointed out, it is interesting to consider the sign of the correlations. Correlations de valence+ and valence- with enthusiasm and enjoyment, both seem coherent, since higher valence+ lead to higher enthusiasm and enjoyment, while higher valence- lead to lower enthusiasm and enjoyment. Less consistent are the correlations with arousal, in which a positive relationship was expected.

Table 62 shows the lineal correlations among enthusiasm and enjoyment (survey) with valence+, and valence- (Facet *iMotions*).

Table 62: Factors Enthusiasm and Enjoyment (Affective engagement survey) versus Intensity or Arousal, Valence+ and Valence- (Affective engagement Facet iMotions)

		Factorial Engagement: 2.Affective 2.Enjoyment (Survey)	Factorial Engagement: 2.Affective 1.Enthusiasm (Survey)	Engagement Affective: Valencia+ (Facet iMotions)	Engagement Affective: Valencia- (Facet iMotions)
Factorial Engagement: 2.Affective 2.Enjoyment (Survey)	Pearson correlation	1	,000	-,071	-,183*
	Sig. (bilateral)		1,000	,354	,017
	N	176	176	171	172
Factorial Engagement: 2.Affective 1.Enthusiasm (Survey)	Pearson correlation	,000	1	-,121	-,109
	Sig. (bilateral)	1,000		,116	,155
	N	176	176	171	172
Engagement Affective: Valencia+ (Facet iMotions)	Pearson correlation	-,071	-,121	1	,030
	Sig. (bilateral)	,354	,116		,694
	N	171	171	175	174
Engagement Affective: Valencia- (Facet iMotions)	Pearson correlation	-,183*	-,109	,030	1
	Sig. (bilateral)	,017	,155	,694	
	N	172	172	174	176

*. Correlation is significant at the level 0,05 (bilateral).

Source: Author

Table 62 show that only enjoyment and valence - metrics are significantly associated. Its relationship is negative. This result is consistent as it indicates that valence - is inversely related to enjoyment. Although the non-significance of the remaining correlations has already been pointed out, in relation to the signs, the negative relationship between enthusiasm and enjoyment with valence + is surprising, since as liking for the ad should increase. enthusiasm and enjoyment.

So that, Hypothesis 1b2 (“There is a correlation between consumer engagement affective results measured through a survey and through some neuroscience algorithms”) is partially supported because, although most of the correlations between the metrics considered are not significant, a significant correlation was found:

- Negative: Enjoyment (Affective engagement, survey) and Valence – (FACET-*iMotions*).

4.4.2 Results about video ads effectiveness in mobile, PC and TV

The second group of hypothesis integrates those that propose that advertising videos inserted in different devices generate different results in various metrics related to dimensions of consumer engagement. In other words, a video ad has different scores on consumer neuroscience metrics depending on the device on which it communicates.

As was expressed, when proposing the hypotheses in Chapter 3, each one was broken down into two sub-hypotheses corresponding, respectively, to the comparisons between mobile and PC and between mobile and TV. Hypotheses referred to:

H2a: Cognitive workload of video ads.

H2b: Attention in mobile video ads.

H2c: Recall memory in mobile video ads.

H2d: Arousal in mobile video ads.

H2e: Valence in mobile video ads.

H2f: Video ads intrusiveness.

<u>Hypothesis 2a</u>

Hypothesis 2a refers to cognitive workload of video ads. To validate, or not, this hypothesis we will use EEG technique and two T test independent means, one for mobile versus PC and another for mobile versus TV. Tables 63 and 64 show the results, respectively.

Table 63 shows the T test results corresponding to the workload in mobile vs. PC.

Table 63: T Test. Mobile versus PC

		F	Sig.	t	df	Sig. (bilateral)	Mean difference	Standard error difference
Engagement Cognitive: Workload (EEG iMotions)	Equal variance assumed	,008	,930	2,863	108	,005	,06164294	,02153460
	Equal variance not assumed.			2,861	107,254	,005	,06164294	,02154246

	Device	N	Mean	Standard deviation	Standard error mean
Engagement Cognitive: Workload (EEG iMotions)	Mobile	57	**,6261599**	,11231220	,01487611
	PC	53	**,5645169**	,11343397	,01558135

Source: Author

Once the Levene test for equality of variances has been carried out, which is not significant, the results indicate the existence of a significant mean difference (at level 0.005). As can be seen, the cognitive workload of mobiles is greater than that of PCs. Thus, the results obtained in the T test support Hypothesis 2a1: cognitive workload in mobile is higher than in PC.

Table 64 shows the T test results corresponding to the workload in mobile vs TV.

Table 64: Test T: Mobile versus TV

		F	Sig.	t	df	Sig. (bilateral)	Mean difference	Standard error difference
Engagement Cognitive: Workload (EEG iMotions)	Equal variance assumed	2,061	,154	5,540	111	,000	,10606117	,01914413
	Equal variance not assumed			5,551	106,590	,000	,10606117	,01910642

	Device	N	Mean	Standard deviation	Standard error mean
Engagement Cognitive: Workload (EEG iMotions)	Mobile	57	**,6261599**	,11231220	,01487611
	TV	56	**,5200987**	,08972376	,01198984

Source: Author

As in the previous T test, once the Levene test for equality of variances has been carried out, which is not significant, the results indicate the existence of a significant mean difference (at level 0.000). As can be seen, the cognitive workload of mobiles is greater than that of TV.

This result support Hypothesis 2a2: cognitive workload mean is higher in mobile video ads than in TV.

Regarding the workload difference between mobile and PC and TV results show difference in means between all of them. Mobile (M= 0,63 SD=0,11), PC (M= 0,56 SD=0,11) and TV (M= 0,52 SD=0,08). Difference in means between Mobile and PC is (0,07), difference between mobile and TV is (0,11) and difference between PC and TV is (0,04). Hypotheses are supported.

<u>Hypothesis 2b</u>

Hypothesis 2b refers to attention in mobile video ads. In order to contrast this hypothesis, we will use interest (Kopernica) metric, to measure attention, and two T test independent means (one for mobile versus PC and another for mobile versus TV). Tables 65 and 66 show the results, respectively.

Table 65 shows the T test results corresponding to the interest (attention) in mobile vs. PC.

Table 65: T Test. Mobile versus PC. Interest.

		F	Sig.	t	df	Sig. (bilateral)	Mean difference	Standard error difference
Engagement Cognitive: Interest (Kopernica)	Equal variance assumed	5,755	,018	-4,293	106	,000	-,09580796	,02231808
	Equal variance not assumed			-4,166	84,894	,000	-,09580796	,02299915

	Device	N	Mean	Standard deviation	Standard error mean
Engagement Cognitive: Interest (Kopernica)	Mobile	49	,4976531	,13479603	,01925658
	PC	59	,5934610	,09659479	,01257557

Source: Author

As in the previous T test, once the Levene test for equality of variances has been carried out, which is not significant, the results indicate the existence of a significant mean difference (at level 0.000). As can be seen, the attention in PC is higher than in mobile.

This result does not support Hypothesis 2b1: Attention, mean is not higher in mobile video ads than in PC.

Table 66 shows the T test results corresponding to the interest (attention) in mobile vs. TV.

Table 66: T Test. Mobile versus TV. Interest.

		F	Sig.	t	df	Sig. (bilateral)	Mean difference	Standard error difference
Engagement Cognitive: Interest (Kopernica)	Equal variance assumed	4,170	,044	-2,562	96	,012	-,06154082	,02402282
	Equal variance not assumed			-2,562	88,783	,012	-,06154082	,02402282

	Device	N	Mean	Standard deviation	Standard error mean
Engagement Cognitive: Interest (Kopernica)	Mobile	49	,4976531	,13479603	,01925658
	TV	49	,5591939	,10053718	,01436245

Source: Author

As in the previous T test, once the Levene test for equality of variances has been carried out, which is not significant, the results indicate the existence of a significant mean difference (at level 0.000). As can be seen, the attention in TV is higher than in mobile.

As attention mean is not higher in mobile video ads than in TV, Hypothesis 2b2 ("Attention to a mobile video ad is higher than in TV") is not supported.

Regarding interest differences between mobile and PC and TV results show significative difference in means between all of them. Mobile (M= 0,50 SD=0,13), PC (M= 0,59 SD=0,10) and TV (M= 0,56 SD=0,10). Difference in means between Mobile and PC is (0,09), difference between mobile and TV is (0,06) and difference between PC and TV is (0,03). We can see that interest in mobile is lower than PC and TV, but those differences are not very big, being the maximum 0,09 between mobile and PC.

<u>Hypothesis 2c</u>

Hypothesis 2c refers to recall memory in mobile video ads. To validate, or not, this hypothesis we will use survey data and four T test independent means, two considering free recall (one for mobile versus PC and another for mobile versus TV) and two considering cued recall (one for mobile versus PC and another for mobile versus TV). Tables 67, 68, 69 and 70 show the results, respectively.

Table 67 shows the T test results corresponding to free recall in mobile vs. PC.

Table 67: T Test. Mobile versus PC. Free recall.

		F	Sig.	t	df	Sig. (bilateral)	Mean difference	Standard error difference
Free recall (Survey)	Equal variance assumed	,006	,938	,039	115	,969	,003	,067
	Equal variance not assumed			,039	114,932	,969	,003	,067

	Device	N	Mean	Standard deviation	Standard error mean
Free recall (Survey)	Mobile	59	**,85**	,363	,047
	PC	58	**,84**	,365	,048

Source: Author

Once the Levene test for equality of variances has been carried out, which is not significant, the results indicate that there are no significant differences in free recall between mobile and PC.

Table 68 shows the T test results corresponding to cued recall in mobile vs. PC.

Table 68: T Test. Mobile versus PC. Cued recall.

		F		Sig.	t	df	Sig. (bilateral)	Mean difference	Standard error difference
Cued recall. (Survey)	Equal variance assumed	8,903		,003	-1,441	115	,152	-,067	,047
	Equal variance not assumed				-1,446	95,614	,151	-,067	,046

	Device	N	Mean	Standard deviation	Standard error mean
Cued recall (Survey)	Mobile	59	**,90**	,305	,040
	PC	58	**,97**	,184	,024

Source: Author

As in the previous T tests, once the Levene test for equality of variances has been carried out, which is not significant, the results indicate that there are no significant differences in cued recall between Mobile and PC. These results do not support Hypothesis 2c1: recall means are not lower in mobile video ads than in PC.

Table 69 shows the T test results corresponding to free recall in mobile vs. TV.

Table 69: T Test. Mobile versus TV. Free recall.

		F	Sig.	t	df	Sig. (bilateral)	Mean difference	Standard error difference
Free recall (Survey)	Equal variance assumed	,954	,331	,487	116	,627	,034	,070
	Equal variance not assumed			,487	115,267	,627	,034	,070

	Device	N	Media	Standard deviation	Standard error mean
Free recall (Survey)	Mobile	59	**,85**	,363	,047
	TV	59	**,81**	,393	,051

Source: Author

As in the previous T test, once the Levene test for equality of variances has been carried out, which is not significant, the results indicate that there are no significant differences in free recall between mobile and TV.

Table 70 shows the T test results corresponding to cued recall in mobile vs. TV.

Table 70: T Test. Mobile versus TV. Cued recall.

		F	Sig.	t	df	Sig. (bilateral)	Mean difference	Standard error difference
Cued recall (Survey)	Equal variance assumed	,000	1,000	,000	116	1,000	,000	,056
	Equal variance not assumed			,000	116,000	1,000	,000	,056

	Device	N	Mean	Standard deviation	Standard error mean
Cued recall (Survey)	Mobile	59	,90	,305	,040
	TV	59	,90	,305	,040

Source: Author

As in the previous T tests, once the Levene test for equality of variances has been carried out, which is not significant, the results indicate that there are no significant differences in cued recall between mobile and TV.

Therefore, Hypothesis 2c2 is not supported because neither the free recall mean difference nor the cued recall mean difference are significantly different between the mobile device and the TV device and, consequently, recall memory in mobile video ads is not lower than in TV.

Hypothesis 2d

Hypothesis 2d refers to arousal in mobile video ads. In order to contrast this hypothesis, we will use a Kopernica metric called intensity and two T test independent means, (one for mobile versus PC and another for mobile versus TV). Tables 71 and 72 show the results, respectively.

Table 71 shows the T test results corresponding arousal or intensity in mobile vs. PC.

Table 71: T Test. Mobile versus PC. Intensity or arousal.

		F	Sig.	t	df	Sig. (bilateral)	Mean difference	Standard error difference
Engagement Affective: Intensity or Arousal (Kopernica)	Equal variance assumed	1,478	,227	-,816	106	,416	-,05820699	,07131262
	Equal variance not assumed			-,809	98,111	,421	-,05820699	,07196257

	Device	N	Mean	Standard deviation	Standard error mean
Engagement Affective: Intensity or Arousal (Kopernica)	Mobile	49	,4339388	,38823163	,05546166
	PC	59	,4921458	,35221341	,04585428

Source: Author

Once the Levene test for equality of variances has been carried out, which is not significant, the results indicate that there are no significant differences in arousal or intensity between Mobile and PC. This result does not support Hypothesis 2d1: arousal mean is not higher in mobile video ads than in PC.

Table 72 shows the T test results corresponding to arousal in mobile vs. TV.

Table 72: T Test. Mobile versus TV. Intensity or arousal.

		F	Sig.	t	df	Sig. (bilateral)	Mean difference	Standard error difference
Engagement Affective: Intensity or Arousal (Kopernika)	Equal variance assumed	6,595	,012	-,741	95	,460	-,05366122	,07238024
	Equal variance not assumed			-,743	92,380	,459	-,05366122	,07223796

	Device	N	Mean	Standard deviation	Standard error mean
Engagement Affective: Intensity or Arousal (Kopernica)	Mobile	49	**,4339388**	,38823163	,05546166
	TV	48	**,4876000**	,32067379	,04628527

Source: Author

As in the previous T test, once the Levene test for equality of variances has been carried out, which is not significant, the results indicate that there are no significant differences in arousal or intensity between mobile and TV. Hypothesis 2d2 also is not supported for intensity or arousal because arousal in mobile video ads is not higher than in TV.

Hypothesis 2e

Hypothesis 2e refers to valence in mobile video ads. To validate, or not, this hypothesis we will use valence metrics, from Kopernica and Facet-iMotions, and eight T test independent means two (one for mobile versus PC and another for mobile versus TV) for each following four metrics: valence+ and valence– (Kopernica), and valence+ and valence– (Facet-*iMotions*). Tables 73, 74, 75 and 76 show the results for mobile and PC, while tables 77, 78, 79 and 80 show the results for mobile and TV.

Table 73 shows the T test results corresponding to valence+ (Kopernica) in mobile vs. PC.

Table 73: T Test. Mobile versus PC. Valence + Kopernica.

		F	Sig.	t	df	Sig. (bilateral)	Mean difference	Standard error difference
Engagement Affective: Valence + (Kopernica)	Equal variance assumed	,008	,931	1,175	106	,243	,07403490	,06300648
	Equal variance not assumed			1,169	100,321	,245	,07403490	,06330514

	Device	N	Mean	Standard deviation	Standard error mean
Engagement Affective: Valence + (Kopernica)	Mobile	49	**,5052959**	,33492947	,04784707
	PC	59	**,4312610**	,31839242	,04145116

Source: Author

Once the Levene test for equality of variances has been carried out, which is not significant, the results indicate that there are no significant differences in valence+ (Kopernica) between mobile and PC.

Table 74 shows the T test results corresponding to valence- (Kopernica) in mobile vs. PC.

Table 74: T Test. Mobile versus PC. Valence - Kopernica.

		F	Sig.	t	df	Sig. (bilateral)	Mean difference	Standard error difference
Engagement Affective: Valencia - (Kopernica)	Equal variance assumed	,008	,931	-1,175	106	,243	-,07403490	,06300648
	Equal variance not assumed			-1,169	100,321	,245	-,07403490	,06330514

	Device	N	Mean	Standard deviation	Standard error mean
Engagement Affective: Valencia - (Kopernica)	Mobile	49	**,4947041**	,33492947	,04784707
	PC	59	**,5687390**	,31839242	,04145116

Source: Author

As in the previous T tests, once the Levene test for equality of variances has been carried out, which is not significant, the results indicate that there are no significant differences in valence- (Kopernica) between mobile and PC.

Table 75 shows the T test results corresponding to valence+ (Facet-*iMotions*) in mobile vs. PC.

Table 75: Mobile versus PC. Valence + Facet iMotions.

		F	Sig.	t	df	Sig. (bilateral)	Mean difference	Standard error difference
Engagement Affective: Valencia+ (Facet iMotions)	Equal variance assumed	7,009	,009	1,450	116	,150	,30986552	,21363093
	Equal variance not assumed			1,475	59,017	,145	,30986552	,21001107

	Device	N	Mean	Standard deviation	Standard error mean
Engagement Affective: Valencia+ (Facet iMotions)	Mobile	60	**,3146000**	1,62662153	,20999594
	PC	58	**,0047345**	,01919683	,00252067

Source: Author

Once the Levene test for equality of variances has been carried out, which is not significant, the results indicate that there are no significant differences in valence + (Facet iMotions) between mobile and PC.

Table 76 shows the T test results corresponding to valence - (Facet-iMotions) in mobile vs. PC.

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Table 76: Mobile versus PC. Valence - Facet iMotions.

		F	Sig.	t	df	Sig. (bilateral)	Mean difference	Standard error difference
Engagement Affective: Valencia- (Facet iMotions)	Equal variance assumed	6,358	,013	3,130	116	,002	1,96321356	,62719182
	Equal variance not assumed			3,130	97,935	,002	1,96321356	,62719182

	Device	N	Mean	Standard deviation	Standard error mean
Engagement Affective: Valencia- (Facet iMotions)	Mobile	59	**3,4107729**	4,07288628	,53024463
	PC	59	**1,4475593**	2,57301431	,33497793

Source: Author

As in the previous T tests, once the Levene test for equality of variances has been carried out, which is not significant, the results indicate that there are no significant differences in valence- (Facet *iMotions*) between mobile and PC.

Hypothesis 2e1 is not supported because valence in mobile video ads is not more negative than in PC.

Table 77 shows the T test results corresponding to valence+ (Kopernica) in mobile vs. TV.

Table 77: T Test. Mobile versus TV. Valence + Kopernica.

		F	Sig.	t	df	Sig. (bilateral)	Mean difference	Standard error difference
Engagement Affective: Valencia+ (Kopernica)	Equal variance assumed	1,624	,206	1,054	95	,295	,06693550	,06350748
	Equal variance not assumed			1,056	93,463	,294	,06693550	,06340906

	Device	N	Mean	Standard deviation	Standard error mean
Engagement Affective: Valencia+ (Kopernica)	Mobile	49	**,5052959**	,33492947	,04784707
	TV	48	**,4383604**	,28828048	,04160970

Source: Author

Once the Levene test for equality of variances has been carried out, which is not significant, the results indicate that there are no significant differences in valence + (Kopernica) between mobile and TV.

Table 78 shows the T test results corresponding to valence- (Kopernica) in mobile vs. TV.

Table 78: Mobile versus TV. Valence- Kopernica.

		F	Sig.	t	df	Sig. (bilateral)	Mean difference	Standard error difference
Engagement Affective: Valencia- (Kopernica)	Equal variance assumed	1,624	,206	-1,054	95	,295	-,06693550	,06350748
	Equal variance not assumed			-1,056	93,463	,294	-,06693550	,06340906

Source: Author

	Device	N	Mean	Standard deviation	Standard error mean
Engagement Affective: Valencia- (Kopernica)	Mobile	49	**,4947041**	,33492947	,04784707
	TV	48	**,5616396**	,28828048	,04160970

Source: Author

As in the previous T tests, once the Levene test for equality of variances has been carried out, which is not significant, the results indicate that there are no significant differences in valence- (Kopernica) between mobile and TV.

Table 79 shows the T test results corresponding to valence+ (Facet-*iMotions*) in mobile vs. TV.

Table 79: Mobile versus TV. Valence+ Facet *iMotions*.

		F	Sig.	t	df	Sig. (bilateral)	Mean difference	Standard error difference
Engagement Affective: Valencia+ (Facet iMotions)	Equal variance assumed	4,386	,038	1,099	115	,274	,23928772	,21770065
	Equal variance not assumed			1,127	61,686	,264	,23928772	,21237492

	Device	N	Mean	Standard deviation	Standard error mean
Engagement Affective: Valencia+ (Facet iMotions)	Mobile	60	**,3146000**	1,62662153	,20999594
	TV	57	**,0753123**	,23932045	,03169877

Source: Author

Once the Levene test for equality of variances has been carried out, which is not significant, the results indicate that there are no significant differences in valence + (Facet iMotions) between mobile and PC.

Table 80 shows the T test results corresponding to valence- (Facet-*iMotions*) in mobile vs. TV.

Table 80: Mobile versus TV. Valence- Facet *iMotions*.

		F	Sig.	t	df	Sig. (bilateral)	Mean difference	Standard error difference
Engagement Affective: Valencia- (Facet iMotions)	Equal variance assumed	,953	,331	1,440	115	,152	1,02406254	,71092602
	Equal variance not assumed			1,442	113,716	,152	1,02406254	,71017020

	Device	N	Mean	Standard deviation	Standard error mean
Engagement Affective: Valencia- (Facet iMotions)	Mobile	59	**3,4107729**	4,07288628	,53024463
	TV	58	**2,3867103**	3,59785720	,47242180

Source: Author

As in the previous T tests, once the Levene test for equality of variances has been carried out, which is not significant, the results indicate that there are no significant differences in valence- (Facet *iMotions*) between mobile and TV.

Therefore, Hypothesis 2e2 is not supported because means difference results are not significant for mobile versus TV, both for valence+ and valence– in Kopernica and *iMotions* algorithms. Valence in mobile video ads is not more negative than in TV.

Hypothesis 2f

Hypothesis 2f refers to mobile video ads intrusiveness. To validate, or not, this hypothesis we will use survey data and two T test independent means (one for mobile versus PC and another for mobile versus TV). Tables 81 and 82 show the results, respectively.

Table 80 shows the T test results corresponding to intrusiveness (Survey) in mobile vs. PC.

Table 81: Mobile versus PC. Intrusiveness (Survey).

		F	Sig.	t	df	Sig. (bilateral)	Mean difference	Standard error difference
Intrusiveness (survey)	Equal variance assumed	2,272	,134	,650	115	,517	,119	,183
	Equal variance not assumed			,650	114,985	,517	,119	,183

	Device	N	Mean	Standard deviation	Standard error mean
Intrusiveness (survey)	Mobile	59	**2,12**	1,001	,130
	PC	58	**2,00**	,973	,128

Source: Author

Once the Levene test for equality of variances has been carried out, which is not significant, the results indicate that there are no significant differences in intrusiveness between Mobile and PC.

Hypothesis 2f1 ("Mobile video ads are more intrusive than video ads in PC") is not supported because mobile video ads are not significantly more intrusive than ads in PC.

Table 82 shows the T test results corresponding to intrusiveness (Survey) in mobile vs. TV.

Table 82: Mobile versus TV. Intrusiveness (Survey).

		F	Sig.	t	df	Sig. (bilateral)	Mean difference	Standard error difference
Intrusiveness (survey)	Equal variance assumed	1,213	,273	-,168	116	,867	-,034	,202
	Equal variance not assumed			-,168	112,823	,867	-,034	,202

	Device	N	Mean	Standard deviation	Standard error mean
Intrusiveness (survey)	Móbile	59	**2,12**	1,001	,130
	TV	59	**2,15**	1,186	,154

Source: Author

Once the Levene test for equality of variances has been carried out, which is not significant, the results indicate that there are no significant differences in intrusiveness between mobile and TV.

Therefore, Hypothesis 2f2 is not supported for intrusiveness measured for survey data and, consequently, mobile video ads are not more intrusive than ads in TV.

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CHAPTER 5. CONTRIBUTIONS, IMPLICATIONS, LIMITATIONS AND FUTURE LINES

This Doctoral Thesis it's part of the effort that researchers and practitioners have done and continue to do, to get thorough knowledge about the impact that digital advertising has in the advertising industry, furthermore, the impact that mobile advertising has on consumers and the effectiveness that this advertising brings to brands.

As mobile is currently the main device that consumers use to access internet, this Doctoral Thesis concentrates in analyzing all aspects, about mobile advertising: Current expenditure, main mobile platforms used by consumers, formats and strategies used by brands, and finally, a number of problems such as mobile screen size compared to PC or TV. To our knowledge, the comparison of the effect of several videos on different devices –mobile, PC and TV- on measures related to the dimensions of consumer engagement is the first research that compares these three devices with different size screens that consumers use regularly in their lives.

The mobile screen size is a problem for brands when they must design ads. One of the solutions, among others, is the use of full screen video-ads, as video is the main content consumed in mobile. This Doctoral Thesis incorporates the analysis of the impact that full screen video-ads has on mobile small screen size problem.

To measure mobile advertising effectiveness this Doctoral Thesis combines two methodologies, survey and consumer neuroscience. Survey is a traditional methodology while consumer neuroscience methodology is relatively novel.

One of the main problems that the consumer neuroscience methodology faces is the lack of metrics and their standardization. This Doctoral Thesis uses two different Software Vendors algorithms, Kopernica and Facet, and compares the results, based on their metrics, to identify whether they provide different results, or not. To our knowledge it is the first study that compares these two algorithms and the first one to use the new Kopernica algorithm from *Neurologyca*.

Based on the mentioned analysis, two sets of hypotheses were proposed:

1. A set of hypotheses based on the analysis of the correlation between the two algorithms above, and the correlation between consumer neuroscience metrics and metrics based on the traditional survey methodology.

2. Another set that uses consumer neuroscience metrics, -cognitive workload, interest, arousal and valence- and survey metrics -recall and intrusiveness- It analyze the

differences between mobile, PC and TV, the three main devices which consumers currently interact with.

Results of all these hypotheses were analyzed in detail. First, a descriptive analysis was made with aggregate data and by device; later, exploratory factor analysis was also used and, finally, correlation analysis, in cognitive and affective dimension, between Kopernica and FACET algorithms metrics was done.

In this chapter, the conclusions and the implications on the advertising industry of each set generated by hypotheses are commented:

1. The contributions and implications resulting from the analysis of the correlation between different algorithms and with the survey

2. The contributions and implications of each of the hypothesis about differences between the three devices, mobile, PC and TV.

Finally, limitations of this research were commented, and several future research lines proposed.

5.1 **Conclusions and contributions: set 1 of hypotheses**

Metrics related to the cognitive dimension provided by the various algorithms of consumer neuroscience technologies are not correlated; neither metrics related to the affective dimension provided by the various algorithms of consumer neuroscience technologies.

Regarding cognitive dimension, the correlation of the interest (Kopernica) with the workload (*iMotions*) is negative, and not significant. This is also the case with the correlation between the interest (Kopernica) and the cognitive state (*iMotions*). As can be seen, this correlation is negative, but not significant.

This result indicates that the cognitive dimension that these algorithms measure is different. Since attention and interest should theoretically be positively related, the lack of correlation between them raises questions about what each algorithm measures.

In relation to the affective dimension, neither of the two valence metric correlations with the algorithms considered is significant. Although the non-significance of the results has already been pointed out, it is striking that, for example, the valence + corresponding to the Kopernica algorithm is negatively correlated with the same construct measured by the iMotions algorithm. In this case, since the construct is the same, the question arises as to which of the two algorithms, if any, adequately measures the construct.

Our results show that correlations between Kopernica metrics and iMotions metrics are not significant. Facet and Kopernica results of valence using same stimulus and participants in the same place and at the same time is an example. There are two main explanations for these results. First, Software Vendors are different which main explain the different results; further, they do not explain algorithms composition, so it is not possible to understand where those difference come from. Second, regarding valence measured through FEA, Software Vendors use different databases of faces expressions to compare with the ones obtained during the experiments in order to identify the emotions, and as consequence results are also different.

As all the results obtained by different neuroscience algorithms examined show that the correlations are not significant, we conclude that hypothesis H1a is supported. Therefore, there is no relation between the results obtained with the various neuroscience algorithms considered. This result raises questions about which is best applicable neuroscience algorithm to measure the cognitive effectiveness of video ads.

These findings are not surprising as they correspond to those obtained by other researchers (Alcañiz et al. 2017; Varan et al. 2015) and reveal, once again, the lack of standardization of consumer neuroscience metrics, an important problem of this methodology.

Results, corresponding to the cognitive and affective dimensions of consumer engagement provided by the survey and the various algorithms of consumer neuroscience technologies, show one significant correlation, so hypothesis H1b is partially supported.

When the survey is used to obtain consumer engagement data, and data on this construct is also obtained by consumer neuroscience techniques, a positive relation between both results is expected. A positive association between the results of survey data and data from neuroscience technologies would indicate that both methodologies are convergent in the measurement of engagement, which strengths the research results. On the contrary, the non-correlation between the results raises several questions. First, do the various methodologies really measure engagement? Second, if so, which one provides the best results? Third, should the various methodologies be used in a complementary way in order to have a more comprehensive view of the ad's effectiveness?

Correlations between attention and absorption (survey) with workload and cognitive state (EEG-engagement, *iMotions*) were not significant, although is interesting to point out, that both seem coherent, since higher workload can lead to less attention but, at the same time, greater absorption, as we comment in previous analysis. Also, correlations between enthusiasm and enjoyment (affective engagement survey) versus intensity or arousal, valence + and valence - (affective engagement Kopernica) were not significant. That said, it is interesting to comment on the meaning of the relationship found: Valence + and valence - correlations with enthusiasm and enjoyment, both seem coherent, since higher valence + lead to higher enthusiasm and enjoyment, while higher valence - lead to lower enthusiasm and enjoyment. Less consistent are the correlations with arousal, in which a positive relationship was expected.

The only significant correlation was found between enjoyment (affective engagement, survey) and valence – (FACET-*iMotions*), which were negatively correlated. This result is consistent as it indicates that valence - is inversely related to enjoyment. Although the non-significance of the remaining correlations has already been pointed out, in relation to the signs, the negative relationship between enthusiasm and enjoyment with valence + is surprising, since as liking for the ad should increase enthusiasm and enjoyment.

Although there is a significant correlation and therefore, hypothesis H1b is partially supported, we cannot suggest any implication for practitioners based on this finding, as the other correlations are not significant.

5.2 **Conclusions and contributions: Set 2 of hypotheses.**

Both hypotheses, H2a1 and H2a2 are supported, due to the existence of a significant mean difference, cognitive workload in mobile is higher in PC and TV. Despite full screen video ads are used, cognitive workload in TV is lower than PC or mobile. As we can see, differences between the three devices are small, maximum is 0,11. In line with this, results suggest that the TV bigger screen size reduce workload, however it is worth to mention that PC has the minimum workload value (Min=0,27) and not the TV despite its bigger size screen (Min=0,34). Also, it is interesting to note that minimum workload value in mobile and TV are the same (0,34), in line with our idea of similar values among the three devices due the increase of screen size in mobiles and the consumption of full screen videos on mobiles.

Regarding hypotheses H2b, results show that attention is higher in PC and TV than in mobile. Hypothesis H2b1 and H2b2 are not supported. There are significant mean differences in attention but means in PC and TV are significantly higher than in mobile. Video ads on TV and on PC get more attention than on mobiles. These findings are opposite to what was hypothesized and MMA's (2020) results.

Higher interest in PC than TV is in line with Brasel and Gips' (2011) results, in terms of gaze duration higher on PC than TV, and with Babiloni (2019). We do not have a clear explanation why PC gets the higher interest compared to other two devices, since the larger screen size is not a valid explanation.

Our findings suggest that, just mobile full screen video format, it's not enough to capture consumers attention, although, it may have contributed to reduce the difference in attention with the other two devices, PC and TV.

Hypothesis H2c1 and H2c2 are not supported because neither the free recall means difference, nor the cued recall mean difference are significantly different between the mobile and PC or TV devices. Consequently, recall memory in mobile video ads is not lower than in PC or TV. Means are very similar in both free and cued recall and even the same (mean and standard deviation) in cued recall between mobile and PC. Most of participants remember quite well brands used in the stimulus and these results are different from Muñoz-Leiva et al. (2019), who suggests that participants in studies do not recall most ads.

Our explanation is that, as participants had to answer free and cued recall questions in the survey immediately after they finished the consumer neuroscience experiment, so they were able to remember brands more easily than if they had completed the survey later. Also, doing the experiment in the laboratory with all the consumer neuroscience equipment can lead to biases because in the experimental context participants probably increase their concentration, being higher than in normal life, and remember better the brands.

Hypothesis H2d1 and H2d2 are not supported. Results show that there is no significant mean difference in intensity or arousal on mobile versus TV, although the mean is lower in mobile and in PC.

Hypothesis H2d1 and H2d2 are not supported. Results point out that there is no significant mean difference in intensity or arousal on mobile versus PC or TV. Although this lower mean in arousal in mobile is in line with Lombard et al. (2000) and Reeves at al. (1999), we suggest that the increase in size in new mobile devices and the use of video ads full screen may have reduced the effect of screen size in arousal, so it is not registered difference in arousal, in line with Wesel and Moser (2017).

Coming back to Reeves et al. (1999), who posits that higher arousal of bigger size screens could positively affect memory recall, we cannot confirm it, as there is no difference in arousal between the three devices, mobile, PC and TV.

Valence hypotheses H2e1 and H2e2 are not supported because means difference results are not significant for mobile versus PC or TV, both for valence+ and valence– in Kopernica and *iMotions* algorithms. The valence value in mobile video ads is not more negative than in PC or TV.

Despite means difference are not significant, based on our findings, it is interesting to stress that negative valence mean in mobile have a difference of 1,96 against PC and 1,02 against TV, which is consistent with Werlen and Moser (2017) findings, that valence was more negative on a small screen compared to a large screen. We conclude that mobile video ads in full screen may reduce the difference in negative valence against PC or TV ads, but we do not have previous data to compare with.

Finally, hypotheses H2f1 and H2f2 are not supported, because mobile video ads are not more intrusive than ads on PC or TV.

Although mean for mobile is higher than PC, surprisingly, TV intrusiveness mean is higher than in mobile and it is not consistent with Truong and Simmons (2010) conclusion, that smaller screen size made participants are more susceptible to advertising intrusiveness on their mobile phones when compare with bigger size screens.

Our explanation is that participants that saw the stimulus in TV don't like the content of the ad, therefore the perception of intrusiveness was higher.

The age of the participants may also be a contributing factor to explain higher intrusiveness of the ad on TV than on PC, as most of them were young people that do not usually watch.

Probably the difference in intrusiveness in mobile versus other devices may be lower due to the use of full screen video ads to present the stimulus.

5.3 **Implications for marketing managers.**

Based on the two sets of hypotheses above, we analyze different implications for marketing managers as following:

With regards the first set of hypotheses, the findings of our research reveal the following implications:

- It is better to use one software vendor, tools for studies with consumer neuroscience, for all experiments to have same algorithm for all analysis, even if there is no consensus about which is the best one.

- May be necessary to implement a common database for all FEA analysis.

- Seems necessary to establish standard definitions of each consumer neuroscience metric and how to measure them.

- Is convenient to develop guidelines for reporting results of each consumer neuroscience technology that may help standardize measurement. In this line, Fiedler et al (2020) eye-tracking guideline is a good reference.

With regards the second set of hypotheses, our findings suggest that practitioners should:

- Take care in the design of ads so that they do not contribute to increase cognitive workload. As cognitive workload is higher in mobile than PC or TV with same video stimulus, ads in mobile should be with less text in big size font that are easy to read and few images that communicate main message. In this line, findings suggest also to use better video, in advertising design in mobile, than text in order not to increase workload.

- Design ads specifically for mobile devices that take advantage of mobile full screen. As portrait position is most used in mobile, as we mention before, it is recommended to use video format that take better advantage of full screen like interstitials format.

- Design mobile ads different from PC or TV ads to take care about low attention from mobile. As we suggest above full screen videos are interesting, but these videos should be personalized, if possible, to capture consumers' attention.

- Design mobile ads taking into consideration the small size of your screen to have an effective recall. One important measure of advertising effectiveness is recall and our findings suggest that practitioners when designing ads do not have to take much care about screen size. We suggest that content of the video may contribute more to the recall of the ad than screen size.

- Design mobile ads, from the perspective of increasing arousal, different from PC or TV ads. We suggest that these ads should be, when it is possible, in video format full screen, like interstitials, to get better results in arousal. When it is not possible to use video ads in full screen format, we recommend to the practitioners use another variable like personalization in order to reduce screen size impact in arousal.

- Maximize consumers positive emotional associations with the brand, while minimizing negative associations. For it, practitioners when designing mobile ads should use full screen video ads that may reduce negative emotions.

- Design mobile ads to decrease intrusiveness impact. We recommend to practitioners use video format full screen.

5.4 **Limitations.**

Several limitations have been identified, during and after research was conducted, that may affect results and implications. These limitations should be comment to be considered when assessing the implications and propose new future research lines.

The main limitations identified are related to carrying out the experiment in a laboratory, sample size, mobile phone handling, and stimuli.

Regarding to the experiment in laboratory, limitations stem from the fact that participants were probably conditioned, producing laboratory biases. Neuroscience laboratory may:

- Generate stress when participants see all the technological devices that they must wear, like EEG sensors on the scalp or GSR on the finger, and probably this stress may affect the results.
- Increase the concentration of the participants. Probably participants are more concentrated in experiments in the laboratory than they are in normal life, so they remember much better brands.
- Enhance attention of the participants. Although any information on the objective of the research was given to the participants in the experiment when they entered the laboratory, there is always an alert to know which is the purpose of the research, that may affect the results. This bias does not happen when participants are out of the laboratory using their mobiles, PC or interacting with an smart TV.
- Affect emotional state of the participants. Laboratory coordinator explanations, while preparing the participant for the experiment, are affected by the emotional state of the coordinator every day, that could influence the emotional state of the participants and influence the results.

Regarding sample size, limitations stem from the fact that consumer neuroscience studies use small sample sizes, between 30 and 100 participants. Although researchers as Meng-Hsien et al. (2018) point out this perceived limitation is often due to some misperceptions regarding neuroscience data, our findings suggest that sample size may be also another limitation.

- In some of the output data from technological equipment, like EEG or FEA, we got no values in some participants, due to different problems: movements of the participant, bad face detection or errors of the equipment. Consequently, we suggest that samples in consumer neuroscience studies should be between 50 and 100 participants minimum.

Regarding mobile handling, limitation derive from participants did not handle the mobile in their hands. Mobile was in a fix position in the mobile device “Stand de Tobii” and that is not the natural way consumers handle and navigate with the mobile; so, this type of handling may affect results.

- In this point another limitation may be that mobile phone was always in portrait position, which is the main position consumers use, so videos were always seen this way but actually, depending on content, consumers use landscape position, for example, to see series.

- Also, participants did not use their on mobile phones; so probably some measures may be affected.

Regarding stimuli, we use content in platforms based in famous TV programs "*El Hormiguero*", "*Got talent*" and a *YouTube* cheesecake receipt, but so we put a limitation on which content they could navigate, and this may emotionally affect the experience when participants saw embedded video ads. In addition, there was a limitation about stimulus personalization. It was not possible to use previous consumer data from mobile to personalize ads. This lack of personalization probably affects some results.

5.5 **Future research lines.**

The analysis carried out on neuroscience technologies, as well as the limitations identified in our study, constitute the basis for proposing future lines of research. This proposal is specified in the following lines:

To do this experiment not in laboratory but in normal life, with consumers using their mobiles and interacting with TV or a PC in their favorite platforms. Using FEA and Eye-tracking, with users' camera, at home can be manage by new software vendors like *Neurologyca* and *iMotions*.

To analyze definitions for each of the metrics used by different software vendors and academics to propose and define standards for each one of those metrics.

- To compare mobile videos ads in landscape and portrait position to see if cognitive workload is lower in landscape and has similar results to other devices like PC or TV reducing workload differences.

- To use two sets of ads -personalize ads based on consumer data and ads that are not personalized- and compare attention on different devices -mobile, PC and TV- to see what percentage of attention is due to screen size and what percentage is due to personalization.

- To examine if the age affects attention and perceived intrusiveness as young people do not watch TV.

- To use more than one ad per device to analyze free or cued recall based on the content of different ads and analyze which of the two factors -content or screen size- explains better ad recall. In this line, also may be interesting to test groups of different ads as they usually appear in internet platforms and analyze recall based on the position of ads in different devices to understand which is the impact of different positions in different devices.

- To analyze which is the contribution of two factors -personalize content and video format full screen- on arousal and check if personalized content contribution is higher that video format, so practitioners may use another mobile format.
- To explore arousal in mobile with different mobile formats, like banner (most used) and native, vs other devices like PC or TV.

- To design personalized stimuli to compare them with no personalized stimuli and analyze positive and negative emotions and consumer’s intrusiveness perceptions in different devices.

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APPENDIXES

6.1 Consumer engagement scales

Customer engagement scale in an online social platform. 18 items.

Table 83: Customer engagement scale in an online social platform.

Items	Dimension 1: Absorption (Cognitive)
1	1. Using this online social platform is so absorbing that I forgot about everything else.
2	2. I am rarely distracted when using this online social platform.
3	3. I am immersed in this online social platform.
4	4. My mind is focused when using this online social platform.
5	5. I pay a lot of attention to this online social platform.
	Dimension 2: Dedication (Emotional)
6	1. I am enthusiastic in this online social platform.
7	2. This online social platform inspires me.
8	3. I found this online social platform full of meaning and purpose.
9	4. I am excited when using this online social platform.
10	5. I am interested in this online social platform.
11	6. I am proud of using this online social platform.
	Dimension 3: Vigor (Behavioral)
12	1. I can continue using this online social platform for very long periods at a time.
13	2. I feel strong and vigorous when I am using this online social platform.
14	3. I feel very resilient, mentally, as far as this online social platform is concerned.
15	4. In this online social platform, I always persevere, even when things do not go well.
16	5. I devote a lot of energy to this online social platform.
17	6. I try my hardest to perform well on this online social platform.
18	7. Time flies when I am using this online social platform.

Source: Cheung et al. (2011)

Customer Engagement Scale. 10 items

Table 84: Customer Engagement Scale

Items	Dimension 1: Conscious attention
1	1.Anything related to _____ grabs my attention
2	2.I like to learn more about ______
3	3.I pay a lot of attention to anything about _______
	Dimension 2: Enthused participation
4	1.I spend a lot of my discretionary time ____
5	2.I am heavily into _______
6	3.I am passionate about _____
7	4.My days would not be the same without ___
	Dimension 3: Social connection
8	1.I love ______ with my friends
9	2.I enjoy ______ more when I am with others
10	3.______ is more fun when other people around me do it, too

Source: Vivek (2013)

Consumer Brand Engagement Scale. 10 items.

Table 85: Consumer brand engagement scale.

Items	Dimension 1. Cognitive processing
1	1. Using (brand [hereafter B]) gets me to think about (B)
2	2. I think about (B) a lot when I'm using it
3	3. Using (B) stimulates my interest to learn more about (B)
	Dimension 2: Affection
4	1. I feel positive when I use (B)
5	2. Using (B) site makes me happy
6	3. I feel good when I use (B)
7	4. I'm proud to use (B)
	Dimension 3: Activation
8	1. I spend a lot of time using (B), compared with other (category) brands
9	2. Whenever I'm using (category), I usually use this (B)
10	3. (B) is one of the brands I usually use when I use (category)

Source: Hollebeek et al. (2014)

Customer Engagement for Online Brand Communities Scale. 22 items.

Table 86: Customer Engagement for Online Brand Communities Scale

Items	**Dimension 1: Cognitive**
	1.1 Attention
1	1. I spend a lot of time thinking about (EF)
2	2. I make time to think about (EF)
	1.2 Absorption
3	1. When interacting with (EF), I forget everything else around me
4	2. Time flies when I am interacting with (EF)
5	3. When I am interacting with (EF), I get carried away
6	4. When interacting with (EF), it is difficult to detach myself
	Dimension 2: Affective
	2.1 Enthusiasm
7	1. I feel enthusiastic about (engagement focus [hereafter EF])
8	2. I am interested in anything about (EF)
9	3. I find (EF) interesting
	2.2 Enjoyment
10	1. When interacting with (EF), I feel happy
11	2. I get pleasure from interacting with (EF)
12	3. Interacting with (EF) is like a treat for me
	Dimension 3: Behavioral
	3.1 Sharing
13	1. I share my ideas with (EF)
14	2. I share interesting content with (EF)
15	3. I help (EF)
	3.2 Learning
16	1. I ask (EF) questions
17	2. I seek ideas or information from (EF)
18	3. I seek help from (EF)
	3.3 Endorsing
19	1. I promote (EF)
20	2. I try to get others interested in (EF)
21	3. I actively defend (EF) from its critics
22	4. I say positive things about (EF) to other people

Source: Dessart et al. (2016)

Consumer's Engagement with Brand-Related Social-Media Content Scale. 17 items.

Table 87: **Consumer's Engagement with Brand-Related Social-Media Content Scale.**

Items	Dimension 1: Consumption
1	1. I read posts related to Brand X on social media
2	2. I read fan page(s) related to Brand X on social networking sites
3	3. I watch pictures/graphics related to Brand X
4	4. I follow blogs related to Brand X
5	5. I follow Brand X on social networking sites
	Dimension 2: Contribution
6	1. I comment on videos related to Brand X
7	2. I comment on posts related to Brand X
8	3. I comment on pictures/graphics related to Brand X
9	4. I share Brand X related posts
10	5. I "Like" pictures/graphics related to Brand X
11	6. I "Like" posts related to Brand X
	Dimension 3: Creation
12	1. I initiate posts related to Brand X on blogs
13	2. I initiate posts related to Brand X on social networking sites
14	3. I post pictures/graphics related to Brand X
15	4. I post videos that show Brand X
16	5. I write posts related to Brand X on forums
17	6. I write reviews related to Brand X

Source: Schivinski et al. (2016)

6.2 Questionnaire.

Questionnaire sample used for data collection.(Spanish)

First part:

1. ¿Qué marca/marcas recuerdas haber visto?
2. ¿Recuerdas haber visto un anuncio de [Oreo/Samsung/Dominos pizza]? Elegir una o varias.
3. Enumera los elementos que recuerdes de ese anuncio:
4. ¿Cómo calificarías tu nivel de molestia de 1 a 5 (Siendo 1 nada molesto y 5 muy molesto con la publicidad de [Oreo/Samsung/Dominos pizza] que has visto?

Second part: Dessart Survey

Elige una de las marcas que recuerdas: [Oreo/Samsung/Dominos pizza] para contestar a estas preguntas:

5. Pienso muchas veces acerca de esta marca. (Valora de 1 a 5)
6. Parte de mi tiempo pienso en esta marca. (Valora de 1 a 5)
7. Cuando interactúo con esta marca, me olvido de todo lo demás. (Valora de 1 a 5)
8. El tiempo vuela cuando interactúo con esta marca (Valora de 1 a 5)
9. Cuando interactúo con esta marca, me dejo llevar. (Valora de 1 a 5)
10. Cuando interactúo con esta marca me es difícil desconectar. (Valora de 1 a 5)
11. Estoy entusiasmado con esta marca (Valora de 1 a 5)
12. Estoy interesado en todo lo que tenga que ver con esta marca (Valora de 1 a 5)
13. Esta marca me parece interesante. (Valora de 1 a 5)
14. Cuando interactúo con esta marca me siento contento. (Valora de 1 a 5)
15. Obtengo placer al interactuar con esta marca (Valora de 1 a 5)
16. Interactuar con esta marca es un regalo para mí. (Valora de 1 a 5)
17. Comparto mis ideas con esta marca (Valora de 1 a 5)
18. Comparto contenido interesante con esta marca (Valora de 1 a 5)
19. Ayudo a esta marca (Valora de 1 a 5)
20. Hago preguntas a esta marca (Valora de 1 a 5)
21. Busco ideas o información sobre esta marca (Valora de 1 a 5)
22. Busco ayuda de esta marca (Valora de 1 a 5)
23. Promuevo esta marca (Valora de 1 a 5)
24. Intento que otros se interesen por esta marca (Valora de 1 a 5)
25. Defiendo a esta marca de aquellos que la critican (Valora de 1 a 5)
26. Digo cosas positivas sobre esta marca a otras personas (Valora de 1 a 5)

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